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Examining Utilization of Online Learning Platforms: A Case of Undergraduates in Vocational Colleges in Sichuan, China

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Abstract

Purpose: Due to the COVID-19 pandemic, online learning has become the trend of education development. This study examined the effects of perceived ease of use, perceived usefulness, attitude, social influence, facilitating conditions, and behavioral intention toward undergraduates' use behavior of online learning platforms in Sichuan, China. **Research design, data, and methodology**: This research adopted a quantitative method, and questionnaires were utilized to collect data. There were 500 copies of questionnaires used in the analysis. The IOC (Item-Objective Congruence) and Pilot test were applied to measure the reality and validity of the constructs prior to collecting data. The data was analyzed through confirmatory factor analysis (CFA) and structural equation modeling (SEM). **Results**: The relationships between perceived ease of use and perceived usefulness, perceived ease of use and attitude, and perceived usefulness and attitude were confirmed. Attitude, social influence, and facilitating conditions were significant predictors of behavioral intention. Behavioral intention significantly affected use behavior. Nevertheless, perceived usefulness had no significant impact on behavioral intention. **Conclusion:** Henceforth, to improve the learning platform's utilization rate, the developer of the online learning platforms should improve the simplicity and convenience of the platform usage. Academic practitioners can make online learning one of the compulsory tasks for vocational undergraduates.

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

JEL Classification Code: E44, F31, F37, G15

1. Introduction

What is online learning? Anderson (2008) defined learning as using the Internet to get educational resources, connect with teachers and other students, and get help while learning. This helped to gain knowledge, build individual understanding, and develop from the learning process. In Khan's study (Anderson, 2008), online learning was a novel method to teach people far away using the Internet. Online learning was also usually called e-learning, which meant conducting learning through the Internet, which fell into the domain of distance education (Moore & Kearsley, 2011). According to Keengwe and Kidd (2010), learning based on the web was developed from 1990 to 1995; from 1995 to 2005, e-learning became the new norm in the education area, and from 2005, it entered the new era of mobile learning and social networking.

Online learning has been adopted in higher education for many years and has gradually taken a more important role. However, most of the growth in online education occurred in North American and European countries until the outbreak of COVID-19, which accelerated the global acceptance of online learning. Adeoye et al. (2020) pointed out that although online learning had gradually become an important educational strategy, the breakout of COVID-19 boosted the process. With 91% of the students globally affected by the closure of educational institutions, online learning became critical in addressing the crisis. Hossain et al. (2021) stated that COVID-19 might be a turning point for the advancement of online learning in Bangladesh because all the state

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universities and private universities were trying to give courses through online platforms like "Zoom," "Hangour Meet."

In response to the COVID-19 pandemic, the Chinese government issued multiple policies to regulate and promote online learning usage. Based on "The 45th Statistical Report on Internet Development in China" by the China Internet Network Information Center (CNNIC, 2020), the Chinese Ministry of Education has launched 22 online learning platforms and set up 24000 online high-quality courses to guarantee the normal operation of higher education. Until March 2020, the online education population of China had reached 423 million, a 222 million increase compared with that at the end of 2018. Sichuan, the central city in southwestern China, also regards online learning as a crucial part of its educational development, especially in higher education. A series of surveys have focused on online learning in this region (Cao & Jittawiriyanukoon, 2022; Fan et al., 2022; Hao, 2023; Min, 2020; Wang, 2023; Yao et al., 2022; Zhang et al., 2019). However, the factors affecting the undergraduates' utilization of online learning in vocational colleges have not been sufficiently examined. Therefore, this research aimed to study the factors influencing undergraduate use behavior in vocational colleges in Sichuan Province.

2. Literature Review

2.1 Perceived Ease of Use

Cheng et al. (2019) presented it as how simple the students perceived using PBWorks to be. Saade and Bahli (2005) discovered that perceived ease of use means how students think about the simplicity level of using Internet-based learning systems (ILS). Kleijinen et al. (2004) presented it as how much customers could use the service in their everyday life. Chang et al. (2005) concluded that people would use an e-public service system if it were simple and easy. Moon and Kim (2001) believed that the linkage between usefulness and ease of use was positive in terms of self-service technology. Rotchanakitumnuai and Speece (2009) proposed that ease of use affected the level of perceived usefulness.

Moreover, ease of use affected users' attitudes towards adopting electronic services. Chen et al. (2002) demonstrated that attitude was positively affected by perceived ease of use in convenience stores' employment of self-service systems. Wu et al. (2010) pointed out how easy a network intelligence service was to use affected a user's attitude towards using it. Based on reviews of previous studies, the hypothesis was framed as follows.

