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Factors Influencing College Students' Use Behavior of Online Learning Platforms in Sichuan, China

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Abstract

Purpose: After the COVID-19 pandemic, online learning has become an essential approach for undergraduates to pursue study in higher education institutions. This study investigates the factors that affected the college students' use behavior when applying to online learning platforms in Sichuan, China, including perceived ease of use, usefulness, attitude, social influence, facilitating conditions, behavioral intention, and use behavior. **Research design, data, and methodology:** 500 undergraduates in a college were taken as the research respondents. The validity and reliability of the variables were confirmed through the IOC (Item-Objective Congruence) and Pilot test (n=43) prior to collecting data. Construct validity (convergent and discriminant validities) and goodness of model fit were confirmed through the test of Confirmatory Factor Analysis (CFA), and relationships among variables were validated through the Structural Equation Model (SEM). **Results:** Perceived ease of use strongly affects perceived usefulness. Both perceived ease of use and perceived usefulness are strong predictors of attitude. Behavioral intention is influenced by attitude, perceived usefulness, and social influence. Positive behavioral intention leads to use behavior. However, facilitating conditions have no significant impact on behavioral intention. **Conclusion:** The research results provide teachers and administrations of the higher education system with a perspective to optimize their teaching methods and policies to promote college students' utilization of online learning platforms.

Keywords : Online Learning, Perceived Usefulness, Attitude, Behavioral Intention, Use Behavior

JEL Classification Code: E44, F31, F37, G15

1. Introduction

Online learning is an old concept that did not just come after the Internet and information technology. It has been around for a while. In 17th-century England, interested citizens could sign up for correspondence courses. Teachers send materials and homework to the students, and then students send them back to teachers for evaluation (Frecker & Bieniarz, 2021). People's communication improved in the early 1900s, and they began to gain knowledge through the radio. Teachers at the University of Wisconsin created a ham radio station in 1919. It was the first legal radio station that focused on education. Soon after the television was invented, more people could go to college because of the creation of telecourses, where people could study through the television. However, the development of distance learning did speed up when the 1990s witnessed the evolution of communication technology (Frecker & Bieniarz, 2021).

The quick development of online learning was largely due to the recent 20 years' rapid growth of mobile communication and Internet. Boca (2021) claimed that the utilization of the computer Internet has transformed the scope of education, which brought education to a new stage called Education 4.0.-- the new era of communication technology provided education with more potential. Online learning allows for customizing the learning experience to fit one's needs and preferences, helping students individually when needed. It offered all students great education and learning chances, no matter where they lived. Skilled teachers use the Internet and many digital resources to teach

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(Watson, 2008).

With the increase in the Chinese economy, the Chinese demand for online education has been growing very fast, and the outbreak of COVID-19 accelerated the expansion of online learning in higher education. The pandemic crisis forced many universities in China to utilize online learning systems, although this conduct was not a norm before (Xue et al., 2020). Based on the 45th Statistical Report on Internet Development in China" by China Internet Network Information Center (CNNIC, 2020), until March 2020, the online education population of China had reached 423 million, with a 222 million increase compared with the end of 2018.

The popularity of online learning applications in college education increased during the COVID-19 pandemic. There is a great need to study the effect of digital platforms on online learning and what may influence students' adoption of online platforms. This study studied the factors that affected college students' behavior when applying to online learning platforms in Sichuan, China.

2. Literature Review

2.1 Perceived Ease of Use

Venkatesh and Davis (2000) stated that perceived ease of use was the conception of the extent to which an individual decided to apply the technology. According to Davis et al. (1989), perceived ease of use meant the extent to which someone considered it would be to utilize a specific system. Kleijnen et al. (2004) presented it as how much customers could use the service in their everyday life. Based on Davis's (1989) study, perceived ease of use significantly determines whether someone would want to use a new technology. Robey and Farrow (1982) stated that if people noticed the ease of using one system, they were more likely to think it was useful. Brown and Licker (2003) stated that how much a new technology was conceived as useful was determined by their belief in its ease of use. Bhattacherjee (2000) put forward that the degree of ease of use affected the user's attitude. The simplicity of learning a system would confirm the customer's usefulness (Wu & Chen, 2005). Liu and Gao (2013) specified that attitude toward users' inclination to adopt mobile web was greatly influenced by perceived ease of use. Chauhan (2015) study showed that the user's attitude towards adopting mobile money was positively affected by how easily it could be used. Thus, this study proposes below hypotheses:

