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Measuring First-Year Students' Behavioral Intention and Use Behavior of Chaoxi Online Learning Platform to Study Mental Health Course in Chengdu, China

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Abstract

Purpose: Facing the extreme demands of students in using online learning, most online education enterprises act quickly to improve the system to ensure smooth teaching and learning. This paper aims to measure first-year students' behavioral intention to use Chaoxi online learning platform to study mental health courses in Chengdu, China. The research model is based on perceived usefulness, perceived ease of use, self-efficacy, attitude, subjective norms, behavioral intention, and use behavior. **Research design, data, and methodology:** This quantitative study was conducted to distribute the questionnaire to 500 first-year students from three selected colleges. The sampling methods are judgmental, stratified random, and convenience sampling. The study was measured with the index of item-objective congruence (IOC) and pilot test (n=50) to ensure content validity and construct reliability. Confirmatory Factor Analysis (CFA) and Structural Equation Model (SEM) were the main statistical tools. **Results:** Perceived ease of use significantly impacts perceived usefulness and attitude. Self-efficacy and subjective norms significantly impact attitude. Behavioral intention is impacted by attitude but not self-efficacy and subjective norms. Furthermore, use behavior is impacted from behavioral intention. **Conclusions:** The developers, senior managers, and teachers of higher education institutions should focus on improving the quality and performance of the Chaoxi learning platform.

Keywords : Self-Efficacy, Attitude, Subjective Norms, Behavioral Intention, Use Behavior

JEL Classification Code: E44, F31, F37, G15

1. Introduction

China's educational modernization in 2035 advocates that schools should fully use information technology and constantly reform curriculum (Feijóo et al., 2021). According to the 45th statistical report on Internet development in China, by March 2020, the number of online education users in China has reached 423 million, an increase of 110.2% over the end of 2018, accounting for 46.8% of the total number of Internet users. Among them, the number of students is the largest, accounting for 26.9% of Internet users. The number of people receiving online education is also increasing year by year.

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At the beginning of 2020, in the face of the sudden COVID-19, schools in China had to delay their opening. 265 million students switched from offline to online courses to meet teaching needs in special situations. Facing the needs of users of large-scale online learning, many online education enterprises act quickly, improve the online learning platform, develop enough application functions, and constantly meet the needs of teachers and students for online teaching and learning. During the epidemic, the number of daily active users of many online education applications reached more than 10 million (Feijóo et al., 2021).

First, all kinds of schools actively explore online education. The Ministry of education has launched 22 online course platforms and opened 24,000 online courses, which provides a strong guarantee for regular colleges and universities to stop classes and teaching. Second, some office applications offer cross-border online education. Nailing, Tencent conferences, and other office applications have become widely used online education platforms for teachers and students across the country. Because the function, interactivity, and stability of online platforms greatly impact Teachers' online teaching, vocational colleges need to choose a mature and reliable platform to carry out online teaching.

At present, ChaoXi learning Platform, blue ink cloud class, vocational education cloud, and other platforms have been used in most vocational colleges. The platform is relatively mature with relatively comprehensive functions. This paper aims to measure first-year students' behavioral intention to use Chaoxi online learning platform to study mental health courses in Chengdu, China. This study attempts to fill the research gap that limited research has explored students' behavioral intention and use behavior towards e-learning in China. The research model is based on perceived usefulness, perceived ease of use, self-efficacy, attitude, subjective norms, behavioral intention, and use behavior.

2. Literature Review

2.1 Perceived Ease of Use

Perceived ease of use refers to "the degree to which a person believes that using a particular system would be free from effort," and perceived usefulness refers to "the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis, 1989). Many studies have proved that perceived ease of use is an important factor in improving the behavioral intention of information technology use (Chen et al., 2011). Teo (2011) believed that the system's ease of use could improve users' participation and enhance users' sense of belonging. The technical term "perceived ease of use" means that users expect the new technology to be simple and convenient without too complex procedures.