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

Gao and Bai (2014) pointed out that perceived usefulness meant people's perception of their enhanced performance by using the technology. Perceived usefulness also refers to the extent of helpfulness one conceived a new technology might be to assist them in completing a particular mission (Fenech, 1998). Saade and Bahli (2005) proposed that perceived usefulness was how much the students perceived the Internet-based learning systems (ILS) to boost their academic performance. Perceived usefulness was a positive factor in shaping how users felt about something. (Zhao et al., 2018). Mailizar et al. (2021) claimed that whether the e-learning service was useful largely depended on the students' attitudes. Perry's (2017) study found that attitude toward purchase was positively affected by perceived usefulness. Carter (2008) believed that the linkage between usefulness and attitudes was positive. Pikkarainen et al. (2004) argued that perceived usefulness significantly promoted users' intention to accept the technology of ICT services, which were considered easy to use. Customers' inclination toward conducting a life insurance app was positively affected by their judgment of its usefulness (Lee et al., 2015). Davis (1989) proposed that perceived usefulness was a major factor in people's adoption of information technology and an instance of external incentive (Davis, 1993). Moses et al. (2013) concluded that perceived usefulness strongly influenced whether science and mathematics teachers would use notebook computers. Lupton (2014) concluded that the perceived usefulness of health services greatly influenced consumers' intentions. Chen and Tseng (2012) presented that perceived usefulness significantly affected users' intention to use E-learning tools. Liu et al. (2010) found that perceived usefulness was the most influential predictor of the intention to use the online learning system. Many previous studies also indicate that e-learning usage intention was directly affected by perceived usefulness (Al-Gahtani, 2016; Elkaseh et al., 2016; Lee et al., 2014; Tarhini et al., 2014, 2016). Therefore, the hypothesis was framed as follows:
H3: Perceived usefulness has a significant impact on attitude.
H4: Perceived usefulness has a significant impact on behavioral intention.

2.3 Attitude

According to Huang et al. (2007), it refers to a customer's evaluative judgment on whether the new technology would be brought to use. MacKenzie et al. (1986) defined attitude as how likely people tended to choose a positive or negative

response towards an incentive of certain advertisements. Attitude is a person's judgment of something, ranging from good to bad (Albarracin & Shavitt, 2018). Blackwell et al. (1995) indicated that attitude could be defined as the likelihood of people's choice towards a positive or negative response to an incentive. Students' attitude towards Edmodo (an educational social network site) strongly influenced their behavioral intention to adopt it (Unal & Uzun, 2020). Watjatrakul (2013) stated that someone's attitude affected how likely they were to use a free service they chose to do on their own. The university academies' attitude toward MOOCs significantly impacts their behavioral intention toward developing and using them (Ab Jalil et al., 2019). Weng et al. (2018) argued that the teachers' attitude toward multimedia greatly influenced their intention to use multimedia teaching. Moran et al. (2010) believed that attitude impacted users' intention to adopt the ICT platform. Based on reviews of previous studies, the hypothesis was framed as follows:
H5: Attitude has a significant impact on behavioral intention.

2.4 Social Influence

Wiafe et al. (2019) regarded social influence as how much individuals' decision to resort to technology could be affected by other people's judgment about it. Yang (2010) concluded that social influence refers to the extent of one taking the significant people's views on whether he or she should employ mobile shopping. The researcher defined social influence as people's conversion in their feelings, thinking, attitude, or actions after communicating with other people or groups (Rashotte, 2007). In the case of mobile government, social influence was an active factor that motivated the intention of utilization (Liu et al., 2014). Nikou and Bouwman (2014) proposed that social influence was a strong determinant that affected behavioral intention. Ukut and Krairit (2019) perceived social influence as how the users of a technology judge other people's responses towards them within their social or reference circle. Ismail (2010) believed that the behavioral intention of student users of social media was highly affected by social influence. Watjatrakul (2013) proposed that an individual's behavioral intention toward a free technology service was directly and indirectly affected by the social influence of the service. Tan (2013) concluded that social influence strongly affected users' intentions regarding English E-learning services. El-Masri and Tarhini (2017) confirmed that social influence could affect how likely they were to want to utilize a technology. Therefore, the hypothesis was framed as follows:
H6: Social influence has a significant impact on behavioral intention.