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

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

2.2 Perceived Usefulness

Cheng et al. (2019) defined it as how useful the students thought PBWorks would be for finishing group discussions. Perceived usefulness means a person believes that adopting an updated technology could facilitate or promote one's ability (Davis, 1989, 1993). Sánchez et al. (2013) claimed that perceived usefulness referred to how much the system was conceived to enhance people's academic ability. Liu and Gao (2013) specified that perceived usefulness greatly influenced the attitude toward users' inclination to adopt the mobile web. Pituch and Lee (2006) presented that the users' attitude toward computer employment was strongly influenced by how useful they thought it would be. Bhattacherjee (2000) stated that how much new technology was conceived as useful influenced the attitude toward using it. Lee et al. (2015) proposed that the usefulness of a life insurance app service one conceived affected his/her attitude toward using it. Rahayu and Wirza (2020) proved that if the participants viewed the online learning system's usefulness, they would take a positive attitude toward it. Watjatrakul (2013) demonstrated that perceived usefulness affected the behavioral intention to use a new technology. Perry (2017) believed that in terms of adopting 3D-printed apparel, perceived usefulness was a determinant of usage intention. Huang et al. (2007) perceived that the user's strong belief in the usefulness of e-learning would generate upbeat thinking about it, increasing the possibility of using it. Thus, this study proposes below hypotheses:

H3: Perceived usefulness has a significant impact on attitude.

H4: Perceived usefulness has a significant impact on behavioral intention.

2.3 Attitude

Fishbein and Ajzen (1975) defined *attitude* as people's good or bad feelings about using a specific technology. Davis (1993) claimed that attitude was the extent of integration a person assessed to which job and a particular system could be combined. Cheng et al. (2019) defined it as how much the students wanted to share messages and feedback in group discussions through PBWorks. Attitude was defined as how users thought of the latest technology emotionally (Agarwal & Prasad, 1998). Davis et al. (1989) said that attitude greatly influenced predicting people's behavioral intentions. Chang (1998) found that people's good feelings about a specific technology would positively impact their adoption. Attitude had an essential impact on people's willingness to use e-voting system websites (Alomari, 2016). It indicated that attitude was not an indicator of individuals' behavior despite the relevance between the two (Festinger, 1962). Van den Berg et al. (2006) put forward that teachers' attitudes towards online education determined whether any online education would be successfully adopted. Lin et al. (2014) proposed that students' attitudes toward using E-learning systems would greatly influence their behavioral intentions. Thus, this study proposes below hypothesis:

H5: Attitude has a significant impact on behavioral intention.

2.4 Social Influence

Martin and Herrero (2012) stated that social influence meant the level to which the impact people one believed were important to them (friends or family) might have on their choice of using certain technologies. Social influence refers to how important the users view the significant people's conceptions and view them in terms of whether they should utilize the innovation (Venkatesh et al., 2003). Hsiao and Tang (2014) claimed that social influence refers to how others' confidence in e-booking can affect individuals. Other people's advice greatly affected and determined the adoption of one technology or product (Mallat et al., 2006). Social influence was considered a strong predictor of behavioral intention (Hoque et al., 2016). Batara et al. (2017) stated that a positive connection existed between social influence and people's intention to utilize new ICT systems. Gao et al. (2022) proved that social influence was the most significant determinant of students' behavioral intention towards online learning platforms in Sichuan. Fan et al. (2021) argued that the result of the study supported the hypothesis of social influence influencing college students' intention to use U-Learning. Thus, this study proposes below hypothesis:

H6: Social influence has a significant impact on behavioral intention.

