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Analysis of Undergraduate Students' Behavioral Intentions and Usage Behavior of Online Learning Platforms in Chengdu, Sichuan, China

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Abstract

Purpose: This study examines the factors affecting behavioral intention and usage behavior of online learning platforms among undergraduate students in Xihua University in Chengdu, Sichuan, China. A conceptual framework is developed through the Theory of Planned Behavior (TPB), the technology acceptance model (TAM) and its extended Model (TAM2), and the unified theory of technology acceptance and use (UTAUT). The researcher determines key variables which are social influence, perceived usefulness, perceived ease of use, attitudes, subjective norms, and perceived behavioral control behavioral intention and usage behavior. **Research design, data, and methodology:** The target population is 500 participants. The study applied quantitative method to distribute online questionnaires. The sampling method used are purposive and convenience sampling. The data were analyzed by Confirmation Factor Analysis (CFA) to test the validity and reliability. In addition, Structural Equation Modeling (SEM) model was used to evaluate the hypotheses. **Results:** The results showed that behavioral intention and use behavior were significantly influenced by social influence, perceived usefulness, perceived ease of use, attitudes, subjective norms, and perceived behavioral control. **Conclusions:** The findings imply that users' behavioral intentions are crucial to online learning adoption and suggests that platform designers should fully improve and upgrade online learning platform systems.

Keywords : Online learning platform, Attitude, Behavior Intention, Use Behavior, Structural Equation Modeling

JEL Classification Code: E44, F31, F37, G15

1. Introduction

The online education industry has been overgrown with the development and popularity of advanced information technologies, such as cloud computing, big data, and mobile telecommunications (Sun & Song, 2017). The introduction of smartphones, PC, iPad, and other mobile terminals can effectively integrate mobile phones, PDAs, and PC teaching service resources, support the wide acceptance of users' online learning and offline learning, for users to create a cross-platform, interactive learning environment, therefore, online learning platform and commonly used by college students (Liu, 2017). However, the online learning platforms also has great uncertainty while bringing convenience

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(Taylor & Todd, 2014). Currently, the online learning platform is facing severe problems, such as the low completion rate of courses, the weak continuous participation of users, and the interaction between users and teachers. It is common for many users to give up after initially logging in and using the online learning platform. For this reason, students' engagement and learning ability have once again attracted a great deal of academic attention, directly affecting the quality of online teaching in universities and profoundly influencing the future development of online teaching in Chinese universities.

Although the resources of China's online learning platforms are rich enough, the information technology is complete enough; the user group is large enough. The coverage is wide enough, but many factors can still affect the effectiveness of online learning. For that reason, this study aims to investigate the influence of social influence, perceived usefulness, perceived ease of use, attitude, subjective norms, perceived behavioral control on behavioral intention towards use behavior of college students in Chengdu, Sichuan, China. The exploration of the key factors of college students' use of online learning platforms can assist platform developers to understand better the users' needs for the improvement of the online learning platform.

2. Literature Review

2.1 Social Influence

In the UTAUT model, social influence is an important factor that affects an individual's willingness to use information technology, which refers to the degree to which an individual feel influenced by the group around him or her. The psychological motivation for social influence to affect an individual's willingness to use technology is that individuals tend to follow the opinions of others in the group in order to enhance their relationship with the group. Several studies (Calisir et al., 2013; Karaali et al., 2011; Terzis et al., 2012) have explored the significant association between social influence and the perceived usefulness of technology use by individuals. The most notable one was conducted by Eckhardt et al. (2009), who explained how the source (peer group) and reservoir (adopters and non-adopters) of the system explained the social influence on adoption, thus increasing the cumulative subjective norm. Therefore, social influences may affect students' perceived usefulness and perceived ease of use of online learning, so the following hypotheses are proposed.

H1: Social influence has a significant effect on perceived usefulness.

H2: Social influence has a significant influence on perceived ease of use.

