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Influencing Factors of Behavioral Intention and Use Behavior of Online Learning Platforms Among Public College Students in Chengdu, Sichuan Province, China

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Abstract

Purpose: The rapid development of Internet technology and the rapid popularization of mobile terminals have promoted the vigorous development of online education. Based on the theory of technology acceptance models, this study highlights the factors influencing the behavioral intention and use behavior of Chinese public vocational school students to use online learning platforms. In this framework, the researchers examined social influence, perceived usefulness, perceived ease of use, attitudes, subjective norms, and the relationship between perceived behavioral control and behavioral intention and use behavior. **Research design, data, and methodology:** This quantitative study employed 500 vocational school students who have been using online learning platforms in Chengdu, Sichuan Province, China. The sampling techniques involve purposive and convenience sampling. IOC validation ensured the content validity and the pilot test (n=30) with Cronbach's alpha reliability (CA) test results were approved. Statistical analyses were conducted by confirmatory factor analysis (CFA) and structural equation modeling (SEM). **Results:** The results showed that social influence, perceived ease of use, perceived usefulness, subjective norms, perceived behavioral control, attitude significantly influence behavioral intention, and usage behavior. **Conclusions:** Finally, relevant suggestions are made for the improvement and development of online learning platforms in order to increase students' willingness to use them.

Keywords : Online Learning Platform, Attitude, Behavior Intention, Use Behavior, Structural Equation Modeling

JEL Classification Code: E44, F31, F37, G15

1. Introduction[1]

With the development of Internet applications, online learning has developed rapidly in recent years (Allen & Readman, 2013). According to the China Internet Network Information Center's 48th "Statistical Report on the development of the Internet in China," as of June, the number of online education users in 2021 had reached 325 million, and China's online learning market is expected to reach $85.05 billion. More and more people are taking part in online courses, which have become mainstream because of their flexibility and customizable personal interests and needs. In China, there are two main types of online learning platforms: one is an online learning platform whose main

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objective is to provide online courses; for example, online learning platforms such as Tencent classroom, online classroom, and Netease cloud classroom, which provide large-scale open courses, are not limited to full-time students, social workers can also learn relevant courses according to their own needs; another is an online learning platform with the main goal of developing web-based teachings, such as Super Star Learning, Chinese University MOOCs, intelligent vocational education and other teaching management systems, these platforms are designed to help teachers to carry out online teaching, students can use the platform to provide a variety of learning tools and a wealth of learning resources for online learning.

The researchers believe that the online learning platform has the following characteristics and advantages: it makes the learning move from physical space to virtual space, and the learners can learn anytime and anywhere without the restriction of time and place, especially with the development of mobile internet and the popularization of intelligent terminals, learners can effectively use the fragmented time to realize ubiquitous learning; Instead of passively accepting the knowledge transmitted by the teacher, learners can learn at their own pace and choose their own learning content according to their own learning needs, thus realizing individualized learning and making learning move from closed to open, it provides rich online learning resources for learners, promotes the sharing of high-quality educational resources, and makes the learners in remote and poor areas have the opportunity to acquire high-quality learning resources Make the learner from the self-contained learning into the linked learning, for learners to provide a wide range of communication opportunities, online learners can connect with learners and education experts all over the world through online learning platform to help learners build a learning community.

The purpose of this study is to explore the factors that influence the willingness and behavior of students to use online learning platforms in Chengdu, Sichuan Province, China. In this study, Chengdu textile vocational school students in Chengdu, Sichuan Province, China, were selected as the sample, we identify eight main variables, such as social influence, perceived usability, perceived usefulness, subjective norms, perceived control, and attitude, and propose a framework for this study, the purpose of this study was to examine the influencing factors of their behavioral intention and use behavior in the use of online learning platform.