2.5 Facilitating Conditions

Taylor and Todd (1995) concluded that facilitating conditions was a construct of external control perception, which was associated with the notion of aiding facilities. Moreover, they also claimed that facilitating conditions meant how much the technology and organization conditions were perceived to promote service use. Hsiao and Tang (2014) perceived facilitating conditions as an extrinsic factor indicating the amount of required supplies people could get to conduct a behavior, including funds, time, or other supplies. Thompson et al. (1991) described it as the perception that the possible users believed what they needed to employ a technology would be fulfilled. Teo and Van Schalk (2009) defined facilitating conditions as environmental factors that people perceive to affect their intention to conduct a behavior. Raman et al. (2014) confirmed that facilitating conditions were a strong motivation for teachers' intention to use smart boards. Tan (2013) demonstrated that facilitating conditions positively influenced people's use of technology. Talukder et al. (2019) believed that in terms of m-government usage, the better-facilitating conditions were provided, the higher the intention people attained to use it. According to Boontarig et al. (2012), facilitating conditions were also regarded as an influential predictor of the behavioral intention to adopt healthcare services via smartphones. Oliveira et al. (2014) presented that in mobile banking usage; behavioral intention was influenced by facilitating conditions. It showed that health IT utilization intention was positively impelled by facilitating conditions, supported by a study conducted by Aggelidis and Chatzoglou (2009). Based on reviews of previous studies, the next hypothesis was proposed:
H7: Facilitating conditions has a significant impact on behavioral intention.

2.6 Behavioral Intention

Davis et al. (1989) stated behavioral intention as a predictor of people's utilization of a certain application. Behavioral intention also refers to a factor that assesses the chances one would utilize an innovation (Venkatesh et al., 2003). The capacity of behavioral intention to reveal officials' views of the e-government system employment made it a critical factor in researching the system's adoption (Kirat Rai et al., 2020). Chauhan and Jaiswal (2016) stated that in the case of Enterprise Resource Planning Software acceptance, behavioral intention functioned as a positive determinant of use behavior. In the findings of Yu and Huang (2020), the researcher demonstrated that user's higher intention led to higher frequency of use behavior. The use behavior was strongly impacted by behavioral intention towards 3G mobile value-added services, supported by Kuo and Yen's

(2009) research. The behavioral intention of adopting social media was a positive determinant of use behavior in Egypt (Salim, 2012). Jati and Laksito (2012) claimed that the users' behavior intention directly affected how much the e-learning system was used. Based on reviews of previous studies, the hypothesis was framed as follows:

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

2.7 Use Behavior

Use behavior meant customers' purchase frequency via mobile shopping services (Tak & Panwar, 2017). Handoko (2019) defined use behavior as people's established use of information technology. Chua et al. (2018) defined use behavior as a factor that validates how users adopt a technology. Straub et al. (1995) argued that there were two methods to measure actual use behavior: one was the objective way, and the other was the subjective way. Taylor and Todd (1995) believed that behavioral intention was crucial in determining customers' use of behavior technology. Triandis (1977) indicated that behavioral intention was an important factor that predicted the actual use behavior. The actual conduct of a behavior resulted from people achieving the competency of conducting it (Fogg, 2009).

3. Research Methods and Materials

3.1 Research Framework

Previous research frameworks and two important theories were taken to shape the study's conceptual framework. The theories applied in the study were UTAUT and UTAUT2, which provided a study base for all the research measurements comprising perceived ease of use, social influence, perceived usefulness, attitude, facilitating conditions, behavioral intention, and use behavior. Figure 1 presents the conceptual work of the study.

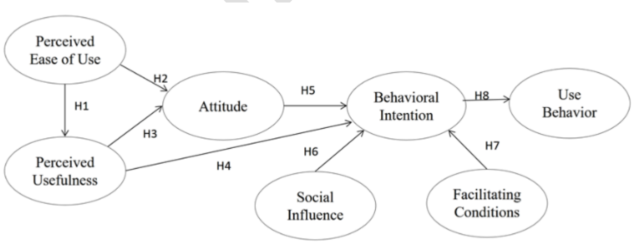

Figure 1: Conceptual Framework

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 has a significant impact on behavioral intention.