2.2 Perceived Ease of Use

Davis (1989) defined perceived ease of use as the ease of use that users perceive when using a system and concluded that perceived ease of use has a significant positive effect on users' perceived usefulness and intention to use (Mallat et al., 2009). It has been shown that perceived ease of use positively and significantly impacts users' willingness to use new technologies (Kim et al., 2007; Liébana -Cabanillas et al., 2014). Researchers investigating users' willingness to use online learning platforms have confirmed a significant positive effect of perceived ease of use and perceived usefulness on attitudes toward use (Thong et al., 2006). In addition, researchers have found that perceived ease of use is a positive predictor of willingness to use online learning platforms (Wangpipatwong et al., 2008). Some studies have shown that the perceived ease of use of online learning platforms is critical to users' willingness to use them. Some scholars have studied undergraduate students' willingness to use online learning platforms in their studies and found that both perceived usefulness and perceived ease of use were influential factors in users' attitudes towards using them, and they both had a significant impact on users' willingness to use them (Cheung & Vogel., 2013). Based on the above analysis, this study makes the following hypotheses.

H3: Perceived ease of use has a significant influence on perceived usefulness.

H5: Perceived ease of use has a significant influence on attitude.

2.3 Perceived Usefulness

Perceived usefulness can be defined as the degree to which a person believes using a particular system will improve his or her performance (Davis, 1989). Perceived usefulness is a key determinant of attitudes that encourage 21st-century bank users to adopt more innovative and user-friendly technologies that give them greater freedom to complete transactions, pay bills, and perform other banking transactions (Pikkarainen et al., 2004). Perceived usefulness was found to significantly impact both users's attitude and intention to use the service (Purwanegara et al., 2014; Shaikh & Karjaluoto, 2015). Indeed, the willingness of individuals to use a particular system in a transaction depends on their perceived use of that system (Hanafizadeh et al., 2014). Therefore, the greater the perceived usefulness of a mobile service, the more positive the attitudes and intentions towards its continued use, and therefore the greater the likelihood of using. Thus, a hypothesis is developed:

H4: Perceived usefulness has a significant influence on attitude.

2.4 Subjective Norm

A subjective norm can be defined as a person's perception that most people who are important to him think he should or should not perform the behavior (Ajzen & Fishbein, 1975). The importance of subjective norms regarding attitudes has previously been established in the context of Internet applications (Nysveen et al., 2005). Thus, individuals are expected to come up with an incentive to comply with choices offered by people who are important to them (Hoehle et al., 2012). In the context of this study, subjective norms are considered to be a key determinant of users' attitudes. Subjective norms significantly influence users' attitudes (Nysveen et al., 2005; Schierz et al., 2010), which may deplete the negative effects of low usefulness and moderate their attitudes towards the intention to continue using online learning platforms. In testing its effect on attitudes in the present study, the effect of subjective norms on the usefulness-attitude pathway is demonstrated in a hypothesis:
H6: Subjective norm has a significant influence on attitude.

2.5 Perceived Behavioral Control

Shasha and Leelakasemsant (2022) referred perceived behavioral control as the summary of the individual's judgment on whether the behavior to be carried out is easy or not. Li and Wu (2019) argue that subjective norms and perceived behavioral control contribute to attitudes. Norms and perceived behavioral control contribute to attitudes. However, their study only involved the analysis of additional pathways, but they did not mention the mediation effect. Instead, increasing the pathway between perceived behavioral control and attitudes, as well as the remaining mediating effects, is important for the needs of the study. For the present study, increasing the pathway between perceived behavioral control and attitudes is very important. Theoretically, changes in individuals' perceptions contribute to their attitudes. Therefore, this study examines the relationship between perceived behavioral control and attitudes with accompanying mediating effects. Influencing only a person's attitude towards acting can indirectly change their intentions. Given this reasoning and the literature above supporting the path toward attitudes, the following hypothesis is proposed for this study.
H7: Perceived behavioral control has a significant influence on attitude.