2. Literature Review

2.1 Social Influence

Venkatesh et al. (2003) described social influence as the level at which individuals consider the opinions of others regarding the adoption of innovative systems and is therefore considered a key component of behavioral intention. In educational research, Tosuntas et al. (2014) and Hossain et al. (2017) highlighted a valid association between social influence, perceived usefulness, and perceived ease of use. In the context of this study, social influence indicates learners' attitudes towards believing that others significantly determine that they should use the learning platform for learning. This study pointed out that social influences may affect students' perceived usefulness and perceived ease of use of online learning, Considering the literature, the hypotheses of this study are proposed:

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

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

2.2 Perceived Ease of Use

According to the TAM, perceived ease of use directly determines perceived usefulness—direct determinants of perceived usefulness under TAM (Davis, 1989). Individuals who believe using technology is effortless will likely believe it is useful. The direct and indirect effects of perceived ease of use have been documented by empirical evidence accumulated over two decades. The direct and indirect effects of perceived ease of use on perceived usefulness (Davis, 1989; Venkatesh & Davis, 2000). Research in China has found that "ease of use" is the third most important factor influencing university students' choice of the online learning platform. Researchers have analyzed that the advantage of online learning is that it saves time. If users do not feel relaxed when using an online learning platform but find it complicated and time-consuming, their willingness to use it will be significantly reduced (Guo, 2017). In this study, perceived ease of use refers to the extent to which users perceive the platform as easy to use when using an online learning platform. 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

Through in-depth interviews and practical experience, the researcher found that students' online learning acceptance behavior stems from students' willingness to accept online learning. Therefore, in this study, the research team will determine the research mode, combining TPB and TAM theories to focus on analyzing students' intentions. Moon and Kim (2001) showed that perceived usefulness positively affects students' attitudes toward technology adoption in learning. Haryanto and Kaltsum (2016) & Salloum et al. (2019). It also strengthens this mechanism. 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

Subjective norms are associated with perceived social influence/pressure to indulge in a particular behavior (Ajzen, 1991; O'Neal, 2007). Subjective norms reveal individuals' beliefs about how their reference group will perceive them as having a certain behavior. Previous studies have shown a significant correlation between attitudes and subjective norms. Chang (1998), Shimp and Kavas (1984), Vallerand et al. (1992), and Tarkiainen and Sundqvist (2005) found in their study that there is a significant causal path between subjective norms and attitudes leading to behavior (purchase intent). Chang (1998) It is suggested that the influence of the social environment on shaping personal attitudes should be studied. Tarkiainen and Sundqvist (2005) I took note of Zhang's suggestion. The Finnish study found an important pathway from subjective norms to attitudes toward use. Therefore, in order to further investigate this causal path to test the relationship between social norm and attitude per below:
H6: Subjective norm has a significant influence on attitude.

2.5 Perceived Behavioral Control

Ajzen (1991) termed perceived behavioral control as the awareness of their own ability and the level of self-control. Li and Wu (2019) believed that subjective norms and perceived behavioral control contribute to attitudes. However, their study only involves the analysis of additional paths and does not mention the mediation effect. It is an important part of this study to add a mediation path between behavior control and attitude and other factors. As noted in the literature (Davidson, 2021), theoretically, changes in individuals' perceived ability to avoid threats contribute to their attitudes. Therefore, this study also aims to explore the relationship between perceived behavioral control and attitude:
H7: Perceived behavioral control has a significant influence on attitude.

2.6 Attitude

Many previous studies using the TPB model have shown that attitude is an important predictor of consumers' intentions to engage in certain health-related behaviors (Conner et al., 2001; Hewitt & Stephens, 2007; Patch et al., 2005; Rah et al., 2004; Sun et al., 2006). For example, Sun et al. (2006) integrated TPB and HBM to explain women's behavioral intentions to buy products in Guizhou, China. The results show that attitude is the precondition of using intention. 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. Fan et al. (2021) stated that positive attitude toward online learning system would highly promote users' acceptance and intention to use the system. Therefore, this study hypothesizes that:
H8: Attitude has a significant influence on behavioral intention.

