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How Do Undergraduate Students Adopt Online Learning in Chengdu, China During COVID-19?

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Abstract

Purpose: 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 user behavior. **Research design, data, and methodology:** The target population is 500 undergraduates. The sample techniques are purposive, stratified random, convenience, and snowball samplings. Before collecting the data, The Item Objective Congruence (IOC) Index and the pilot test (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). **Results:** The results reveal that perceived ease of use significantly impacts perceived usefulness and behavioral intention. Attitude and facilitating conditions significantly impact behavioral intention. Behavioral intention has a significant impact on user behavior. On the contrary, perceived usefulness and social influence have no significant impact on behavioral intention. **Conclusions:** 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.

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

Online learning has expanded dramatically recently, as endorsed by "information and communication technology (ICT)." Online learning provides several key advantages when compared with traditional offline education. Firstly, online learning offers student-centric where instructions can be customized and instant feedback received (Balacheff & Kaput, 1996). Next, online learning can promote accessibility and quality with cost-effectiveness (Lynch & Kim, 2017). Lastly, online learning provides ease of use and accessibility for learning opportunities in remote areas with limited resources (Baum & McPherson, 2019). According to Organisation for Economic Co-operation and Development (2021), 1.5 billion students in 188 countries/economies were

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locked out of their schools during the pandemic. These advantages extended during the pandemic's lockdown in early 2020, when most of the world's educational institutions were disrupted by limited physical contact for health and safety reasons.

While various nations were forced to implement online learning to safeguard the continuous studying derived from social-distance measures, the Ministry of Education in China restricted physical classrooms and encouraged students to use online learning. Consequently, online learning adoption has been experimented with on a large scale across China (McBurnie et al., 2020). Some drawbacks of online learning have been found regarding learning efficiency, socializing capability, and engagement (Reimers & Schleicher, 2020). However, students with privilege or who are affordable can continue their education with online learning resources, while students in rural or remote areas need more access (Dhawan, 2020). Guo and Wan (2022) postulated that online learning has great potential to substitute offline education in people's daily lives, not only during the pandemic. Since the suspension due to the pandemic, over 200 million students in China have extended their learning continuity since then. Online learning can be the enlightenment for digital education improvement in China and worldwide.

Furthermore, although many studies have assessed the technology adoption model, which can be varied from different perspectives such as e-textbooks (Hsiao & Tang, 2014), synchronous and asynchronous video (Cohen, 2022), ubiquitous learning (Lin, 2013), hybrid education (Luo et al., 2022), internet banking (Martins et al., 2014), and ERP system (Wongsabsin, 2021), not sufficient research has projected the most suitable framework to determine the user behavior of online learning. Therefore, 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)

Technology Acceptance Model (TAM) originated to explain the adoption of information technology and users' behavior (Davis, 1989). It has been widely discussed in the sense of what motivations behind users to use a new technological system (Davis et al., 1989). 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 user behavior.

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

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. Many studies used UTAUT to investigate online learning adoption. Tran and Nguyen (2021) pointed out that 52% of the UTAUT R-square accounts for behavioral intention. Thus, UTAUT is becoming more significant as an efficient model of adoption of different technologies since online, and internet-based technologies have emerged and grown exponentially (Martins et al., 2014).

2.3 Perceived Ease of Use

Perceived ease of use is a key construct in the Technology Acceptance Model (TAM) that originated to explain the adoption of information technology and users' behavior (Davis, 1989). Perceived ease of use in this study is defined as "student's motivation and knowledge of whether or not an online learning system is simple to use, and students expect that the usage of online learning system is not difficult to use" (Min et al., 2022). According to TAM, this research addresses the relationship between perceived ease of use and perceived usefulness**.** It has been elaborated that students' psychological state to explain the intention and use behavior to use online learning is how easy and beneficial such a system offers them (Leaderer et al., 2000). 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). Min et al. (2022) attested that students' motivation comes from evaluating the effort put into using online learning. It involves the online learning system and tools that make students easily engage and repeatedly use to accomplish their learning tasks. Hence, this study can be hypothesized that:

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

In TAM, perceived usefulness is one of the main variables in users' adoption of the new system technology (Chuttur, 2009). In general, perceived usefulness is "the degree to which a person believes that using a particular system would enhance his or her job performance." Several scholars mentioned perceived usefulness as "the prospective user's subjective probability that using a specific application system will increase his or her expected performance" (Davis, 1989; Venkatesh et al., 2012). This study supports that students believe that online learning has various advantages, which leads to the strong need to engage in online learning modules. Lin (2013) assumed that useful online learning could endorse a strong intention to use students. Teo et al. (2003) applied TAM and emphasized that the high usefulness of a system reassures a higher degree of participation in system technology. Based on the above discussions, this research hypothesized that:

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

2.5 Attitude

Chauhan (2015) defined attitude as users' psychological and mental state that can be expressed toward particular things. Attitude is "an individual's evaluation which can be positive or negative emotion towards the specific object" (Fishbein & Ajzen, 1981). The definition of attitude toward using technology is "a disposition to respond favorably or unfavorably to an object, person, institution or event" (Ajzen, 2005). Attitude in the TAM is "an individual's evaluation or feelings about using the system technology" (Davis et al., 1989). This study supports that students believe that online learning has various advantages, which leads to the strong need to engage in the online learning module. Chauhan (2015) stated that attitude could predict behavioral intentions to use a system technology. Attitude designates the intrinsic motivation to use technology, which impacts a person's behavior. Users may have negative or positive feelings about using technology (Chiu et al., 2017). Based on the above discussions, this research hypothesized that:

H4: Attitude has a significant impact on behavioral intention.

2.6 Social Influence

Venkatesh et al. (2003) posted that social influence is "the degree to which an individual perceives that it is important that others believe he or she should use a new system." Bervell et al. (2017) stated that social influence is a crucial aspect of the technology adoption model, especially UTAUT. Luo et al. (2022) posited that social influence is "the influence of other persons considered significant on the decision of potential adopters to accept a new technology." Fishbein and Ajzen (1981) originated subjective norms, which were adapted to social influence by Venkatesh et al. (2003). Vermeir and Verbeke (2006) added that social impact coveys good and bad influences. According to Min et al. (2022), social influence as a dominance of other important persons affects learners' decision to use 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." Therefore, a hypothesis is developed:

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

2.7 Facilitating Conditions

Facilitating conditions are "the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of a system" Support infrastructure can be conceptualized as the tools and applications that facilitate the use of information technology (Venkatesh & Davis, 2000). Abbad et al. (2009) signified that facilitating conditions are "the degree to which users believe in the existence of an organization or infrastructure in the form of resources and support for system use, which relates to e-learning adoption of students." Venkatesh et al. (2003) indicated that an individual believes that an effective organization is required to facilitate the system use. Thus, the facilitation condition is a key variable in UTAUT. Xie et al. (2022) mentioned 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." According to the earlier discussions, a hypothesis is projected:

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

2.8 Behavioral Intention

Davis et al. (1989) defines behavioral intention as "the strength of one's intention to perform a specific behavior or use an information system." Behavioral intention is a powerful variable of the TAM and UTAUT model (Venkatesh & Davis, 2000). Behavioral intention or intention to use a particular technology is "an intrinsic motivation of individuals to perform behavior" (Davis, 1989). Kanwal et al. (2010) assessed the technology acceptance model of UTAUT and emphasized numerous determinants impacting the intention to use. Davis (1989) initiates the concept of behavioral intention to affect the use of behavior. Behavioral intention has also demonstrated the linkage of actual use behavior in the theory of the UTAUT model by Venkatesh et al. (2003). Thus, the last hypothesis is stated per the following:

H7: Behavioral intention has a significant impact on use behavior.

2.9 Use Behavior

The user behavior sometimes called actual system use, is "the performance of the actual behavior being measured" (Fishbein & Ajzen, 1981). Davis (1989) constructed the technology adoption model to investigate how users would be encouraged and motivated to use information technology. In the online learning system, usage behavior is "the frequency or degree of the use of the online learning system as well as whether and how frequently an individual uses the information system." (Efiloğlu Kurt, 2019). Queiroz and Wamba (2019) acknowledged that the intention to accept a particular technology occurs when a user actively sources to utilize a particular technology. To accomplish organizational benefits, the successful use of the technology should be promoted (Venkatesh et al., 2012) to generate a return on investment and gain market competitiveness (Kshetri, 2018). Cao and Jittawiriyanukoon (2022) revealed that behavioral intention strongly influences the use behavior of e-learning.