2.6 Attitude

Attitudes and behavioral intentions Individuals' attitudes are thought to determine the willingness to engage in a behavior (Chatzoglou & Vraimaki, 2009). It has been established that attitudes are a person's evaluation of behavior, which leads to the decision to act (Chennamaneni et al., 2012). A person's positive attitude towards knowledge sharing can motivate him/her to share knowledge (Chatzoglou & Vraimaki, 2009; Chennamaneni et al., 2012). An individual's intention to share knowledge is influenced by his or her evaluative judgment of the outcome of sharing knowledge. Positive outcomes can motivate individuals to share knowledge (Chatzoglou & Vraimaki, 2009; Chennamaneni et al., 2012). According to Chennamaneni et al. (2012), it is argued that the more positive an individual's attitude towards knowledge sharing is, the higher the individual's behavioral willingness to share knowledge. Therefore, this study hypothesizes that.
H8: Attitude has a significant influence on behavioral intention.

2.7 Behavioral Intention

Behavioral intention refers to an individual's willingness and effort to perform a potential behavior. Scholars have argued that intentions may capture the various motivational factors that influence individuals to perform a behavior. However, most studies have limited their Dwivedi et al. (2011) claim to have established a significant relationship between behavioral intention and use behavior. Some studies (Alaeddin et al., 2018; Bailey et al., 2017; Kumar et al., 2018; Wulandari, 2017) consider behavioral intention as a proxy for user behavior. However, other studies have warned about measuring behavioral intentions without assessing the use of the technology system (Wu & Du, 2012). Some studies (Sivathanu, 2019) have established a significant relationship between behavioral intention and the actual use of the learning platform. However, given the COVID-19 pandemic, no studies have investigated the impact of this relationship on behavioral intention and use behavior on learning platform use. Therefore, the following hypothesis is formulated.
H9: Behavioral intention has a significant influence on use behavior.

3. Research Methods and Materials

3.1 Research Framework

Many scholars have achieved a series of research results, for example, on the acceptance and adoption of IT by individuals, mainly from the perspective of individual psychological behavior, such as the Theory of Rational Behaviour (TRA), the Technology Acceptance Model (TAM) and its extension (TAM 2) and the Integrated Theory of Technology Adoption and Utilisation (Unified Theory of Acceptance and Use of Technology, UTAUT). The researcher built on previous theoretical research to construct the conceptual framework for this study, which identified eight influences in the previous literature: i.e., perceived usefulness (PU) and perceived ease of use (PEOU) as the main variables, attitudes (ATT) as the most intermediate variable, and added social influence (SI), subjective norms (SN), and perceived control (PBC) as external variables. The dependent variables were behavioral intention (BI) and user behavior (UB), and the research framework is shown in Figure 1.

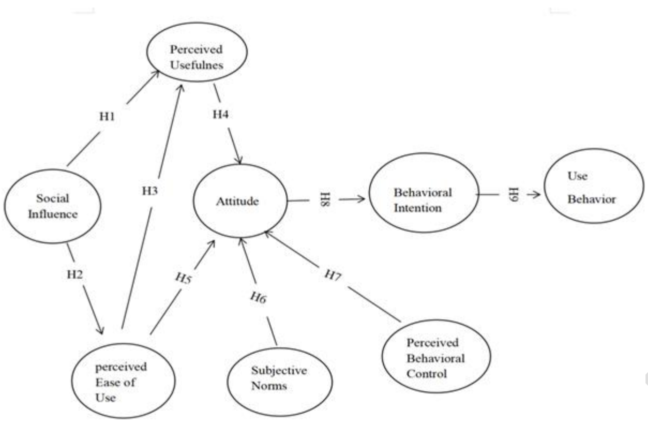

Figure 1: Conceptual Framework

H1: Social influence has a significant effect on perceived usefulness.
H2: Social influence has a significant influence on perceived ease of use.
H3: Perceived ease of use has a significant influence on perceived usefulness.
H4: Perceived usefulness has a significant influence on attitude.
H5: Perceived ease of use has a significant influence on attitude.
H6: Subjective norm has a significant influence on attitude.
H7: Perceived behavioral control has a significant influence on attitude.
H8: Attitude has a significant influence on behavioral intention.
H9: Behavioral intention has a significant influence on use behavior.