2.7 Behavioral Intention

According to the rational action theory, a person's actions are controlled by his will. That is, "make decisions according to one's wishes." The determinants of a person's behavior are based on his or her intention to act" (Ajzen & Fishbein, 1980). Usage behavior through online learning platforms has always been driven by the intention to use. That is, better learning platform systems may lead to a higher willingness of users to use learning platforms. In addition, if there are appropriate facilities and favorable situations in colleges and universities. Behavioral intentions lead to positive use behavior of online learning platforms (Chauhan & Jaiswal, 2016). De Haan et al. (2016) Another study found that the increasing penetration of mobile devices also leads to positive use behavior of online learning platforms. The willingness to use online learning platforms in colleges and universities is also related to positive use behavior (Grewal et al., 2018). Hence, a hypothesis is indicated:
H9: Behavioral intention has a significant influence on use behavior.

2.8 Use Behavior

User behavior in the context of online learning is a crucial aspect that impacts the effectiveness and outcomes of digital education platforms (Fan et al., 2021). Understanding how learners interact with online learning environments, engage with content, and navigate through various activities can provide valuable insights for designing more engaging and effective educational experiences (Chauhan & Jaiswal, 2016). User behavior in online learning refers to the actions, interactions, and engagements of learners within digital educational platforms. This knowledge can inform instructional design, interventions, and enhancements to create more effective and engaging online learning experiences (Grewal et al., 2018).

3. Research Methods and Materials

3.1 Research Framework

In order to better understand the behavioral intention and usage behavior of college students towards online learning platforms, much research based on some well-known theories has been carried out before the Conceptual Framework of this research was formed. In this section, we begin with three theoretical models. These include technology acceptance model or TAM (perceived usefulness, perceived ease of use, attitudes, and subjective norms), the theory of planned behavior or TBP model (perceived behavioral control), and The Unified Theory of Acceptance and Use of Technology or UTAUT (social influence, behavioral intention and use behavior). Among them, TAM is the first technology system mainly used in technology system research (Luarn & Lin, 2005). In the online learning literature, researchers have also used Utaut to study the use of online learning systems (Chiu et al., 2006; Wang et al., 2009). Based on these three theoretical models, the model to be verified in this study is shown in Figure 1. social influence, perceived usefulness, perceived ease

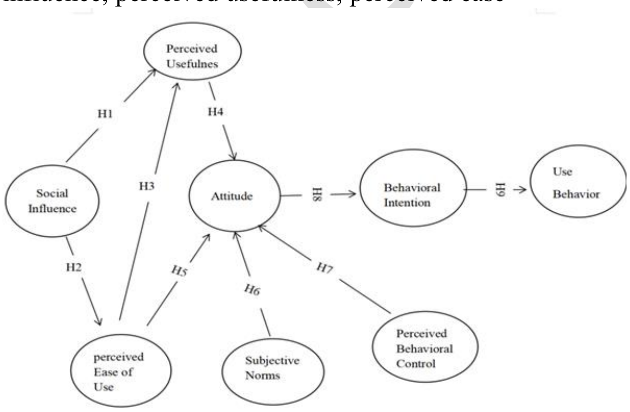

Figure 1: Conceptual Framework

H1: Social influence has a significant influence 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

The research model and preliminary scale were established based on theory and literature review. Salloum et al. (2019), Fathema et al. (2015), Chu and Chen (2016), Selim (2007), Rizun and Strzelecki (2020). The study developed the measurement scale of variables. These are the latest research results on the acceptance and behavior of students using online learning platforms based on the TAM and TPB models. The scale used in this study inherits the previous research results and is adjusted and tested according to the research background of online learning platforms in China. Quantitative research was used in the study. Therefore, the authors hope to develop their online learning perspective to make the research more objective and inclusive. The English version of the survey instrument was then translated into Chinese, and three professors conducted IOC validation to ensure the content validity with all items are approved at a score of 0.6 or over. Subsequently, the pilot test of 30 samples were investigated. Therefore, the researcher tested the appropriateness of the factors and the scale by analyzing the α of the internal consistency reliability. Cronbach's alpha reliability (CA) test results show that all items were passed at a score of 0.7 or above (Hair et al., 2010). The first phase employed confirmatory factor analysis (CFA). It involved the analysis of a measurement model to test the reliability and validity of the proposed research model. In contrast, the second phase involved analyzing and hypothesis testing a structural model (SEM) and model assessment implications.