Perceived ease of use directly determines the usefulness of the factors based on the technology acceptance model or TAM (Davis, 1989). Evidence shows that in the past two decades, people have accumulated much empirical experience in using perceived ease of use, reflected in both direct and indirect research on perceived ease of use (Davis, 1989). Many previous studies have applied these two variables to detect users' use of specific new technology systems. The results show they are consistent with TAM (Ma & Liu, 2004). Therefore, the user's attitude towards the free volunteer service system directly affects the user's ease of use and usefulness when using the system, and the user's experience and judgment on ease of use and usefulness will, in turn, affect the user's willingness to use the free volunteer service. Based on the previous studies, a hypothesis is suggested:

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

Perceived usefulness is "a person believes that using a particular system would enhance the level of his or her job performance." Perceived usefulness means users think technology will improve their learning effect (Davis, 1989). Therefore, perceived usefulness affects individuals' willingness to adopt new technology. Gefen et al. (2003) have found that applying new technology is closely related to perceived ease of use and adaptability in any environment. Bhattacherjee (2001) aims to study cognitive beliefs and how they affect an individual's willingness to continue using online banking and proposes that users' perceived usefulness after use is one of the key factors affecting their satisfaction. This empirical study's results are consistent with TAM's conclusions (Lee, 2009). Therefore, when students realize that a learning platform can improve their learning ability and achievement, their attitude towards using the learning platform will be greatly strengthened. Hence, a hypothesis is developed:

H3: Perceived usefulness has a significant impact on attitude.

2.3 Attitude

Attitude is the individual acting on positive or negative assessment (Fishbein & Ajzen, 1975). Attitude means "a person's overall evaluation" of behavior (Ajzen, 2005). Attitude can test one positive or negative evaluation of a particular action, and the expected result can be predicted according to the formation of the view (Lee, 2009). Attitude is a belief that affects a person's behavioral intention. Attitude is the psychological tendency of individuals to evaluate certain behavioral advantages (Ha & Janda, 2012). The user intends to use the system at TAM to use the system's overall attitude premise (Davis, 1989). For decades, researchers have discussed the theoretical construction of attitudes to identify the causes of intent. Many studies have shown that the attitude toward using the system positively affects the willingness to use the system (Lee, 2009). When Chinese students think it is useful, they will use the mobile library to form a positive attitude, affecting their behavioral intention. In other words, they will want to use it more and more strongly. Subsequently, a hypothesis is stated:

H7: Attitude has a significant impact on behavioral intention.

2.4 Self-Efficacy

Bandura (1977) defined self-efficacy for users of its organization and implementation to specify the type of action needed for the performance ability of judgment. Self-efficacy is for a person to perform the recommended expectations of adaptive behavior ability. Self-efficacy refers to the individual's feeling and understanding of their ability, not the unique attribute of self-concept (Bong & Skaalvik, 2003). High and low self-efficacy have a positive correlation with students' academic performance. Generally speaking, students with high self-efficacy are more likely to achieve better results, have a positive attitude toward mobile library applications, and have a stronger willingness to continue using them (Tang et al., 2014).

Self-efficacy reflects that Chinese students can conduct successfully execution the extent of the use of mobile library applications. Compared with low self-efficacy of students, Generally, students with a more efficient sense of ability are more likely to achieve better learning results. They have a positive attitude and a more intense continued use willingness (Tang et al., 2014). Some researchers believe that self-efficacy, as an individual's external perception, plays a very important role in personal motivation, attitude, and behavior intention (Ajjan et al., 2014; Xiao et al., 2015). When self-efficacy is relatively high, current college students have more confidence in their technical ability and have better adaptability in using specific applications (Goh, 2011). The assumptions lead to a proposed hypothesis:

H4: Self-efficacy has a significant impact on attitude.

H6: Self-efficacy has a significant impact on behavioral intention.

2.5 Subjective Norm

Subjective norms come from the social field. Everyone lives in a certain social environment, and people, things, and things in the social environment influence their behavior. Awaludin (2014) proposed that subjective norm refers to a kind of pressure related to other people, things, and things. Subjective norms are normative beliefs or reference communities (Tarkiainen & Sundqvist, 2005). Hsu et al. (2014) pointed out in the research that subjective norms have more or less influence on users' attitudes and behavioral intention to choose a specific technology. Subjective norm refers to family members, friends, colleagues, and other important social pressure (Farah, 2017). The relationship between attitude and the subjective norm has been discussed through the mechanism of the effect of the cross. Has been found a relatively high relationship between consumer attitudes and subjective norms (Rivis & Sheeran, 2003). In addition, it was found in the literature empirical evidence of TPB's obvious and direct impact on the attitude of subjective norms of mobile commerce. Accordingly, this research hypothesizes that:

H5: Subjective norm has a significant impact on attitude.