3.2 Research Methodology

Using a quantitative study, the researcher acquires a non-probability sampling strategy to administer on-site and online questionnaires to undergraduate students at Xihua University in Chengdu, Sichuan, China. The questionnaire was divided into three parts; the first was a screening question designed to distinguish between users and non-users of the online learning platform. The second part is the demographic characteristics of the respondents, including age, gender, grade, and usage. The third part consisted of 28 measuring items based on Venkatesh et al. (2003), measured on a five-point Likert scale, with "1" indicating strong disagreement and "5" ranging from "completely disagree" to "strongly agree"; the item quality was screened using the Item Objective Congruence (IOC) index with three qualified experts and professionals prior to data collection. The pilot test examined a small sample population before conducting a large-scale survey distribution (Cooper & Schindler, 2014). The number of participants taking the pilot test may range from 10 to 30 (Brown & Hill, 1998). This study used Cronbach's Alpha coefficient values to measure the internal consistency reliability of the pilot test for 30 Xi Hua University students who were accepted with scores of 0.7 and above (Sarmento & Costa, 2019).

3.3 Population and Sample Size

The target group is Xihua University in the western part of Chengdu, Sichuan Province, China. It is a key comprehensive undergraduate university in Sichuan Province. The basic capacity-building project for universities in China's central and western regions focuses on supporting universities, focusing on undergraduate education and postgraduate training. There are 22 disciplines, including ten disciplines of engineering, science, management, law, economics, art, culture, teaching, agriculture, and medicine, 2 provincial-level first-class disciplines, 8 provincial-level key disciplines, 32 master's degree program, totaling of 34,050 students. Researchers have chosen this university for several reasons. Firstly, this higher education institution represents undergraduate students located in Chengdu. Secondly, there are over 30,000 students enrolled at this institution, and finally, almost all of the students at this institution have experience using online learning platforms. The minimum sample size for the complex assessment framework in the structural equation model should be 200 and 500 samples (Kline, 2011). We selected 500 students as the final sample for this study through judgment and quota sampling.

3.4 Sampling Technique

The study applied nonprobability method to use purposive and convenience sampling technique. Purposive sampling is to examine 500 undergraduate students who have been using online learning platforms in Xihua University in Chengdu, Sichuan, China. The study applied convenience sampling to distribute online questionnaires. The survey was conducted during October to December 2021. The questionnaire was constructed in the online tool of “Questionnaire Star.” A total of 550 questionnaires were distributed, with 500 valid responses and a response rate of 90.9%, and this data was then used to generate the results and analyze them.

4. Results and Discussion

4.1 Demographic Information

The sample for this study was undergraduate students at Xihua University, Sichuan, China. The questionnaires were distributed. 500 valid questionnaires were returned. From Table 1. the majority of respondents were 280 females (56%), and 220 (44%) were males. 21.6% were between the ages of 17 and 18. Most respondents were between 19 and 20, accounting for 229 or 45.8% of all respondents, followed by 21-22 years old with 126 respondents (25.2%). Fourth year students show with 198 (39.6%), followed by the third year with 136 (27.2%). The majority of respondents had 1 to 3 years of experience using online learning platforms 362 (72.4%), compared with 32 (6.4%) for over three years. The respondents logged onto online learning platform 3-4 days a week of 368 (73.6%).

Table 1: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	220	44
	Female	280	56
Age Range	17-18	108	21.6
	19-20	229	45.8
	21-22	126	25.2
	23-24	31	6.2
	24 above	6	1.2
Grade Level	Freshman	105	21
	Sophomore	61	12.2%
	Junior	136	27.2%
	Senior	198	39.6%
Experience using an online learning platform	1–3 months	4	0.8%
	4-6 months	41	8.2%
	7–12 months	61	12.2%
	1-3 years	362	72.4%
	>3 years	32	6.4%
Frequency of use of online learning platforms	> 6 days a week	19	3.8%
	5-6 days a week	111	22.2%
	3-4 days a week	368	73.6%
	1-2 days a week	2	0.4%

4.2 Confirmatory Factor Analysis (CFA)

For CFA analysis, the analysis was made through convergence validity, discriminant validity, and scale reliability (Fraering & Minor, 2005). Convergence validity checks whether the measures for each structure in the model are reflected by their indicators (Gefen et al., 2000). This will ensure a single dimension of the multi-project system and help eliminate unreliable indicators (Bollen, 1989). However, discriminant validity tests whether measures of different concepts that are considered unrelated are statistically other (Gefen et al., 2000). The complete reliability of Hair et al. (2010) reliability, convergence validity, and discriminant validity of recommendations (Hair et al., 2010).