3.3 Population and Sample Size

The target group is students from Chengdu Textile College, a public junior college in Chengdu, Sichuan Province, China. Directly under the Education Department of Sichuan Province, it is an independent textile college in southwest China. There are 11 secondary colleges and one teaching department, offering more than 40 specialties and three application-oriented undergraduate specialties, with about 15,000 students. The researchers chose this school for several reasons. First, this higher education institution school represents junior college students located in Chengdu. Secondly, the institution ranks among the top three in Chengdu, Sichuan Province. Finally, almost all the institution's students have experience using online learning platforms. The minimum sample size for a complex evaluation framework in structural equation modeling should be between 200 and 500 samples (Kline, 2010). We selected 500 students as the final sample for this study.

3.4 Sampling Technique

The study applied nonprobability method to use purposive and convenience sampling technique. Purposive sampling is to examine 500 vocational school students who have been using online learning platforms in Chengdu, Sichuan Province, China. For convenience sampling, the author completed the final questionnaire and conducted a formal quantitative survey. From October to December 2022, 532 students from Chengdu Textile College who had experience in using online learning platforms were tested, and 500 valid questionnaires (response rate = 94.3%) were obtained after excluding invalid responses. Secondly, Jamova and SPSS 26.0 were used to calculate the collected data.

4. Results and Discussion

4.1 Demographic Information

The respondents were freshmen to juniors from Chengdu Textile College. The demographic characteristics of the respondents are summarized in Table 1. Most respondents were female, with 364 (72.8%) and 136 (27.2%) males. 23.2% were aged 17-18. Most respondents were between 19 and 20, accounting for 309 respondents or 61.8% of all respondents, followed by 21 to 22 years old with 66 respondents (13.2%). The most significant number of respondents were in their second year of university, with 235 (47%) of all respondents, followed by 150 (30%) in their first year of university. The majority of respondents had 1 to 3 years of experience using online learning platforms 395 (79%), compared with 2 (0.4%) in more than three years. Most respondents used around 5-6 days a week of online learning platform, showing 343 people, 68.6%.

Table 1: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	136	27.2%
	Female	364	72.8%
Age Range	17-18	116	23.2%
	19-20	309	61.8%
	21-22	66	13.2%
	23-24	4	0.8%
	24 above	5	1%
Grade Level	Freshman	150	30%
	Sophomore	235	47%
	Junior	65	13%
	Senior	50	10%
Experience using an online learning platform	1–3 months	5	1%
	4-6 months	13	2.6%
	7–12 months	85	17%
	1-3 years	395	79%
	>3 years	2	0.4%
Frequency of use of online learning platforms	> 6 days a week	25	5%
	5-6 days a week	343	68.6%
	3-4 days a week	123	24.6%
	1-2 days a week	9	1.8%

4.2 Confirmatory Factor Analysis (CFA)

This study used confirmatory factor analysis (CFA) to assess research variables. The measurement model adds a better understanding of the reliability of the survey data, validity, and the extent to which the model was fitted. Convergent validity examines whether the measures for each construct in the model are reflected by their indicators (Gefen et al., 2000). This will ensure the unidimensionality of the multi-item structure and will help eliminate any unreliable indicators (Bollen, 1989). However, discriminant validity tests whether measures of concepts considered unrelated are statistically different (Gefen et al., 2000). The convergent validity and discriminant validity were measured. Hair et al. (2010)'s recommendations were to test composite reliability (CR) and average variance extracted (AVE). CR should be greater than 0.7 to establish good reliability, AVE should be greater than 0.5, and CR should be larger than AVE to establish convergent validity. However, the total AVE of the mean of the variables should be greater than their correlation values to support discriminant validity (Hair et al., 2010). Cronbach's alpha reliability (CA) should be equal to 0.7 or over, and factor loading should be should be equal to 0.5 or over. As a results of Table 2, all estimates are significant.