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

3.2 Research Methodology

The participating students who used the three online platforms in Sichuan Aerospace Vocational Colleges filled out the questionnaires in paper or digital form, depending on whether they were in the researcher's class. The questionnaire was filled out by the respondents at their responsibility. Before distributing the questionnaires, the item-objective consistency (IOC) for content consistency was listed as the survey tool. The reliability of every structure was confirmed through a pilot test with a modified survey tool. In addition, a pilot study of 43 participants was carried out for a reliability test of the questionnaire. The expert supported all the scale items with scores over 0.6, and the internal consistency of the variables was measured above 0.7 (Nunnally, 1978). The collected and saved in an Excel format were then transformed into SPSS data. The questionnaire was mainly composed of questions about the usage of online learning platforms. SEM and CFA analyzed all the quantitative data collected to check whether the framework structure was valid and whether the relationship between the constructs was supported via two statistical tools, AMOS and SPSS.

3.3 Population and Sample Size

A sample size is important to the survey scale. Neuman (2003) stated that the accuracy that has to be achieved according to the researcher's target sample and the sample's overall characteristics determined the sample size. In order to get the sample size, the items in the Soper's (2006) calculator were set at different figures. 0.2 was set for the anticipated effect size, 0.8 for the desired statistical power level, 7 for the number of latent variables, 27 for the number of observed variables, and 0.05 for the probability level. The results obtained from the calculation of modeling structural equations are 425 for the minimum detectable result, 109 for the minimum sample size of the model structure, and 425 for the recommended minimum sample size. Comrey and Lee (2013) believed that in terms of variables analysis, 500 cases were great. Hence, the sample size for the study was set at 500.

3.4 Sampling Technique

The researcher used three sampling methods to determine the sample size in the study. Judgmental sampling was used to differentiate the college students with experience using the three online platforms (Rain classroom, Zhidao, China University MOOC) in the Computer Science Department, where the survey was conducted. The quota method was utilized to select the groups of participants based on the proportions of the total users of the three platforms. Given (2008) concluded that convenience sampling meant it was easy for the researchers to get the study objects of the target population. Therefore, the researcher distributed the questionnaires to undergraduates online and offline in the college, making the samples much more accessible and convenient for the researcher to obtain.

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 researcher presented the 500 participants' demographic features displayed in Table 2. Among the 500 respondents, male students constituted 52% of the total contributors, and females accounted for 48%. Most participants have experience in using the platforms for over six months. For the time spent on the platforms, the majority ranged from 1 to 3 hours. Nearly 75 % of the respondents only used the learning platforms to study materials related to their major. Over 60% of participants chose mobile phones to conduct online learning.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	262	52%
	Female	238	48%
Experience in Online Learning Usage	Less than 6 moth	72	14%
	From 6 month to 1 year	246	49%
	Over 1 year	182	36%
Time Spent on Online Learning Platforms a week	Less than 1 hour	61	12%
	From 1 hour to 3 hours	330	66%
	Over 3 hours	109	22%
Purposes of Studying through Online Learning Platforms	Only Study Materials related to their major	370	74%
	NOT Only Study Materials related to their major	130	26%
Device preferred for online learning	Mobile phone	317	63%
	Computer	183	37%

4.2 Confirmatory Factor Analysis (CFA)

The confirmatory factor analysis (CFA) model measures the relationship between variance and covariance and the level of their convergence and discriminant effectiveness (DiStefano & Hess, 2005). Convergent validity tests the level to which the measurements in the same construct are correlated (Churchill, 1979). There are three indicators to test convergent validity--- average variances extracted (AVE), composite reliability (CR), and factor loadings (; Fornell & Larcker, 1981; Pallant, 2000). In this study, the value of AVE was tested over 0.5 (Henseler et al., 2009); the P-value was less than 0.50, while the results of factor loading were over 0.5(Chen & Tsai, 2007); CR was beyond 0.7 (Diamantopoulos et al., 2012). Moreover, Cronbach's alpha values showed that all the variables in the conceptual framework were related to each other as the values were above 0.7.

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	0.857	0.721-0.888	0.860	0.674
Perceived Usefulness (PU)	Lee et al. (2015)	3	0.901	0.790-0.926	0.900	0.751
Attitude (ATT)	Lee et al. (2015)	4	0.919	0.818-0.901	0.920	0.743
Social Influence (SI)	Alam et al. (2020)	5	0.938	0.703-0.976	0.941	0.763
Facilitating Conditions (FC)	Alam et al. (2020)	4	0.944	0.879-0.933	0.945	0.810
Behavioral Intention (BI)	Hsiao and Tang (2014)	4	0.930	0.808-0.916	0.930	0.770
Use Behavior (UB)	Alam et al. (2020)	4	0.929	0.815-0.926	0.929	0.766