It is suggested that CR should be greater than 0.7 to establish good reliability, AVE should be greater than 0.5, and CR should be greater than AVE to confirm convergence validity. However, the mean of the variables should have a total AVE greater than their correlation value to support discriminant validity (Hair et al., 2010).

As shown in Table 2, all four validity criteria for convergence were met, with factor burdens ranging from 0.512 to 0.919 for all observed variables. All variables were more significant than the suggested minimum value of 0.5, and t-values were significant at 0.001. All were significant at the 0.001 level. AVE values ranged from 0.558 to 0.830 and exceeded the minimum value of 0.5. Composite reliability (CR) values ranged from 0.860 to 0.937 and exceeded the minimum value for all dimensions. It exceeded the minimum value of 0.7. It was significant at the 0.001 level for all. Acceptable convergent validity was achieved for all factors in this study.

Table 2: 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
Social influence (SI)	(Calisir et al., 2013)	5	0.852	0.512-0.854	0.860	0.558
Perceived ease of use (PEOU)	(Davis, 1989)	4	0.937	0.865-0.906	0.937	0.788
Perceived usefulness (PU)	(Pikkarainen et al., 2004)	3	0.935	0.900-0.919	0.937	0.830
Subjective Norm (SN)	(Ajzen & Fishbein, 1977)	3	0.920	0.883-0.901	0.921	0.795
Perceived Behavioral Control (PBC)	(Li &Wu, 2019)	3	0.911	0.827 -0.917	0.914	0.781
Attitude (ATT)	(Chennamaneni et al., 2012)	3	0.908	0.862-0.890	0.910	0.770
Behavioral Intention (BI)	(Wu & Du, 2012)	3	0.880	0.783-0.876	0.882	0.715
Use Behavior (UB)	(Wu & Du, 2012)	4	0.895	0.774-0.859	0.886	0.661

As shown in Table 3, these tests include the researchers' use of goodness-of-fit measures, including the chi-square statistic (CMIN/df), goodness-of-fit index (GF1), root mean square error of approximation (RMSEA), comparative fit index (CFI), canonical fit index (NFI), adjusted fit index (AGFI) and tucker-Lewis index (TLI), the results of the model provide an excellent fit to the data. It is clear from Table 3 that all fit indices are within the recommended range. It can be used in the study.

Table 3: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	<5.00 (Hair et al., 2010)	2.336
GFI	≥0.85 (Sica & Ghisi, 2007)	0.903
AGFI	≥0.80 (Sica & Ghisi, 2007)	0.872
NFI	≥0.80 (Arbuckle, 2012)	0.970
CFI	≥0.80 (Hair et al., 2010)	0.949
TLI	≥0.80 (Hair et al., 2010)	0.963
RMSEA	<0.080 (Pedroso et al., 2016)	0.052
Model Summary		**In harmony with empirical data**

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

The average variance extracted (AVE) value for each facet was determined to determine the discriminant validity of each factor. The AVE value should be greater than or equal to 0.50. As shown in Table 4, the diagonal lines indicate the square root of Ave: 0.747, 0.911, 0.888, 0.877, 0.892, 0.884, 0.846, and 0.813. The square root of the AVE value is greater than the structure. The relevant covariance or correlation coefficient between in general, the discriminant validity of this measurement model is acceptable and supports inter-dimensional discriminant validity.