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	0.800	0.507-0.861	0.852	0.543
Perceived ease of use (PEOU)	Davis (1989)	4	0.916	0.812-0.883	0.907	0.709
Perceived usefulness (PU)	Pikkarainen et al. (2004)	3	0.909	0.811-0.917	0.912	0.775
Subjective Norm (SN)	Ajzen and Fishbein (1977)	3	0.867	0.792-0.877	0.869	0.689
Perceived Behavioral Control (PBC)	Li and Wu (2019)	3	0.890	0.825-0.871	0.892	0.733
Attitude (ATT)	Chennamaneni et al. (2012)	3	0.870	0.793-0.858	0.869	0.690
Behavioral Intention (BI)	Wu and Du (2012)	3	0.900	0.843-0.885	0.902	0.753
Use Behavior (UB)	Wu and Du (2012)	4	0.880	0.771-0.858	0.880	0.648

Examine the relationship between the structures in the proposed research model (Arbuckle, 2012). This is done using a maximum likelihood estimation (MLE) procedure to estimate the model's parameters, where all the analysis is done with the variance-covariance matrix (Hair et al., 2010). To assess the model's goodness of fit, Kline (2010) and Hair et al. (2010) recommend some fit metrics that should be considered. These measures are the root-mean-square residuals (RMSR) and the root-mean-square average. Including chi-square statistic (CMIN/DF), squared error of approximation (RMSEA), comparative fit index (CFI), adjusted goodness-of-fit index (AGFI), goodness-of-fit index (GFI), normalized fit index, and tucker-Lewis index. The results of the model provide a good fit for the data. It is clear from Table 3 that all the fit indices are within the recommended range.

Table 3: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	<5.00 (Hair et al., 2010)	2.296
GFI	≥0.85 (Sica & Ghisi, 2007)	0.903
AGFI	≥0.80 (Sica & Ghisi, 2007)	0.878
NFI	≥0.80 (Arbuckle, 1995)	0.933
CFI	≥0.80 (Hair et al., 2006)	0.961
TLI	≥0.80 (Hair et al., 2006)	0.954
RMSEA	<0.080 (Pedroso et al., 2016)	0.051
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

In this study, the researcher considered the AVE values value to determine the discriminant validity of each factor. The AVE value should be greater than or equal to 0.50. Because the AVE value by itself does not prove discriminant validity, discriminant validity is achieved if the square root of the AVE value for each architecture is greater than the square root of the AVE value for each architecture in terms of the correlation between the dimensions. The AVE value must be compared to each architecture's correlation coefficient with other architectures. The correlation coefficients of the other architectures are compared. Therefore, first, we must obtain a matrix in which we can see all the architectural correlations, all the architectural correlations. Afterward, we equated the square root AVE values with the other correlation coefficients and inserted them diagonally, exceeding the critical points' values in Table 4. This ensures the convergent validity and discriminant validity of this study.

Table 4: Discriminant Validity

	SI	PU	PEOU	ATT	SN	PBC	BI	UB
SI	**0.715**							
PU	0.435	**0.880**						
PEOU	0.346	0.474	**0.842**					
ATT	0.44	0.696	0.721	**0.831**				
SN	0.363	0.471	0.511	0.686	**0.830**			
PBC	0.328	0.505	0.627	0.715	0.723	**0.856**		
BI	0.34	0.526	0.608	0.740	0.700	0.851	**0.868**	
UB	0.348	0.525	0.641	0.794	0.726	0.840	0.927	**0.805**

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

4.3 Structural Equation Model (SEM)

Following CFA, a structural equation model (SEM) estimates a particular set of linear equations and determines the model's fit. SEM can measure the relationship between variables (Table 5). After adjustment, the model meets all the index standards, and the model fitting is obtained in SEM.

