THE PERCEPTION OF COLLEGE STUDENTS TOWARDS BEHAVIORAL INTENTION TO USE CHAOXI ONLINE LEARNING PLATFORM IN CHENGDU, CHINA

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Abstract

The use of online learning in higher education after the decline of COVID-19 has been debated. This quantitative study investigates factors impacting students' behavioral intention to use Chaoxi online learning platform in Chengdu, China. The questionnaire was distributed to 500 third-year students from three selected colleges in Chengdu. 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. The results showed that perceived ease of use significantly impacts perceived usefulness. Perceived usefulness and subjective norms significantly impact attitude. Subjective norms, self-efficacy, and attitude significantly impact behavioral intention towards use behavior. Nevertheless, perceived ease of use and self-efficacy directly impact attitude but not significant.

Introduction

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 (Nolasco, 2022). 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 (Xia, 2020).

According to the survey report on online teaching of university teachers during the epidemic period (CIQA), the focus of teacher development at Xiamen University, teachers often use platforms. According to the frequency of use, the order is the Chaoxi learning platform (10.84%), China Chaoxi learning platform (9.28%), WeChat (8.36%), and Tencent classroom (7.72%). Due to the Chaoxi learning platform ranking first among the platforms used

by universities, this paper aims to measure third-year students' behavioral intention to use Chaoxi online learning platform in Chengdu, China.

Objectives of the Study

      1. To examine the factors impacting students' behavioral intention to use Chaoxi online learning platform in Chengdu, China.

      2. To measure the causal relationship between perceived usefulness, perceived ease of use, self-efficacy, attitude, subjective norms, behavioral intention, and use behavior.

      3. To provide recommendations for improving online learning platforms to enhance the use behavior of Chinese students.

Research Framework

      The conceptual framework of this study was developed based on prior theoretical and empirical studies, as shown in Figure 1. The model was adopted from the research of Watjatrakul (2016), Hu and Zhang (2016), and Samsudeen and Mohamed (2019), incorporating perceived usefulness, perceived ease of use, self-efficacy, attitude, subjective norms, behavioral intention, and use behavior.
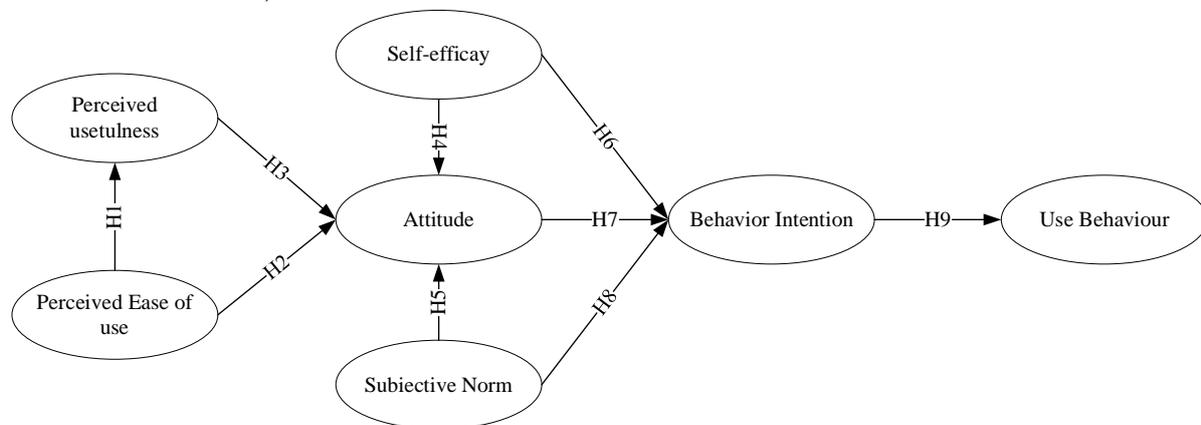

Figure 1 Conceptual Framework

Significance of the Study

      The significance of this study is to promote the function and application of the Chaoxi learning platform. It can provide the significant factors that teachers can use the Chaoxi learning platform and improve teaching effectiveness. In addition, this paper can better analyze students' use behavior of the online learning platform to improve learning efficiency, which can help the online learning platform to improve and upgrade the online platform functions and features continuously.

Literature Review

      1. Perceived Ease of Use (PEU)

      Perceived ease of use refers to the degree to which a person believes a particular system can be used with less effort (Davis, 1989). Venkatesh and Davis (2000) found that the most powerful predictor of users' attitudes toward adopting the technology is how users perceived the ease of use of a particular technology. Perceived ease of use will positively impact users' attitudes toward using the technology system (McKechnie et al., 2006). The research on online learning platforms also confirms that PEU will significantly affect users' perceived usefulness and attitude of students toward the use of online learning platforms (Hsu et al., 2014). Hence, hypotheses are proposed:

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

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

      2. Perceived Usefulness

      Perceived usefulness is when a person believes that using a specific system can improve his work performance in some way (Davis, 1989). Therefore, perceived usefulness affects individuals' attitudes and willingness to adopt a specific new technology (Tai, 2008). Aboelmaged (2010) stated that the realization of using e-business applications to improve performance or efficiency positively influences the attitude of users. Therefore, the following hypothesis is indicated:

      H3: Perceived usefulness has a significant impact on attitude.