Table 4: Discriminant Validity

	SI	PU	PEOU	ATT	SN	PBC	BI	UB
SI	**0.747**							
PU	0.77	**0.911**						
PEOU	0.681	0.711	**0.888**					
ATT	0.745	0.86	0.758	**0.877**				
SN	0.716	0.729	0.671	0.846	**0.892**			
PBC	0.672	0.742	0.742	0.838	0.809	**0.884**		
BI	0.759	0.844	0.759	0.925	0.867	0.932	**0.846**	
UB	0.746	0.822	0.761	0.895	0.839	0.895	0.973	**0.813**

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

4.3 Structural Equation Model (SEM)

In this study, the researcher used the goodness of fit (CMIN/df, GFI, AGFI, CFI, NFI, TLI, RMSEA) to test the proposed model. Most importantly, the model will be adjusted if the goodness of fit output does not meet the criteria. The results of the structural equation model validation and the selected test indicators and model values are shown in Table 5.

Table 5: Goodness of Fit for Structural Model

Index	Acceptable	Statistical Values
CMIN/DF	<5.00 (Hair et al., 2010)	2.186
GFI	≥0.85 (Sica & Ghisi, 2007)	0.910
AGFI	≥0.80 (Sica & Ghisi, 2007)	0.885
NFI	≥0.80 (Arbuckle, 2012)	0.936
CFI	≥0.80 (Hair et al., 2010)	0.964
TLI	≥0.80 Hair et al., 2010)	0.958
RMSEA	<0.080 (Pedroso et al., 2016)	0.049
Model Summary		**In harmony with empirical data**

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 were derived from the analysis of standardized coefficient value and t-value per demonstrated in Table 6. Subsequently, all hypotheses were supported.

Table 6: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-Value	Result
H1: SI → PU	0.961	11.461***	Supported
H2: SI → PEOU	0.814	16.077***	Supported
H3: PEOU→ PU	-0.100	-1.428**	Supported
H4: PU → ATT	0.264	8.428***	Supported
H5: PEOU → ATT	0.110	4.162***	Supported
H6: SN → ATT	0.257	7.010***	Supported
H7: PBC → ATT	0.396	10.429***	Supported
H8: ATT → BI	1.039	23.646***	Supported
H9: BI → UB	0.970	25.560***	Supported

Note: *** p<0.001, ** p<0.01
Source: Created by the author

After establishing good convergence and discriminant validity, the next step is to evaluate the structural model to examine the proposed relationships. As shown in Table 6, the results show that all pathways are supported. In addition, H1, H2, H4, H5, H6, H7, H8, and H9 all have significantly affected forward paths, and only H3 has a significantly affected negative path.

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

This study aims to construct a model of the behavioral intention and the influencing factors of the students' using the online learning platform at Xihua University, Chengdu, Sichuan Province, China. Through questionnaire survey and in-depth analysis, it is found that a conceptual framework has been developed through rational behavior theory (TRA), technology acceptance model (TAM), its extended Model (TAM2), and unified view of technology acceptance and use (UTAUT2). This study has successfully supported a practical, theoretical framework, theoretically and empirically, to understand better the factors influencing students' behavioral intentions and use behavior when using online learning platforms. The behavior intention and behavior of students using online learning platforms are significantly influenced by social influence, perceived usefulness, perceived ease of use, attitude, subjective norm, and perceived control, its influence on the usage behavior, the study variables are effective, and there is a strong correlation between the variables, which is consistent with the conclusions of previous studies.

Social influence is the degree to which a person perceives the importance of “Others” believing they should use technology. In online learning, the opinions of peers and mentors can influence other perspectives and beliefs. The results show that social influence indirectly affects students' behavior and willingness to use e-learning systems. Social influences on individuals may vary depending on culture, age, and education. The results of this study are consistent with those of Masa'deh et al. (2016) and Elkaseh et al. (2015). The results of the study were consistent. Therefore, it was recommended that teachers make it mandatory for students to use the online learning platform and that practitioners persuade users familiar with the system to help promote it to other users. Therefore, when the number of users of the online learning platform reaches a critical mass point, the number of users in the future may overgrow (Tarhini et al., 2015). This underscores the need to consider implementation strategies that develop support in the broader social context. More specifically, our results suggest that subjective norms and perceived control play a crucial role in predicting students' attitudes toward the voluntary use of online learning platforms. Personal standards and perceived control induce a more active learning process (Chung et al., 2010). Therefore, besides providing the necessary training to improve the subjective norms and perceived control of online learning platforms, decision-makers should also offer online and offline support.