H8: Subjective norm has a significant impact on behavioral intention.

2.6 Behavioral Intention

Behavioral intention is a willingness to change from the existing learning method to the future use of an e-learning system (Samsudeen & Mohamed, 2019). As previous researchers have concluded, behavioral intention refers to the psychological degree of execution or non-execution of a behavior (Venkatesh et al., 2003). behavioral intention refers to a person's planned possibilities for application technology (Ukut & Krairit, 2019). It is considered the precursor of use behavior, which indicates that the user is prepared to perform a particular behavior (Venkatesh et al., 2003). Previous studies have pointed out that in the context of an e-learning system, whether an individual uses an electronic system is positively related to the intention of using the system. The stronger the intention of use, the more able he can perform the behavior of use (Zhang et al., 2012). At this point, students and teachers have accepted new technology. ICT user behavior has been discovered to impact use intention behavior significantly. This is similar to the findings of Venkatesh et al. (2003). According to this study, behavioral intention is a decision to use e-learning systems (Salloum & Shaalan, 2019).

H9: Behavioral intention has a significant impact on use behavior.

2.7 Use Behavior

Usage behavior is used to dynamically respond to user actions or perform specific tasks (Venkatesh et al., 2003). Using behavior is to form knowledge, habits, and skills into certain steps in a certain order and way, then adopt correct methods and gradually train according to the sequence determined by task decomposition. Finally, they can complete the task independently and apply their learned knowledge and skills on other occasions (Zhong et al., 2022). The use intention successfully promotes the actual behavior of mobile shopping through smartphones (Hubert et al., 2017). The research of Celik (2016) found that convenience positively influences the behavioral intention of online shopping. Convenience has a significant impact on usage behavior (Weerakkody et al., 2013).

3. Research Methods and Materials

3.1 Research Framework

The conceptual framework of this study was developed based on prior theoretical and empirical studies, as shown in Figure 1. Watjatrakul (2016) emphasized the key variables: perceived ease of use and perceived usefulness. Hu and Zhang (2016) addressed the relationship between perceived usefulness, self-efficacy, attitude, subjective norms, and behavioral intention. Samsudeen and Mohamed (2019) found a link between behavioral intention and use behavior.

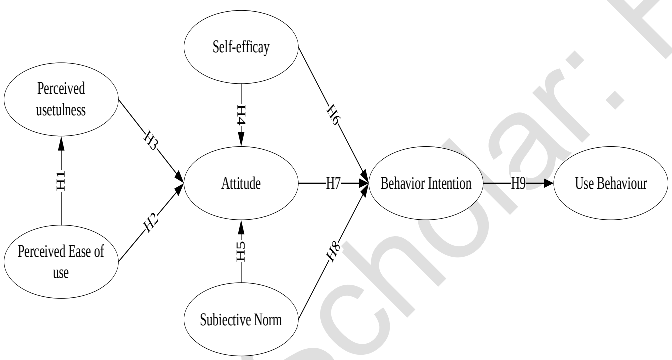

Figure 1: Conceptual Framework

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: Self-efficacy has a significant impact on attitude.
H5: Subjective norm has a significant impact on attitude.
H6: Self-efficacy has a significant impact on behavioral intention.
H7: Attitude has a significant impact on behavioral intention.
H8: Subjective norm has a significant impact on behavioral intention.
H9: Behavioral intention has a significant impact on use behavior.

3.2 Research Methodology

This study applied a quantitative approach to distributing the questionnaire to 500 first-year students from three selected colleges: Chengdu Industrial Vocational and technical college, Chengdu Textile College, and Chengdu Vocational College of Agricultural Science and Technology. The sampling methods are judgmental, stratified random, and convenience sampling. The survey was constructed with three parts: screening questions, measuring items of a five-point Likert scale, and a demographic profile. Five-point Likert scale was used to estimate the full-scale items, with five indicating the strongest agreement and 1 indicating strong disapproval (Salkind, 2010). Confirmatory Factor Analysis (CFA) and Structural Equation Model (SEM) were conducted using SPSS and SPSS AMOS statistical tools.

The study was measured with the index of item-objective congruence (IOC) and pilot test (n=50) to ensure content validity and construct reliability. The index of item-objective congruence (IOC) showed all scale items passed at a score rating from three experts equal to or above 0.6. The Cronbach alpha (CA) coefficient reliability test showed that all items have strong internal consistency equal to or above 0.7 (Sarmento & Costa, 2019). The CA's results include perceived ease of use (0.947), perceived usefulness (0.959), attitude (0.956), self-efficacy (0.962), subjective norm (0.955), behavioral intention (0.954), and use behavior (0.942).