3. Research Methods and Materials

3.1 Research Framework

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

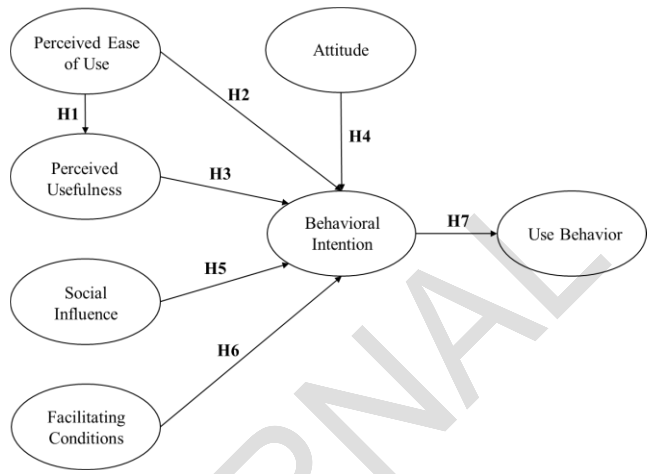

Figure 1: Conceptual Framework

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 the constructs have 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 (0.816), perceived usefulness (0.653), attitude (0.824), social influence (0.860), facilitating conditions (0.938), behavioral intention (0.908), and use behavior (0.631).

3.3 Population and Sample Size

This study's target population is undergraduates 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 undergraduates (n=500).

3.4 Sampling Technique

The data collection was implemented per sampling techniques, which allowed the researcher to systemize the research procedure to achieve the research aims. Hair et al. (2010) suggested that sampling procedures can help a researcher better consider the data collection. This quantitative research applied probability and nonprobability sampling, including purposive, stratified random, convenience, and snowball sampling. For purposive sampling, the research selected undergraduates 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 undergraduate students, 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 Undergraduates	Population Size of Undergraduates
Sichuan University (SCN)	37,000	234
University of Electronic Science and Technology of China (UESTC)	23,000	146
Southwest Minzu University (SWUN)	19,000	120
Total	79,000	500

4. Results and Discussion

4.1 Demographic Information

In Table 2, the demographic information shows that most respondents are males of 50.2 percent, followed by females 42.4, and unspecified 7.4. Most respondents are 21 years old or below (84.6 percent). For the year of study, sophomores are 39.6 percent, followed by seniors and juniors at 34.8 percent and 25.6 percent, respectively. Most students use online learning over 48 hours per week (38.4 percent).

Table 2: Demographic Profile

Demographic and General Data (n=500)		Frequency	Percentage
Gender	Male	251	50.2
	Female	212	42.4
	Unspecified	37	7.4
Age	21 years old or below	423	84.6
	22-30 years old	71	14.2
	31-40 years old	6	1.2
	40 years old or over	0	0.0
Year of Study	Sophomore	198	39.6
	Junior	128	25.6
	Senior	174	34.8
Frequency Of Online Learning Use	1-16 hours/week	56	11.2
	17-32 hours/week	65	13.0
	33-48 hours/week	187	37.4
	Over 48 hours/ week	192	38.4

4.2 Confirmatory Factor Analysis (CFA)

In CFA, the measurement of convergent validity can be done via composite reliability (CR) equal to or above 0.70, Cronbach's Alpha reliability (CA) equal to or above 0.60, factor loading equal to or above 0.50, and average variance extraction (AVE) equal to or above 0.50 (Straub et al., 2004). Thus, all estimates of CFA in Table 3 were significant.