Finally, attitude is an essential determinant of the intention and behavior of using the online learning platform, and the usefulness and ease of use directly affect the attitude of students. Therefore, students who find the system sound in learning will be more likely to adopt e-learning systems. Thus, enterprises and teachers should improve the quality of their online learning platforms by providing adequate and up-to-date content to attract more users of online learning platforms. The results also showed that behavior intention influenced students' acceptance and use of online learning platforms. This structure is a fundamental determinant of using online learning platforms to learn user behavior. In the literature, behavioral intention significantly impacts online learning platforms (Alalwan et al., 2015; Tarhini et al., 2015). Our findings suggest that training is unnecessary for people skilled in technology; however, it is crucial for people with lower skills because these users will form their opinion about using the online learning platform, no matter how useful it is. Therefore, to promote the usability of online learning platforms, system designers should provide a system to facilitate usability.

5.2 Recommendation

This study provides some enlightenment to the theory, methodology, and practice. From a theoretical point of view, the core achievement of this study is to develop a conceptual research model to understand better the impact of Chengdu Xihua University in Sichuan Province, China, students using online learning platform intention and use behavior factors. This study suggests that social influence, perceived usefulness, perceived ease of use, attitudes, subjective norms, and perceived behavioral control play an essential role in using online learning platforms. Another significant contribution of this work is demonstrating the importance of perspective as a pre-factor of intention and use in online learning adoption. This variable was previously considered potentially essential but must be thoroughly investigated in empirical work or about online learning acceptance. Our findings found that users' behavioral intentions, which are crucial to online learning adoption studies, suggest that platform administrators or designers fully consider students' behavioral intentions to improve and upgrade online learning platform systems.

The research helps better understand the characteristics of students at Xihua University in Sichuan Province, China, which can help policymakers, educators, and experts understand students' expectations of learning management platforms. This enables management to deploy such platforms most effectively and helps them improve future strategic decisions about technology. They can decide on the best approach for students before implementing any new technology. In addition, for the system developers of the online learning system, this study provides the opinions of Xihua University, Chengdu, Sichuan Province, China, students on the crucial factors affecting the adoption and acceptance of the system. This will help them understand how to improve their learning management system. Likewise, users (students) can understand the motivations and factors driving their technology adoption.

5.3 Limitation and Further Study

Some potential limitations of this study need to be identified and discussed. First, data are collected from students using a convenient sampling technique and therefore are not necessarily considered representative of the population. Second, although our results support the theoretical model among students at Xihua University, Chengdu, Sichuan Province, China, the generalizability of our findings in other countries, regions, or universities should be treated with caution. Third, this study used cross-sectional analysis and quantitative survey methods to collect data. Although the questionnaire has solid theoretical literature and is carefully distributed to students, pure Quantitative analysis limits the ability to gain insight into the phenomena investigated, which are found mainly in qualitative studies. Therefore, this method is reasonable considering the research implementation, time, and resources. Therefore, future research can use various methods (interviews, qualitative, longitudinal studies, etc.). Understand the adoption and acceptance of the technology.

Furthermore, as user behavior may vary according to culture, society, context, belief, and level of technical acceptance, as our findings are context-specific (Chengdu, Sichuan, China), it would be more typical if we developed a model that could be different for different nationalities and different regions and different universities. This will be valuable in assessing the robustness and effectiveness of research models in different cultural settings. Therefore, future studies can repeat our study in single and multiple samples. In addition, future studies may extend our analysis to integrate other potential structures of interest to increase the explanatory variance of the model. In addition, further research can consider individual differences, such as cultural and demographic characteristics, before a complete picture of the dynamic nature of unique technologies may emerge.

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