2.5 Facilitating Conditions

Venkatesh et al. (2003) concluded that facilitation conditions, such as how well people recognize the aid from the perspective of institutions and technology, would enhance the employment of an updating system. Wiafe et al. (2019) claimed that facilitating conditions meant the level to which individuals could acquire the needed facilities, which assisted them in adopting the technology. Ukut and Krairit (2019) explained to what extent one conceived that the expected users within the institution could reach the resources needed for adopting an updated technology. Tan (2013) concluded that in terms of English E-learning services, facilitating conditions were a strong factor in predicting people's behavior in adopting the system. Teo (2010) believed facilitating conditions was an important factor for the pre-service teachers to form a welcoming opinion on adopting computers under education conditions. Thompson et al. (1991) proposed that whether students intended to adopt e-textbooks was not foretold by facilitating conditions. Facilitating conditions were believed to be a very important construct when an individual started to use something, no matter if it was impelled or conducted willingly, but later, the influence it put on use intention faded away (Payne & Curtis, 2008). Thus, this study proposes below hypothesis:

H7: Facilitating conditions have a significant impact on behavioral intention.

2.6 Behavioral Intention

Alshare et al. (2009) indicated that behavioral intention meant the extent to which one was assured to utilize ES. Behavioral intention was defined as a factor to evaluate the extent of individuals' willingness to make a move (Fishbein & Ajzen, 1975). Behavioral intention was a factor that connected people's desire and conviction with behavior (Malle & Knobe, 1997). Hsiao and Tang (2014) defined it as the chances that one intends to do a specific action. Triandis (1977) indicated that behavioral intention was an important factor that predicted the actual use behavior. Hubert et al. (2017) concluded that intention to use mobile purchase via smartphone had positively led to the behavior to conduct it. Teachers' behavior to post-adopt the interactive whiteboard was enforced by their active intention and supporting opinion of the device aided by right facilitating conditions (Šumak & Šorgo, 2016). Individuals conducted the behavior to employ an e-learning service, which was affected by the impact of their behavior intention (Jati & Laksito, 2012). Thus, this study proposes below hypothesis:

H8: Behavioral intention has a significant impact on use behavior.

2.7 Use Behavior

Venkatesh et al. (2003) portrayed use behavior as how often individuals use a technology. Chua et al. (2018) defined use behavior as a factor that validates how users adopt a technology. Gupta and Arora (2019) claimed that use behavior referred to the intensity of consumers' use of the mobile payment service. The actual conduct of a behavior was the consequence of people achieving its competency (Fogg, 2009). Use behavior was the method and time when people started using the technology, which could be seen by how often and why ICT (Information and Communication Technology) was used (Ukut & Krairit, 2019).

3. Research Methods and Materials

3.1 Research Framework

The previous research frameworks were applied to construct the basis of the study's conceptual framework. The variables included were perceived ease of use, social influence, perceived usefulness, attitude, facilitating conditions, behavioral intention, and use behavior. The conceptual framework is presented in Figure 1.

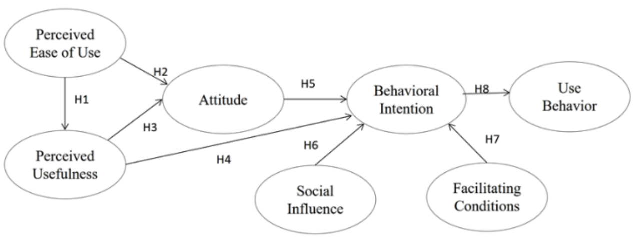

Figure 1: Conceptual Framework

H1: Perceived ease of use has a significant impact on perceived usefulness.
H2: Perceived ease of use has a significant impact on attitude.
H3: Perceived usefulness has a significant impact on attitude.
H4: Perceived usefulness has a significant impact on behavioral intention.
H5: Attitude has a significant impact on behavioral intention
H6: Social influence has a significant impact on behavioral intention.
H7: Facilitating conditions have a significant impact on behavioral intention.
H8: Behavioral intention has a significant impact on use behavior.