      3. Self-Efficacy

      Self-efficacy refers to the individual's feeling and understanding of their ability, not the unique attribute of self-concept (Bong & Skaalvik, 2003). Perceived self-efficacy, on behalf of individual knowledge and effectiveness of implementing the target behavior, is a component of perceived behavioral control. (Jugert et al., 2016). When people realize and firmly believe that their professional knowledge can improve work efficiency or productivity, they will change their attitude toward knowledge sharing and become more willing to share their professional knowledge and experience (Jarvenpaa & Staples, 2001). Based on the above assumptions, the following hypothesis is recommended:

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

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

      4. Attitude

      Attitude is a belief that can be transformed into concrete action, and attitude can also be a positive or negative evaluation of things (Troudi & Bouyoucef, 2020). Students express behavioral intention to use online learning platforms when they have a positive attitude—perceived usefulness relevance between attitudes and behavioral intentions (Park, 2013). Previous studies provide empirical evidence that consumer attitudes will affect their intention to use online banking services (Lai & Li, 2005). Thereby, a hypothesis is developed:

H7: Attitude has a significant impact on behavioral intention.

5. Subjective Norm

Subjective norms directly or indirectly influence the external stimulus of individual-specific behaviors on knowledge-sharing willingness (Zhou et al., 2007). Subjective norms refer to the choice of performing or not performing a certain behavior according to the perceived social pressure (Ajzen, 1991). Shasha and Leelakasemsant (2022) also discovered that subjective norms directly or indirectly affect users' attitudes and behavior intentions when using information systems. Consequently, the below hypotheses are suggested:

H5: Subjective norm has a significant impact on attitude.

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

6. Behavioral Intention

Yi et al. (2006) believe that behavior intention is the probability of whether its intention leads to behavior. Behavioral intention is defined as individuals performing some behavioral intention and intent (Keong et al., 2012). Ajzen and Fishbein (1980) interpret behavioral intention as an assessment of people's motivation to take action or complete a specific behavior. de Haan et al. (2018) found that improving mobile network coverage leads to users' intentional behavior toward using mobile devices. The use of mobile devices in stores is also associated with the willingness of users (Grewal et al., 2018). Hence, it is possible to test this hypothesis:

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

7. Use Behavior

Use behavior can be referred to as a customer using a technical strength (Venkatesh et al., 2003). Usage behavior is usually measured in terms of the actual frequency of technology use. Venkatesh et al. (2012) have conducted several studies on technology use using the concept of 'usage behavior.' Convenient conditions and behavior intention of question-and-answer services based on the network have a significant positive influence on the use of behavior (Deng et al., 2011).

Research Methodology

This study applied a quantitative approach to distributing the questionnaire to 500 third-year students from three selected colleges. 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).

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 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).

1. 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.

2. Sampling Technique

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

Results and Discussion

1. Demographic Results

The demographic profile was collected from 500 respondents. In Table 2, the results show that 57.4 percent of females (287) and 42.6 percent of males (213). For the frequency of ChaoXi Learning Platform, 25.8 percent (129) is 1-3 days per week, 60 percent (300) is 4-6 Days per week, and 14.2 percent (71) is 7 days per week.

2. Confirmatory Factor Analysis (CFA)

In Table 1, Factor loading should be 0.5 or higher (Hair et al., 2010). 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.

Table 1 Confirmatory Factor Analysis Result, Composite Reliability (CR) and Average Variance
Extracted (AVE)

Latent Variables	Source of Questionnaire	No. of Items	Factors Loading	CR	AVE
Perceived Ease of Use (PEU)	Watjatrakul (2016)	5	0.739-0.773	0.869	0.569
Perceived Usefulness (PU)	Watjatrakul (2016)	5	0.700-0.754	0.854	0.539
Attitude (ATT)	Hu and Zhang (2016)	5	0.701-0.763	0.849	0.514
Self-Efficacy (SE)	Hu and Zhang (2016)	5	0.731-0.815	0.880	0.595
Subjective Norm (SN)	Hu and Zhang (2016)	4	0.669-0.760	0.809	0.544
Behavioral Intention (BI)	Samsudeen and Mohamed (2019)	5	0.690-0.787	0.851	0.53
Use Behavior (UB)	Samsudeen and Mohamed (2019)	4	0.682-0.965	0.855	0.533

Source: Created by the author.

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 2. As a result, discriminant validity was ensured.