3.3 Population and Sample Size

The target population of this study is first-year students from three selected colleges: Chengdu Industrial Vocational and Technical College, Chengdu Textile College, and Chengdu Vocational College of Agricultural Science and Technology. The recommended minimum sample size for structural equation models is 425 respondents (Soper, 2022). In this study, 500 were chosen after the received responses and data screening.

3.4 Sampling Technique

The sampling methods are judgmental, stratified random, and convenience sampling. The judgmental sampling is to select first-year students from three selected colleges who have been using the ChaoXi Learning Platform. The sample was randomly stratified into 500 respondents, as shown in Table 1. Convenience sampling was to distribute the survey to the target participants via school managers.

Table 1: Sample Units and Sample Size

College	Total of First-Year Students	Proportionate Sample Size
Chengdu Industrial Vocational and Technical College	5076	177
Chengdu Textile College	4238	148
Chengdu Vocational College of Agricultural Science and Technology	5018	175
Total	**14332**	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

The demographic profile was collected from 500 respondents. In Table 2, the results show that 55.4 percent of females (277) and 44.6 percent of males (223). For the frequency of ChaoXi Learning Platform, 39.6 percent is 1-3 days per week, 45.4 percent is 4-6 Days per week, and 15 percent is 7 days per week.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	223	44.6
	Female	277	55.4
Frequency of Use	1-3 Days/Week	198	39.6
	4-6 Days/Week	227	45.4
	7 Days/Weel	75	15.0

4.2 Confirmatory Factor Analysis (CFA)

In Table 3, Cronbach's Alpha values have strong internal consistency equal to or above 0.7 (Sarmento & Costa, 2019), including perceived usefulness, perceived ease of use, self-efficacy, subjective norms, attitudes, behavioral intentions and use behavior, reaching the alpha values of 0.884, 0.865, 0.872, 0.847, 0.794, 0.869 and 0.897. O'Rourke and Hatcher (2013) mentioned that factor loading should be 0.5 or higher (Hair et al., 2010). Another indicator to measure the reliability and consistency of scale items is composite or construct reliability (CR) and average variance extracted (AVE). According to Fornell and Larcker (1981), the acceptable values of CR and AVE are acceptable at 0.7 or higher and 0.4 or higher, respectively. In this study, all CR results were higher than the threshold. The values of composite reliability range from 0.794 to 0.897. Additionally, AVEs were greater than 0.4, ranging from 0.446 to 0.687.

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 (PEU)	(Watjatrakul, 2016)	5	0.865	0.686-0.930	0.865	0.565
Perceived Usefulness (PU)	(Watjatrakul, 2016)	5	0.884	0.745-0.828	0.884	0.605
Attitude (ATT)	(Hu & Zhang, 2016)	5	0.794	0.537-0.924	0.794	0.446
Self-Efficacy (SE)	(Hu & Zhang, 2016)	5	0.872	0.731-0.779	0.872	0.576
Subjective Norm (SN)	(Hu & Zhang, 2016)	4	0.847	0.699-0.893	0.847	0.584
Behavioral Intention (BI)	(Samsudeen & Mohamed, 2019)	5	0.869	0.742-0.764	0.869	0.570
Use Behavior (UB)	(Samsudeen & Mohamed, 2019)	4	0.897	0.734-0.976	0.897	0.687

In order to ensure the applicability of the model, a confirmatory factor analysis was used to evaluate the measurement model. This study does not need to modify the model because the original model has provided model fitting. The acceptable values of goodness-of-fit indices in Table 4 show the model fit of the statistical values of the indices. The values were CMIN/DF =3.025 GFI = 0.833, AGFI = 0.803, NFI=0.862, CFI = 0.903, TLI 0.891, and RMSEA = 0.064.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	1433.987/474 or 3.025
GFI	≥ 0.80 (Sica & Ghisi, 2007)	0.833
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.803
NFI	≥ 0.80 (Wu & Wang, 2006)	0.862
CFI	≥ 0.80 (Bentler, 1990)	0.903
TLI	≥ 0.80 (Sharma et al., 2005)	0.891
RMSEA	< 0.08 (Pedroso et al., 2016)	0.064

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.