3.2 Research Methodology

The survey adopted quantitative methods as the methodology because the quantitative method explores the sampling framework representing the population characteristics and human behaviors in the natural environment. Based on the study by Hair et al. (2007), data collecting was the major work for the study. Data gathering remained the focus of studies despite the divergence of data collecting strategies (Merriam, 1998; Most et al., 2003; Whitney et al., 1998). Questionnaires were used as a data-collecting device for the quantitative approach of the study.

The survey adopted both online and paper questionnaire forms to collect the data. Before collecting data, the researcher applied IOC (the index of item-objective congruence) to confirm the validity of the scale items. Each item was rated by three content experts with a scale of 1 (for clearly measuring the goal), 0 (the degree of measurement is unclear), –1 (the goal is not measured) (Turner & Carlson, 2003). The scores ranged from the lowest, 0.68, to the highest, 1. A pilot test on 43 participants was taken to test the questionnaires' reliability before being dispensed. All the variables had a coefficient strength above 0.7, which meant all the variables were reliable and suitable as research instruments for the survey. SEM and CFA analyzed all the quantitative data to check whether the framework structure was accurate.

3.3 Population and Sample Size

Salkind (2012) concluded that a group of people likely joining in research to whom you want to summarize the results of a study was defined as the target population. Reddy and Ramasamy (2016) specified population as a set of people, items, or objects from which samples were selected to analyze. In this research, the target population was the college students in the Management Engineering Department of Sichuan Aerospace Vocational College, Chengdu, experienced in using the three chosen online learning platforms, including Rain Classroom, Zhidao, and China University MOOC. The three platforms are the most used in the college. Moreover, the Management Engineering Department is one of the earliest faculties to adopt online learning systems, and the students in the department are quite familiar with the use of the platforms. Fan et al. (1999) concluded that the size of the sample had a great effect on the model fitting evaluation. When the sample size is small, it is impossible to distinguish between the sample covariance matrix and the reproduced covariance matrix. With seven factors and 27 indicators, the suggested minimum sample size was 425, given by Soper's (2006) calculator. Therefore, 600 questionnaires were distributed, and 500 valid copies were used.

3.4 Sampling Technique

The study practiced three sampling procedures: judgment, quota, and convenience. The judgmental sampling was used to select the undergraduates who were experienced in using the chosen three online platforms (Rain classroom, Zhidao, China University MOOC) in the Management Engineering Department in the college where the survey was practiced. The quota sampling was applied to split the groups of students according to the platforms they utilized based on the proportions of the total users of each platform. Feng (2013) explained that convenient sampling, also known as accidental sampling or natural sampling, indicates that analysts select the individuals by accident conveniently or choose those nearest and demanding the least effort to find. Consequently, the researcher collected the data through online and offline methods and through the help of the other teachers in the college. Eventually, 500 students' responses were chosen to carry on the survey.

Table 1: Sample Units and Sample Size

Online Learning Platforms	Population Size	Proportional Sample Size
Rain Classroom	10150	300
Zhidao	5630	170
China University MOOC	950	30
Total	**16730**	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

The demographic features of 500 respondents are displayed in Table 2. Among the 500 respondents, male students constituted 42% of the total contributors, and females accounted for 58%. Most participants have experience in using the platforms over six months. For the time spent on the platforms, the majority ranged from 1 to 3 hours. Nearly 70 % of the respondents only used the learning platforms to study materials related to their major. Over 85% of participants chose mobile phones to conduct online learning.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	210	42%
	Female	290	58%
Experience in Online Learning Usage	Less than 6 moth	80	16%
	From 6 month to 1 year	217	43.4%
	Over 1 year	203	40.6%
Time Spent on Online Learning Platforms a week	Less than 1 hour	65	13%
	From 1 hour to 3 hours	343	68.6%
	Over 3 hours	92	18.4%
Purposes of Studying through Online Learning Platforms	Only Study Materials related to their major	347	69.4%
	NOT Only Study Materials related to their major	153	30.6%
Device preferred for online learning	Mobile phone	429	85.8%
	computer	71	14.2%