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	0.879	0.814-0.886	0.878	0.706
2. Perceived Usefulness (PU)	Lin (2013)	4	0.793	0.686-0.712	0.793	0.490
3. Attitude (ATT)	Hsiao and Tang (2014)	3	0.883	0.812-0.876	0.883	0.716
4. Social Influence (SI)	Shen et al. (2019).	4	0.880	0.766-0.849	0.882	0.653
5. Facilitating Conditions (FC)	Shen et al. (2019).	4	0.835	0.679-0.814	0.836	0.561
6. Behavioral Intention (BI)	Hsiao and Tang (2014)	3	0.789	0.633-0.820	0.793	0.564
7. Use Behavior (UB)	Cao and Jittawiriyanukoon (2022)	3	0.717	0.602-0.720	0.722	0.465

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)	325.626/231 = 1.410
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.949
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.934
NFI	≥ 0.80 (Wu & Wang, 2006)	0.947
CFI	≥ 0.80 (Bentler, 1990)	0.984
TLI	≥ 0.80 (Sharma et al., 2005)	0.981
RMSEA	< 0.08 (Pedroso et al., 2016)	0.029
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	**0.846**						
PEOU	0.764	**0.840**					
PU	0.547	0.546	**0.700**				
SI	0.277	0.264	0.217	**0.808**			
FC	0.445	0.475	0.491	0.200	**0.749**		
BI	0.314	0.283	0.138	0.196	0.328	**0.751**	
UB	0.658	0.584	0.512	0.253	0.641	0.423	**0.682**

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

4.3 Structural Equation Model (SEM)

SEM is the "estimation of a system of linear equations to test the fit of a hypothesized "causal" model." It involves "a visualization of the hypothesized model or a "path diagram" based on prior studies, representing observed or directly measured variables and circles/ ovals typically represent unobserved or latent constructs which are defined by measured variables" (McDonald & Ho, 2002). The structural model represents the path diagram and model, which can be assessed through the goodness of fit, standardized coefficient values, and t-value. The results after the adjustment in Table 6 were acceptable fit with CMIN/DF = 3.924, GFI = 0.873, AGFI = 0.844, NFI = 0.844, CFI = 0.878, TLI = 0.862, and RMSEA = 0.077.

Table 6: Goodness of Fit for Structural Model

Index	Acceptable Values	Statistical Values Before Adjustment	Statistical Values After Adjustment
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015)	1153.205/245 = 4.707	957.404/244 = 3.924
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.833	0.873
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.796	0.844
NFI	≥ 0.80 (Wu & Wang, 2006)	0.812	0.844
CFI	≥ 0.80 (Bentler, 1990)	0.845	0.878
TLI	≥ 0.80 (Sharma et al., 2005)	0.825	0.862
RMSEA	< 0.08 (Pedroso et al., 2016)	0.086	0.077
Model Summary		**Unacceptable Model Fit**	**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

In Table 7, 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	0.546	9.803*	Supported
H2: PEOU→BI	0.147	3.964*	Supported
H3: PU→BI	0.017	0.609	Not Supported
H4: ATT→BI	0.120	4.049*	Supported
H5: SI→BI	0.030	1.449	Not Supported
H6: FC→BI	0.189	4.679*	Supported
H7: BI→UB	0.245	4.899*	Supported

Note: * p<0.05

Hypotheses testing results can be elaborated per the followings:

H1 shows that perceived ease of use significantly impacts perceived usefulness, resulting in the standardized path coefficient value of 0.546 (t-value = 9.803). Perceived ease of use in this study is the student's motivation and knowledge of whether or not an online learning system is simple to use, and students expect that the usage of online learning will be useful to them (Min et al., 2022).

In **H2**, the relationship between perceived ease of use and behavioral intention is supported with a standardized path coefficient value of 0.147 (t-value = 3.964). It has been elaborated that students' psychological state to explain the intention and use behavior to use online learning is how easy and beneficial such a system offers them (Leaderer et al., 2000).

For **H3**, perceived usefulness has no significant impact on behavioral intention, reflecting the standardized path coefficient value of 0.017 (t-value = 0.609). The result contradicts previous claims that perceived usefulness is "the prospective user's subjective probability that using a specific application system will increase his or her expected performance" (Davis, 1989; Venkatesh et al., 2012).