When the square root of the AVE is greater than the coefficient of any intercorrelated construct, discriminant validity is established (Fornell & Larcker, 1981). The square root of AVE for each construct at the diagonal line was greater than the inter-scale correlations, as shown in Table 5. As a result, discriminant validity was ensured.

Table 5: Discriminant Validity

	PU	PEU	SE	SN	ATT	BI	UB
PU	**0.778**						
PEU	0.536	**0.751**					
SE	0.444	0.464	**0.759**				
SN	0.339	0.377	0.449	**0.764**			
ATT	0.382	0.411	0.421	0.367	**0.668**		

	PU	PEU	SE	SN	ATT	BI	UB
BI	0.454	0.441	0.438	0.46	0.495	**0.755**	
UB	0.35	0.315	0.306	0.295	0.267	0.481	**0.829**

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 Table 6, the model fit was evaluated by comparing the indices' statistic values to the acceptable goodness-of-fit values in table 5.8. CMIN/DF = 3.067, GFI = 0.831, AGFI = 0.804, NFI = 0.857, CFI = 0.899, TLI = 0.889, and RMSEA = 0.060 were the indices' statistical values.

Table 6: Goodness of Fit for Structural Model

Index	Acceptable	Statistical Values
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	1481.443/483 or 3.067
GFI	≥ 0.80 (Sica & Ghisi, 2007)	0.831
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.804
NFI	≥ 0.80 (Wu & Wang, 2006)	0.857
CFI	≥ 0.80 (Bentler, 1990)	0.899
TLI	≥ 0.80 (Sharma et al., 2005)	0.889
RMSEA	< 0.08 (Pedroso et al., 2016)	0.060

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

Regression coefficients or standardized path coefficients are used to determine the level of correlation between the independent and dependent variables that the hypothesis proposes. As a result, six of the nine assumptions are supported, as shown in Table 7.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-Value	Result
H1: PEU → PU	0.778	14.563*	Supported
H2: PEU → ATT	0.151	2.073*	Supported
H3: PU → ATT	0.116	1.759	Unsupported
H4: SE → ATT	0.237	3.781*	Supported
H5: SN → ATT	0.424	6.472*	Supported
H6: SE → BI	0.007	0.114	Unsupported
H7: ATT → BI	0.709	8.133*	Supported
H8: SN → BI	0.061	0.913	Unsupported
H9: BI → UB	0.533	11.224*	Supported

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

H1: Perceived ease of use has a significant impact on perceived usefulness. The standardized path coefficient of the association between behavioral intention and use behavior is 0.778, and the t-value is 14.563. This supports the assumption that perceived ease of use directly determines the usefulness of the factors based on the technology acceptance model (Davis, 1989).

H2: It is confirmed that perceived ease of use significantly impacts attitude, with a standardized path coefficient of 0.151 and a t-value of 2.073, so H2 is supported. The results align with previous studies that the student's attitude toward online learning is directly affected by the system's ease of use (Ma & Liu, 2004).

H3: This study reveals that perceived usefulness has no significant impact on attitude, with a standardized path coefficient of 0.116 and a t-value of 1.759. Therefore, the results contradict previous studies that when students realize that a learning platform can improve their learning ability and achievement, their attitude towards using it will be greatly strengthened (Bhattacherjee, 2001; Gefen et al., 2003; Lee, 2009).

H4: The findings confirm the support relationship between self-efficacy and attitude, with a standardized path coefficient of 0.237 and a t-value of 3.781. Accordingly, it explains that when students can control the system, they express a positive attitude toward its use (Davis, 1989; Lee, 2009).

H5: The relationship between subjective norms and attitude is approved, with a standardized path coefficient of 0.424 and a t-value of 6.472. It can be explicated that subjective norms such as family members, friends, colleagues, and other important social pressure have more or less influence on users' attitudes (Farah, 2017).

H6: The findings show that self-efficacy does not significantly impact behavioral intention, with a standardized path coefficient of 0.007 and a t-value of 0.114. It reflects that Chinese students' self-efficacy is irrelevant to their willingness to use the ChaoXi Learning Platform (Tang et al., 2014).

H7: Attitude significantly impacts behavioral intention with a standardized path coefficient of 0.709 and a t-value of 8.133. Attitude is a belief to affect students' behavioral intention to use online learning platforms (Ha & Janda, 2012; Lim & Ting, 2014).