4.2 Confirmatory Factor Analysis (CFA)

Confirmatory factor analysis (CFA) was a method of analysis to assess whether the indicators were related to the constructs (Brown, 2006). Lavrakas (2008) believed construct validity was used to describe the extent of how accurate the measurement was. It indicated the relations between the actual parts of test results and some basic theories or behavioral models. The statistical information in Table 3 presented that all the variables indicated Cronbach's Alpha values were above 0.7 (Nunnally, 1978). Factor loading was measured over 0.5 as a t-value above 1.98 and p-value<0.5 (Hair et al., 2010). The average extracted variance (AVE) was tested beyond 0.4, and the composite reliability (CR) was greater than 0.7 (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 Ease of Use (PEOU)	Lee et al. (2015)	3	0.736	0.674-0.721	0.744	0.492
Perceived Usefulness (PU)	Lee et al. (2015)	3	0.789	0.737-0.761	0.789	0.555
Attitude (ATT)	Lee et al. (2015)	4	0.853	0.722-0.816	0.858	0.603
Social Influence (SI)	Alam et al. (2020)	5	0.843	0.545-0.916	0.851	0.547
Facilitating Conditions (FC)	Alam et al. (2020)	4	0.978	0.940-0.973	0.979	0.920
Behavioral Intention (BI)	Hsiao and Tang (2014)	4	0.810	0.678-0.789	0.813	0.522
Use Behavior (UB)	Alam et al. (2020)	4	0.838	0.668-0.861	0.843	0.575

Table 4 demonstrates all the results of the indices for Absolute Fit Measures, including GFI, RMSEA, CMIN/DFAND AGFI, and Incremental Fit Measures, including TLI, NFI, and CFI, which all met the acceptable criteria. That meant the fitting statistical data constructed by the model showed a good fit.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/df	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	817.498 or 2.698
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.887
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.860
NFI	≥ 0.80 (Wu & Wang, 2006)	0.915
CFI	≥ 0.80 (Bentler, 1990)	0.945
TLI	≥ 0.80 (Sharma et al., 2005)	0.936
RMSEA	< 0.08 (Pedroso et al., 2016)	0.058
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

Hair et al. (2010) stated that discriminant validity was a way to test and guarantee that different variables related to the same conception were not significantly different. Hubley (2014) stated that the test results of the discriminant validity should be much lower than those of the convergent validity. The measurement results demonstrated in Table 5 indicated that the discriminant validity of the variables met the requirements.

Table 5: Discriminant Validity

	PEU	PU	ATT	SI	FC	BI	UB
PEU	**0.701**						
PU	0.589	**0.745**					
ATT	0.531	0.647	**0.777**				
SI	0.355	0.466	0.549	**0.740**			
FC	0.111	0.074	0.128	0.089	**0.959**		
BI	0.534	0.563	0.712	0.524	0.137	**0.722**	
UB	0.491	0.489	0.576	0.544	0.031	0.654	**0.758**

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

4.3 Structural Equation Model (SEM)

Schumacker (2005) defined Structural equation modeling (SEM) as linear structural relationships or latent variable modeling. SEM is traditionally a theoretical model for testing hypotheses, which combines relevant methods and corrects the measurement unreliability in observed variables. Most statistical applications are currently included in SEM models using observation or potential variables. Jöreskog and Sörbom (1993) characterized the SEM as a condition employing the perception and latent variable examination parameters. The testing results of the indices were presented in Table 6, which were all beyond the acceptable criteria. Consequently, the goodness of fit for the structural model was established.