H4 approves the significant impact of attitude on students' behavioral intention, representing a standardized path coefficient value of 0.120 (t-value = 4.049). The result signifies that attitude designates the intrinsic motivation to use technology, which impacts a person's behavior. Users may have negative or positive feelings about using technology (Chiu et al., 2017).

H5 fails to support the relationship between social influence and students' behavioral intention with a standardized path coefficient of 0.030 (t-value = 1.449). Therefore, the result opposes social influence as the dominance of other important persons affects learners' decision to use online learning (Min et al., 2022).

H6 confirms that facilitating conditions significantly impact behavioral intention with a standardized path coefficient value of 0.189 (t-value = 4.679). Consequently, 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 (Venkatesh et al., 2003; Xie et al., 2022).

The results of **H7** present that behavioral intention significantly impacts the use behavior of students with a standardized path coefficient value of 0.245 (t-value = 4.899). Davis (1989) initiates the concept of behavioral intention to affect the use of behavior. Behavioral intention has also demonstrated the linkage of actual use behavior in the theory of the UTAUT model by Venkatesh et al. (2003).

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 results reveal that perceived ease of use significantly impacts perceived usefulness and behavioral intention. Attitude and facilitating conditions significantly impact behavioral intention. Behavioral intention has a significant impact on user behavior. On the contrary, perceived usefulness and social influence have no significant impact on behavioral intention.

The findings are implied. First, perceived ease of use significantly impacts perceived usefulness and behavioral intention. According to TAM, this research addresses the relationship between perceived ease of use and perceived usefulness. Leaderer et al. (2000) elaborated that students' psychological state to explain the intention and use behavior to use online learning is how easy and beneficial such a system offers them.

Second, attitude and facilitating conditions significantly impact behavioral intention. Fishbein and Ajzen (1981) theorized that an individual's evaluation could be positive or negative towards using technology. In addition, Venkatesh et al. (2003) indicated that an individual believes that an effective organization is required to facilitate the system use. Thus, the facilitation condition can also facilitate the behavioral intention of students to use online learning.

Next, behavioral intention significantly impacts user behavior and is approved by the TAM and UTAUT as the motivation behind users to use a new technological system

(Davis et al., 1989; Venkatesh et al., 2003). Kanwal et al. (2010) added that both TAM and could be emphasized to determine the students' behavioral and use behavior of online learning.

Last, this study pointed out that perceived usefulness and social influence have no significant impact on behavioral intention. Zhong et al. (2022) also found non-supported relationships between perceived usefulness and attitude toward students' behavioral intention to use online learning in China. Xie et al. (2022) also revealed that facilitation conditions had no significant influence on behavioral intention. The study explained that when students may perceive more efficiency in the physical classroom and online learning needs to be more practical.

5.2 Recommendation

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. In China, national and local governments, the private sector, and civil society have been working together to ensure that best-fit technologies that serve online learning equally and reduce the gap in online infrastructure across the country. The efforts pursue to grant access to 50 million students and teachers to connect simultaneously with the exploitation of technological resources such as TV broadcasting and social media live streaming. The monitoring and evaluation scheme is built to measure students' learning outcomes, and education programs are adjusted to ensure the highest effectiveness of online education (UNESCO, 2022). Therefore, educators should focus on perceived ease of use, usefulness, attitude, social influence, facilitating conditions, and behavioral intention to drive a higher adoption rate.

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 universities and government should focus on maximizing the online learning technology capability to enhance the adoption of online learning among students in higher education in the region. Facilitating conditions can be endorsed regarding hardware software and online platforms that must be highly developed. Additionally, the universities and government can exploit the opportunity to gain education market competitiveness at the global level by offering online education to other countries in the region.

Online learning is a good solution during the pandemic. However, the main problem of new students enrolling in online courses involves that students perceive low engagement and a high degree of passivity in such a format compared to the traditional classroom. Therefore, for students to accept change, online education's ease of use and usefulness should be promoted. The perceived credibility of online learning is relatively low, and the perceived value in attending a campus institution and social education is essential to develop new skills and knowledge. Thus, social influence can be encouraged to enhance adoption. The problems for students are that many schools have old and outdated hardware and software. Hence, facilitation conditions can be implied as internet infrastructure, fast connectivity, and online learning system must be efficient.

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.

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