The values generated by CFA testing were presented in Table 4, indicating that all the indicators met the good-of-fit criteria. CMIN/DF = 2.790, GFI =0.884, AGFI = 0.855, CFI = 0.961, RMSEA = 0.060, NFI =0.941 and TLI = 0.955.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/df	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	845.351 or 2.790
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.884
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.855
NFI	≥ 0.80 (Wu & Wang, 2006)	0.941
CFI	≥ 0.80 (Bentler, 1990)	0.961
TLI	≥ 0.80 (Sharma et al., 2005)	0.955
RMSEA	< 0.08 (Pedroso et al., 2016)	0.060
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

Hubley (2014) stated that the test results of the discriminant validity should be much lower than those of the convergent validity. Discriminant validity means the process of measuring various ideas or concepts. (Campbell & Fiske, 1959). Fornell and Larcker (1981) stated that comparing the square correlation and AVE (the average variance extraction) of two structures could be the basis of discriminant validity measurement. The discriminant validity is established if the square correlation is less than AVE. 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	**0.821**						
PU	0.698	**0.867**					
ATT	0.676	0.787	**0.862**				
SI	0.573	0.637	0.714	**0.873**			
FC	0.484	0.577	0.588	0.597	**0.900**		
BI	0.582	0.670	0.732	0.653	0.704	**0.877**	
UB	0.514	0.599	0.597	0.621	0.680	0.794	**0.875**

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

4.3 Structural Equation Model (SEM)

Moshagen (2012) expressed that structural equation modeling (SEM) was broadly utilized within the behavioral viewpoint to explore the connections between watched and latent factors. Yuan et al. (2017) expressed that structural equation modeling became a major measurement device in numerous settings to ponder how latent factors were additionally related and inactive variables were connected to their watched indexes. Chin (1998) defined SEM as a powerful statistical tool. It forms a simultaneous statistical test by combining structural and measurement models or CFA. Lei and Wu (2007) described the structural equation model as a general term for specifying many statistical models to assess the effectiveness of substantive theory with empirical data. The testing results of the indices were presented in Table 6, which were all above 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)	1196.809 or 3.937
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.857
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.822
NFI	≥ 0.80 (Wu & Wang, 2006)	0.917
CFI	≥ 0.80 (Bentler, 1990)	0.937
TLI	≥ 0.80 (Sharma et al., 2005)	0.927
RMSEA	< 0.08 (Pedroso et al., 2016)	0.077
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 H4. The standardized path coefficient (β) of 0.902 and t-value of 13.538 *** suggested that Perceived ease of use significantly affected perceived usefulness. Both perceived ease of use and perceived usefulness contributed markedly impact on attitude. However, the effect of perceived useful was much stronger with a standardized path coefficient(β) of 0.887 and t-value of12.974***, while the standardized path coefficient(β) for perceived ease of use was at 0.188 and t-value=2.812 **. Facilitating conditions presented a very influential effect on behavioral intention with a standardized path coefficient (β) of 0.419 and a t-value of 13.654***. Attitude was also a critical determinant of behavioral intention with a standardized path coefficient (β) of 0.470 and t-value of 5.452***, followed by social influence with a standardized path coefficient (β) of 0.138 and t-value of 3.806***. However, perceived usefulness showed no positive effect on students' behavioral intentions. Behavioral intention greatly influenced students' use behavior of the online learning platforms with a standardized path coefficient (β) of 0.862 and t-value of 17.383***.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: PEU → PU	0.902	13.538 ***	Supported
H2: PEU → ATT	0.188	2.812 **	Supported
H3: PU→ ATT	0.887	12.974***	Supported
H4: PU → BI	0.063	0.655	Not Supported
H5: ATT → BI	0.470	5.452***	Supported
H6: SI → BI	0.138	3.806***	Supported
H7: FC → BI	0.419	13.654***	Supported
H8: BI→UB	0.862	17.383***	Supported

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

The results in Table 7 indicated that all the proposed hypotheses were supported except H4. The standardized path coefficient (β) of 0.902 and t-value of 13.538 *** suggested that Perceived ease of use significantly affected perceived usefulness. Both perceived ease of use and usefulness contributed markedly to the impact on attitude. However, the effect of perceived usefulness was much stronger with a standardized path coefficient(β) of 0.887 and t-value of12.974***, while the standardized path coefficient(β) for perceived ease of use was at 0.188 and t-value=2.812 **. Facilitating conditions presented a very influential effect on behavioral intention with a standardized path coefficient (β) of 0.419 and a t-value of 13.654***. Attitude was also a critical determinant of behavioral intention with a standardized path coefficient (β) of 0.470 and t-value of 5.452***, followed by social influence with a standardized path coefficient (β) of 0.138 and t-value of 3.806***. However, perceived usefulness showed no positive effect on students' behavioral intentions. Behavioral intention greatly influenced students' use behavior of the online learning platforms with a standardized path coefficient (β) of 0.862 and t-value of 17.383***.