Table 6: Goodness of Fit for Structural Model

Index	Acceptable	Statistical Values
CMIN/df	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	1003.156 or 3.175
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.872
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.847
NFI	≥ 0.80 (Wu & Wang, 2006)	0.896
CFI	≥ 0.80 (Bentler, 1990)	0.926
TLI	≥ 0.80 (Sharma et al., 2005)	0.918
RMSEA	< 0.08 (Pedroso et al., 2016)	0.066
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

4.4 Research Hypothesis Testing Result

The results in Table 7 indicated that all the proposed hypotheses were supported except H7. Perceived ease of use had a strong impact on perceived usefulness. Both perceived ease of use and usefulness contributed markedly to the impact on attitude. The attitude was the most significant determinant of behavioral intention, followed by perceived usefulness and social influence, while facilitating conditions showed no positive effect on students' behavioral intention. In addition, behavioral intention greatly influences students' use of online learning platforms.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: PEU → PU	1.002	11.605 ***	Supported
H2: PEU → ATT	0.254	2.159 *	Supported
H3: PU→ ATT	0.665	6.867***	Supported
H4: PU → BI	0.161	2.116*	Supported
H5: ATT → BI	0.645	8.146***	Supported
H6: SI → BI	0.252	4.564***	Supported
H7: FC → BI	0.014	0.702	Not Supported
H8: BI→UB	0.605	11.808***	Supported

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

The findings of the hypotheses were summarized as follows:

H1: The standardized coefficient path was 1.002, and the t-value was tested at 11.605, p<0.001. That means perceived ease of use was a powerful determinant of perceived usefulness. It was supported in some previous empirical studies that the respondents would believe online learning systems are useful if the services are easy to practice (Hao, M., 2023; Shah & Attiq, 2016).

H2: The statistical information demonstrated that perceived ease of use influenced students' attitudes toward online learning technology with a standardized path coefficient of 0.254 and t-value of 2.159, $p<0.05$. Dai (2014) also confirmed that college students' attitudes were greatly impacted by perceived ease of use, but the effect was weaker than that between perceived usefulness and attitude. Sánchez et al. (2013) study, it was suggested that perceived ease of use was a prominent indicator that determined subjects' attitudes toward e-learning. Alharbi and Drew (2014) also proved that perceived ease of use significantly predicted the students' attitudes.

H3: Compared with perceived ease of use, perceived usefulness demonstrated a more significant effect on attitude with a standardized path coefficient of 0.665 and a t-value of 6.867, $p<0.001$. How useful the online learning technology was viewed predicted the students' attitude toward it (Alharbi & Drew, 2014; Elkaseh et al., 2016). Teo (2011) discovered that perceived usefulness directly influenced attitude in the process of e-learning. Seif et al. (2012) confirmed perceived ease of use as a strong predictor of attitude.

H4: It was proved in the study that perceived usefulness was a positive predictor of behavioral intention with the common coefficient value at 0.161, t-value at 2.116, and $p<0.05$, although it was not as significant as attitude. Some previous research indicated that behavioral intention to use an e-learning system was predicted by the usefulness assumed by the individuals (Liu et al., 2009; Ong et al., 2004; Sheng et al., 2008). Perceived usefulness while using the e-learning system positively affects behavioral intention to use the system continually (Lee, 2010; Liaw, 2008; Liaw et al., 2007). Liu et al. (2010) applied an extended TAM to explore the factors that affect the intention to use an online learning community. They found that PU was the most influential variable in predicting the intention to use the web-based learning system.

H5: The hypothesis was validated with the common path coefficient of 0.645, t-value at 8.146, and $p<0.001$, showing attitude was the most prominent predictor of behavioral intention compared with other factors in the study. Mailizar et al. (2021) found that attitude significantly influenced subjects' intention in the e-learning context. Several previous studies also confirmed the same relationship between attitude and behavioral intention (Ahmed et al., 2011; Hussein, 2017; Malathi & Rohani, 2011). Different online learning materials and tools were applied in that research to access the relationship, including digital books, social media, and online software. Sujeet and Jyoti (2013) also concluded that the more positive attitude the students held towards online learning technology generated a stronger intention to use it.