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, 1995)	0.936
CFI	≥0.80 (Hair et al., 2006)	0.964
TLI	≥0.80 (Hair et al., 2006)	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

According to the study results, after establishing good convergence and discriminant validity, the next step was to evaluate the structural model to test the proposed relationship. As shown in Table 6, the results show that all paths are supported. In addition, H1, H2, H3, H4, H5, H6, H7, H8, and H9 all significantly affect the positive path.

Table 6: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: SI → PU	0.159	2.971**	Supported
H2: SI → PEOU	0.263	5.786***	Supported
H3: PEOU→ PU	0.816	10.347***	Supported
H4: PU → ATT	0.415	9.914***	Supported
H5: PEOU → ATT	0.569	12.679***	Supported
H6: SN → ATT	0.112	2.383*	Supported
H7: PBC → ATT	0.148	0.040**	Supported
H8: ATT → BI	1.040	16.332***	Supported
H9: BI → UB	0.970	25.560***	Supported

Note: *** p<0.001, ** p<0.01, * p<0.05
Source: Created by the author

H1: Social influence has a significant influence on perceived usefulness. The results were like those of where social influence had a significant positive effect on perceived usefulness. The standardized path coefficient between them is 0.159, and the t-value is 2.971. Therefore, H1 is also supported.

H2: Social influence has a significant influence on perceived ease of use. The standardized path coefficient between social influence and perceived ease of use was 0.263 with a t-value of 5.786, where H2 is supported. This indicates that social influence has a significant positive effect on perceived ease of use.

H3: Perceived ease of use has a significant influence on perceived usefulness. On the other hand, Perceived ease of and Perceived usefulness have a standardized path coefficient of 0.816, with a t-value equal to 10.347. Thus, H3 is correct, indicating a significant positive causal relationship between perceived usefulness and behavioral intention.

H4: Perceived usefulness has a significant influence on attitude. The standardized path coefficient between perceived usefulness and attitude is 0.415 with a t-value of 9.914. This shows that perceived usefulness and attitude have an apparent positive effect. So H4 is supported.

H5: Perceived ease of use has a significant influence on attitude. In addition, the standardized path coefficient between perceived ease of and attitude was 0.569 with a t-value of 12.679. This implies that H5 supports the significant influence between perceived ease of and attitude.

H6: Subjective norms have a significant influence on attitude. Furthermore, the standardized path coefficient between Subjective norms and attitude is 0.112, and the t-value is 2.383. This means there is also a significant correlation between Subjective norms and attitude. H6 is supported.

H7: Perceived behavioral control has a significant influence on attitude. The standardized path coefficient between Perceived behavioral control and attitudes was 0.148 with a t-value of 0.040. This indicates a significant favorable influence of perceived behavioral control and attitudes. Therefore, H7 is supported.

H8: Attitude has a significant influence on behavioral intention. The standardized path coefficient between attitude and the behavioral intention was 1.040, with a t-value of 16.332. This is shown that two variables are significantly correlated, so H8 is supported.

H9: Behavioral intention has a significant influence on user behavior. According to the results in table 6, H9 is supported. The standardized path coefficient between behavioral intention and use behavior is 0.966 with a t-value of 22.790. This means there is a significant effect between behavioral intention and use behavior.

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

The digital transition is now irreversible. This is seen as a breakthrough, particularly in education, a major task requiring focused attention in the coming years. Online learning is the most intuitive result of digital transformation. Governments, universities, and the community have also been promoting the validation process for online courses. However, to promote the intention and behavior of online learning in a more effective and positive direction, universities need to meet several requirements, including mechanisms and policies; university development strategies; and technological infrastructure systems. This study explores the factors that affect the use of online learning platforms by public college students in Chengdu, Sichuan Province, China. The study focused on the Chengdu Institute of Textiles, a vocational school in Chengdu, Sichuan Province, China.