Table 2 Discriminant Validity

	PU	PEU	SE	SN	ATT	BI	UB
PU	**0.734**						
PEU	0.302	**0.755**					
SE	0.301	0.345	**0.772**				
SN	0.274	0.286	0.306	**0.717**			
ATT	0.246	0.172	0.236	0.317	**0.728**		
BI	0.464	0.423	0.482	0.482	0.419	**0.73**	
UB	0.209	0.172	0.235	0.243	0.291	0.451	**0.775**

Note The diagonally listed value is the AVE square roots of the variables.

3. Structural Equation Model (SEM)

A confirmatory factor analysis was used to evaluate the measurement model, whereas a structural equation model was conducted to measure the structural model. The acceptable values of goodness-of-fit indices for both models are demonstrated in Table 3. The measurement model is a satisfactory fit without an adjustment, while the structural model is

an acceptable fit after the adjustment.

Table 3 Goodness of Fit for Measurement and Structural Model

Fit Index	Acceptable Criteria	Source	Measurement Model	Structural Model (Adjusted Model)
CMIN/DF	< 5.00	(Al-Mamary & Shamsuddin, 2015; Awang, 2012)	455.264/474 or 0.960	557.891/483 or 1.155
GFI	≥ 0.80	(Sica & Ghisi, 2007)	0.949	0.939
AGFI	≥ 0.80	(Sica & Ghisi, 2007)	0.939	0.929
NFI	≥0.80	(Wu & Wang, 2006)	0.943	0.930
CFI	≥ 0.80	(Bentler, 1990)	1.000	0.990
TLI	≥ 0.80	(Sharma et al., 2005)	1.000	0.989
RMSEA	< 0.08	(Pedroso et al., 2016)	0.004	0.018

Note: 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. Hypothesis Testing Result

In Table 4, the standardized path coefficient (β) and t-value with the significant value criterion of p<0.05 are criteria to confirm hypothesis testing results of this study.

Table 4 Hypothesis Results of the Structural Equation Model

Hypothesis	(β)	t-value	Result
H1: PEU ⟶ PU	0.372	7.012*	Supported
H2: PEU ⟶ ATT	0.007	0.114	Unsupported
H3: PU ⟶ ATT	0.178	3.247*	Supported
H4: SE ⟶ ATT	0.104	1.816	Unsupported
H5: SN ⟶ ATT	0.300	4.891*	Supported
H6: SE ⟶ BI	0.357	7.475*	supported
H7: ATT ⟶ BI	0.271	5.717*	Supported
H8: SN ⟶ BI	0.362	6.722*	Supported
H9: BI ⟶ UB	0.502	10.232*	Supported

Note: * p<0.05

The findings can be summarized below.

H1 confirms that perceived ease of use significantly impacts perceived usefulness, with a standardized path coefficient value of 0.372 (t-value = 7.012*).

H2 shows the unsupported relationship between perceived ease of use and attitude because it does not meet the standard of p-value <0.05 and with a standardized path coefficient value of 0.007 (t-value = 0.114).

H3 approves that perceived usefulness significantly impacts attitude, with a standardized path coefficient value of 0.178 (t-value = 3.247*).

In H4, self-efficacy has no significant impact on attitude, with a standardized path coefficient value of 0.104 (t-value = 1.816).

H5 reveals that subjective norm significantly impacts attitude, with a standardized path coefficient value of 0.300 (t-value = 4.891*).

H6 denotes the support relationship between self-efficacy and behavioral intention, with a standardized path coefficient of 0.357 (t-value = 7.475*).

H7 supports the relationship between attitude towards use and behavioral intention, with a standardized path coefficient value of 0.271 (t-value = 5.717*).

H8 affirms the relationship between subjective norm and behavioral intention, with a standardized path coefficient value of 0.362 (t-value = 6.722*).

For H9, behavioral intention significantly impacts use behavior, with a standardized path coefficient value of 0.502 (t-value = 10.232*).

Conclusions, Recommendations, Limitations and Future Research

1. Conclusions

The findings investigate factors impacting students' behavioral intention to use Chaoxi online learning platform in Chengdu, China. The statical results from CFA and SEM showed that perceived ease of use significantly impacts perceived usefulness. Hsu et al. (2014) supported that when students perceive the ease of use of online learning platforms, they will perceive the usefulness of such a system. However, the results contradict McKechnie et al. (2006) attitude of students towards the use of online learning platforms can be driven by perceived ease of use. Subjective norms, self-efficacy, and attitude significantly impact behavioral intention towards use behavior. Subjective norms are social influence from teachers and peers, directly or indirectly influencing students' willingness to use Chaoxi online learning platform (Zhou et al., 2007). Additionally, the perception of control over the online system and students' positive attitudes dictates behavioral intention to use the Chaoxi online learning platform (Jugert et al., 2016; Keong et al., 2012; Park, 2013). However, self-efficacy cannot explain attitude, which is not aligned with previous studies (Bong & Skaalvik, 2003; Jarvenpaa & Staples, 2001; Jugert et al., 2016).

2. Recommendations

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.

3. Limitations and Future Research

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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