H6: The results of the study indicated that social influence presented a positive effect on behavioral intention. The structure model testing measured the common path coefficient at 0.252, the t-value at 4.564, and $p<0.001$. The statistical data of the study was consistent with that of some previous researchers (Alblooshi & Abdul Hamid, 2021; Mehta et al., 2019; Nasir et al., 2015; Sedana, 2010; Tarhini et al., 2017). Fagih (2013) also observed social influence as a highly impactful factor in behavioral intention.

H7: The standard path coefficient was measured at 0.014 and the t-value at 0.702, which indicates that facilitating conditions have no significant impact on behavioral intention. The research conducted by Tarhini et al. (2017) and Mousa Jaradat and Al Rababaa (2013) supported the findings in this study by claiming that the impact of facilitating conditions was not positive on behavioral intention to adopt technology services. Some other research also found that facilitating conditions were a weak determinant of behavioral intention (Chang et al., 2007; Limayem & Hirt, 2000). However, the results of the research needed to be more consistent with the theory put forward by Venkatesh et al. (2003) and some other studies (Gunasinghe et al., 2019; Samsudeen & Mohamed, 2019).

H8: For this hypothesis, the researcher observed the standard path coefficient at 0.605, t-value at 11.808, and $p<0.001$, demonstrating a strong correlation between behavioral intention and use behavior. The conclusion that behavioral intention significantly affects use behavior also reinforced the findings of some previous studies (Agudo-Peregrina et al., 2014; Venkatesh & Davis, 2000; Venkatesh et al., 2003). That implies students' strong intention to use a technology leads to an actual use act.

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

This research investigated factors influencing college students' behavior in adopting online learning platforms in Sichuan, China. The correlations between seven variables in the conceptual framework were measured, and seven out of eight assumptions were validated. The variables included perceived ease of use, usefulness, attitude, social influence, facilitating conditions, behavioral intention, and use behavior. Six hundred questionnaires were given out to collect the statistical data, with 500 valid ones used in the research. The confirmatory factor analysis (CFA) and the structural equation model (SEM) were applied to evaluate the fitness of the measurement model and test whether the factors supported the hypotheses.

According to the findings, attitude was the strongest factor that affected students' intention to use the platforms, followed by social influence and perceived usefulness, and facilitating conditions showed no significant impact on behavioral intention. Secondly, perceived ease of use had an impactful effect on perceived usefulness. Then, both perceived ease of use and usefulness greatly influenced attitude, but the impact of perceived ease of use was much weaker than that of perceived usefulness. In addition, behavioral intention displayed a noteworthy influence on use behavior.

5.2 Recommendation

The study's findings identified the factors affecting undergraduates' use behavior of online learning systems, which should be considered in future teaching and online learning course design. Based on Hypothesis 1 to Hypothesis 3, the research identified the relationships between perceived ease of use, perceived usefulness, and attitude. Moreover, based on hypotheses 4 and 5, perceived usefulness and attitude directly affect behavioral intention. In hypothesis 6, social influence was proved to be a critical predictor of behavioral intention. Nevertheless, the relationship between facilitating conditions and behavioral intention in hypothesis 7 was not supported in the study, which implied that the quality of the facilities did not determine students' intention to use them. That means that other people's influence was the major factor in promoting students' intention of using the online learning method. Eventually, a positive behavioral intention would produce students' actual conduct of the platforms, confirmed in hypothesis 8. Therefore, universities and colleges should consider increasing students' usage of the new online learning systems by promoting the convenience and usefulness of the services and providing more help in using them. Teachers need to offer more precise guidance and encouragement when students encounter difficulties in learning. Moreover, the developers of the platforms should collect the students' feedback to optimize the functions. The more convenient and useful the students perceive the platforms, the more inclined they are to use them.

5.3 Limitation and Further Study

The research limitation mainly lies in the number of variables in the conceptual framework and the chosen population. There are only seven potential variables in the framework; hence, in future studies, more factors should be included, and other theories in technology acceptance should be adopted to expand the theoretical research scope. In addition, the study was confined to the area where the researcher lived. Hence, the span of the survey can be extended to other regions of China or countries, which may produce different results.

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