This study effectively investigated the factors affecting the use of online learning platforms by public college students in Chengdu, Sichuan Province, China. Although the researchers separated the population by gender, grade, and major, the results were very similar, with students reporting that the effect of attitude on behavioral intent was most pronounced. The causal relationship between social influence and perceived usefulness (0.159), the causal relationship between social influence and perceived usability (0.263), and the causal relationship between perceived usability and perceived usefulness (0.816) were more significant The causal relationships between perceived usefulness and attitude (0.415), perceived ease of use and attitude (0.569), subjective norms and attitude (0.112), perceived control and attitude (0.148), perceived usefulness and attitude (0.415), perceived ease of use and attitude (0.569), perceived ease of use and attitude (0.112), perceived control and attitude (0.148) Attitude and behavioral intention (1.040) and the causal relationship between behavioral intention and use behavior (0.966).

In summary, social influence has a significant effect on perceived usefulness. Compared with perceived ease of use and perceived usefulness, social influence is the highest factor for perceived usefulness. This means that the opinions or suggestions of others in society are indispensable and more persuasive than your own. Students will see the system as applicable when others think using the learning platform will help their learning. This discovery is consistent with previous research by Claar et al. (2014), Hong et al. (2006), and Shao (2018). Therefore, college students believe that social influence is crucial to choosing online learning platforms. Perceived usefulness has a significant impact on attitudes toward using online learning platforms.

From the investigation, perceived usefulness and perceived ease of use have a significant impact on attitudes. Perceived usefulness and perceived ease of use have the most decisive influence on college students' attitudes toward using online learning platforms. The discovery is consistent with Didyasarin et al. (2017), Kleijnen et al. (2004), and Zhang et al. (2008). If the platform can help them complete their learning tasks while spending less energy and time, students using the online learning platform is a good attitude. In addition, subjective norms and perceived control also significantly impact students' attitudes toward using online learning platforms. Easy-to-use platform technology will encourage student attitudes and thus promote student acceptance and use. Students' attitudes toward using online learning platforms affect their behavioral intentions. This finding is consistent with previous studies that have shown that students' attitudes toward using online learning platforms are consistent with previous studies that have shown that people's behavior depends on their attitudes. In summary, good attitudes among students drive behavioral intentions to use online learning platforms.

5.2 Recommendation

The study's results on the students of Chengdu Textile College show that ease of use, usefulness, subjective norms, and perceived control directly affect the use attitude and indirectly affect the use intention and behavior through the use attitude. Therefore, it is recommended that system developers and university educators design and promote online learning platforms considering the platform's ease of use, usefulness, and the personal specification of operational capabilities. This will increase the positive attitude of the users of the learning platform, promote their intention and use behavior, and enable them to recommend the platform to others. In addition, the findings suggest that social influence indirectly influences attitudes through perceived usefulness and ease of use. In order to improve students' intention to use online learning platforms, school administrators and teachers should organize a series of experience-sharing activities, inviting some beneficiaries of using online learning platforms to explain the importance and benefits of using these platforms; once users know that they will benefit from these platforms, they may be inclined to use online learning platforms for learning. Regarding perceptual control, online learning platform developers should ensure that the platform always provides smooth use and accurate, up-to-date, consistent, well-formatted learning materials of all kinds, as well as simple operation. As a result, users will find this system practical and will be inclined to use it.

5.3 Limitation and Further Study

The study's results were limited to students at higher textile vocational schools in Chengdu, which may affect the validity of the results. In addition, other environmental, systemic, and organizational factors were not part of the study, so the authors should replicate the results at other universities for broader data to promote and seek its applicability. Second, there needs to be more feedback from teachers and parents, which will likely be more informative. Third, the survey only looked at all online learning platforms and did not focus on a particular brand of the learning platform. The model was carried out in social isolation and had a modest but positive impact; therefore, for future research, the model needs to be evaluated in different ways, such as in the organization of investigations after an outbreak has ended. In addition, university factors outside China or Sichuan province may provide different explanations; they can be incorporated into future research.

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