H8: Subjective norm has no significant impact on the behavioral intention with a standardized path coefficient of 0.061 and t-value of 0.913. The results oppose the statement that the subjective norm has been discussed to predict students' intentional behavior using online learning (Rivis & Sheeran, 2003).

H9: Behavioral intention significantly impacts use behavior, resulting in a standardized path coefficient of 0.533 and a t-value of 11.224. At this point, students use behavior can be facilitated by behavioral intention (Salloum & Shaalan, 2019; Venkatesh et al., 2003).

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

Facing the extreme demands of students in using online learning, most online education enterprises act quickly to improve the system to ensure smooth teaching and learning. This paper aims to measure first-year students' behavioral intention to use Chaoxi online learning platform to study mental health courses in Chengdu, China. Confirmatory Factor Analysis (CFA) and Structural Equation Model (SEM) were the main statistical tools. The results show that perceived ease of use significantly impacts perceived usefulness and attitude. Self-efficacy and subjective norms significantly impact attitude. Behavioral intention is impacted by attitude but not self-efficacy and subjective norms. Furthermore, the relationship between behavioral intention and use behavior is supported.

Perceived usefulness, perceived ease of use, and attitude obtained from TAM. Among them, perceived usefulness refers to the degree to which an individual holds an information system that can improve his or her work achievements using shortening the time required to complete a task or providing information promptly (Davis et al., 1989). Perceived ease of use has a great impact on perceived usefulness. The more students think that the Chaoxi learning platform is convenient and easy to use, the more they think it is helpful for their learning. This is consistent with previous research results. At the same time, perceived usefulness and ease of use affect attitudes. Research shows that subjective norms directly impact attitudes and use intentions. Students' attitudes and use intentions of using the Chaoxi learning platform are greatly affected by teachers, classmates, and friends around them.

Self-efficacy also affects students' attitudes and intentions to use the Chaoxi learning platform. When students feel they can use the Chaoxi learning platform well, they are more willing to use it. At the same time, UTAUT's theory points out that the performance of some systems can affect the intention of using technology (Venkatesh et al., 2003). This study found that attitude has a direct impact on behavioral intention, which supports the studies of Ha and Janda (2012), Lim and Ting (2014), Benjangjaru and Vongurai (2018) and Bhattacherjee (2001). The more they think that using the Chaoxi learning platform positively impacts them, the more interested they will be in using it.

5.2 Recommendation

The results of this study show that in order to help students better use the Chaoxi learning platform, the developers of the Chaoxi learning platform should strengthen the application research and publicity, constantly improve its use performance, enhance the usability of the Chaoxi learning platform, and strengthen the publicity of the usefulness of the platform. At the same time, senior managers and teachers in higher vocational colleges should strengthen the guidance of students' use process, give full play to the Chaoxi learning platform, and let students perceive its usefulness. In the process of students' use, senior managers and teachers of higher vocational colleges should strengthen guidance and supervision, promote students' self-efficacy, and enhance students' confidence in using the Chaoxi learning platform. It can also urge students to encourage and communicate with each other before to help learners learn online courses more effectively and improve their willingness to accept the Chaoxi learning platform.

The results of this study show that all factors significantly impact the use of the Chaoxi learning platform. Behavior intention is the strongest predictor of using the Chaoxi learning platform. Other equally important but indirect predictors are attitude, perceived usefulness, perceived ease of use, subjective norms, and self-efficacy. These factors can determine that the developers of the Chaoxi learning platform, senior managers of higher education institutions, or teachers should emphasize the behavioral intention of students to use the Chaoxi learning platform. The developers of the Chaoxi learning platform, senior managers, and teachers of higher education institutions should focus on improving the quality and performance of the Chaoxi learning platform. Encouraging students to use the Chaoxi learning platform or other online learning tools is crucial to the teaching process. In the current or special period, the Chaoxi learning platform can be used as an alternative solution, such as during the COVID-19 pandemic.

5.3 Limitation and Further Study

This study has some limitations. First, three schools of Sichuan University were selected to collect data, so the sample size is limited. Secondly, the topic of this study is only based on the Chaoxi learning platform. Further research can be carried out in other types of e-learning systems or systems for other purposes, such as large-scale open online courses (MOOC), ubiquitous learning (U-learning), or enterprise e-learning. Third, qualitative research can be added to understand students' behavioral intentions better using the Chaoxi learning platform.

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