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

This research examined factors affecting the undergraduates' utilization of online learning in vocational colleges. The survey participants were undergraduates who had experience in online learning in the Computer Science Department of Sichuan Aerospace Vocational College in Sichuan, China. The selected online learning platforms were Rain Classroom, Zhidao, and China University MOOC. The research applied quantitative methods and questionnaires to collect statistical data. Five hundred questionnaires were adopted to analyze the goodness of fit of the measurement model and the correlations between the variables through the confirmatory factor analysis (CFA) and the structural equation model (SEM).

Seven constructs and eight hypotheses were evaluated in the study. Seven hypotheses were verified and established. First, perceived ease of use was a positive determinant of perceived usefulness and attitude, while its impact on perceived usefulness was more significant than that on attitude. Moreover, perceived usefulness was critical in predicting students' attitudes toward online learning. That indicates that perceived ease of use and usefulness are marked factors that influence attitude. A positive attitude then causes strong behavioral intention towards online learning.

Secondly, there is no significant effect of perceived usefulness found toward behavioral intention in this study. Some other researchers also draw a similar conclusion in their studies. Lew et al. (2019) believed that the weak impact of perceived usefulness generated on behavioral intention indicated that the reluctance to accept the e-learning system was no longer a critical element as it was before. Mailizar et al. (2021) found out that with the closure of higher education institutions, online learning was the only option for undergraduates to conduct remote learning during the COVID-19 pandemic. Therefore, perceived usefulness became a weaker factor influencing the students' inclination to use the technology.

Thirdly, facilitating conditions demonstrated the most influential impact on behavioral intention. That implies that students are sensitive to the quality of learning facilities. Whether the necessary resources are provided is a critical element that affects students' intention to use the online learning system.

Fourthly, this study verified that social influence positively impacts behavioral intention, supported by Venkatesh et al.'s (2003) theory that social influence contributes to greater influence on behavioral intention when using new technology is mandatory. This study was conducted during the COVID-19 pandemic when online learning was compulsory for students. That explains the strong effect of social influence on students' behavioral intentions.

Fifthly, it was found in this study that a positive intention would greatly influence one's actual usage of online learning systems, which suggests that students' intention towards the new learning method is crucial to their use behavior. Therefore, promoting students' behavioral intention was an important issue to be addressed in the future.

5.2 Recommendation

As the correlations between perceived ease of use and perceived usefulness, perceived ease of use and attitude, and perceived usefulness and attitude were confirmed in the study, the convenience and simplicity of usage should be considered when developing online learning platforms. Moreover, it is advisable to promote students' attitudes by making them realize how they can benefit from online learning services.

In this study, attitude, social influence, and facilitating conditions were all verified as significant determinants of behavioral intention. As Venkatesh et al. (2003) stated, a mandatory environment enhances the effect of social influence. Therefore, instructors can make online learning one of the compulsory tasks for vocational undergraduates. Online learning can be a useful supplement to traditional learning in the classroom. Tarhini et al. (2015) argued that there would be a rapid growth in the amount of potential online learning users when a critical number of users was reached. This highlights the importance of implementing strategies that seek support from a broader social environment. Besides, the quality of facilitating conditions should be improved in the future, including optimization of the platforms, better campus Wi-Fi, instructors' guidance when students have difficulties using the online learning systems, etc.

5.3 Limitation and Further Study

The factors influencing college students' utilization of online learning platforms in the research study were taken from previous research models. So, only seven variables were examined in the study. The coverage and generalization of the study were limited. Additional variables can be taken to the existing model, improving the predictability in identifying factors that affect learners' utilization of online learning systems. The extension of the constructs could include personal innovativeness, quality of service, curriculum design, course content, and teaching style (Cao, 2022; Handoko, 2019). Otherwise, as the population remained only in one college of a specific region, it probably generated different results in different colleges and regions. For that reason, it is desirable to expand the coverage of the study, which might make the findings more representative and accurate.

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