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An Assessment on Behavioral Intention to Use Chaoxing Learning Platform in The Post-Pandemic Among Third-Year Undergraduates in Anhui, China

Yuze Li*

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Abstract

Purpose: This study investigates the factors that impact assessment on behavioral intention to use Chaoxing Learning Platform in the post-pandemic among third-year undergraduates in Anhui, which are determined by perceived ease of use, perceived usefulness, attitude, behavior intention, facilitating conditions, self-efficacy and subjective norm. **Research design, data, and methodology:** The population are 500 third-year undergraduate students who have at least one year experience, using Chaoxing Learning Platform at three universities in Anhui, China, including Anhui University of Finance and Economics, Bengbu University, and Tongling University. Confirmatory factor analysis and structural equation modeling are statistical techniques used to confirm validity, reliability, model fit and hypotheses testing. **Results:** The results show the supported relationship of perceived usefulness and behavioral intention. Facilitating conditions significantly impact perceived usefulness and behavioral intention. Furthermore, subjective norms significantly impact attitude and behavioral intention. There are non-supported relationships between perceived ease of use, perceived usefulness, attitude, self-efficacy and behavioral intention. **Conclusions:** The results of this study show that educational institutions can enhance the adoption and usage of the Chaoxing Learning Platform among third-year undergraduates in Anhui, China. This will ultimately improve students' overall learning experience and support their academic success in the post-pandemic era.

Keywords: Perceived Ease of Use, Perceived Usefulness, Attitude, Facilitating Conditions, Behavioral Intention

JEL Classification Code: E44, F31, F37, G15

1. Introduction

In 2020, many universities worldwide affected by the COVID-19 outbreak adopted online teaching to complete the new semester, and online education has become a powerful tool to break through the COVID-19 epidemic blockade and save education (Gallagher & Palmer, 2020). In China, the Ministry of Education has directly proposed using online platforms to carry out online learning and implement the requirement of "stopping classes without stopping learning." Universities have actively responded to the call of the

1*Yuze Li, Anhui University of Finance and Economics, China. E-mail: acliyuze@foxmail.com

Ministry of Education, combined with the actual situation of each school, made full use of the existing online teaching resources, relied on various online course platforms, and carried out various forms of online teaching activities (Zhang et al., 2020). Teaching activities include live teaching, recorded teaching, online SPOC, etc. In this process, the Chaoxing learning platform has been widely used in China universities. Now, the impact of the COVID-19 epidemic on offline teaching in colleges and universities in China has been eliminated, and the official mandatory requirements for online teaching have been lifted (Chen et al., 2020). In the post-epidemic period, whether the online teaching platform can continue to be widely used by teachers and students, and what are the main factors affecting the intention of college students to continue to use the Chaoxing e-learning platform after teachers and students have more in-depth applications of the learning platform, are the important contents of the next phase of university teaching research (Lin et al., 2021).

The Chaoxing learning platform is an online network education product developed by China's Beijing Century Chaoxing Information Technology Development Limited Company (CBCCITDLC). Founded in 1993, CBCCITDLC is an education informatization enterprise with over 6,500 employees (Chaoxing Corporation, n.d.). It is a pioneer in the construction of high-quality courses, video courses, open courses, MOOC, and SPOC in China, a leader in the development of teaching management platforms, mobile teaching platforms, and intelligent teaching systems in Chinese colleges and universities, and has one of the largest book digitization processing centers in China. In China, more than 5,000 schools use the Chaoxing platform for teaching, among which there are more than 2,000 universities (Qin, 2020).

Third-year undergraduates in the Anhui group play a crucial role in a study investigating the factors that impact the assessment of behavioral intention to use the Chaoxing Learning Platform in the post-pandemic period, as they represent a pivotal stage in both their academic journey and the evolution of digital learning platforms. Third-year undergraduates are at a critical juncture in their academic journey. They have typically completed a significant portion of their coursework and are approaching their final years of undergraduate study. As they prepare to enter the workforce or pursue further education, their perspectives on digital learning platforms like Chaoxing can greatly influence their future learning habits and preferences.

By the third year, students have gained substantial experience with various online learning tools and platforms, including Chaoxing, due to the COVID-19 pandemic. This experience equips them with insights and comparisons, making them well-positioned to provide valuable feedback on the ease of use and usefulness of Chaoxing as compared to other platforms they may have encountered. To fill the research gap on limited study on the online learning adoption in the post pandemic, this study investigates the factors that impact assessment on behavioral intention to use Chaoxing Learning Platform in the post-pandemic among third-year undergraduates in Anhui, which are determined by perceived ease of use, perceived usefulness, attitude, behavior intention, facilitating conditions, self-efficacy and subjective norm.

2. Literature Review

2.1 Perceived Ease of Use

Perceived ease of use is “the degree to which a potential user believes that learning or using the system or technology can be done without effort” (Davis, 1989). According to Liu et al. (2009), perceived ease of use is “the amount of effort required for someone to use a particular system.” Perceived usefulness is defined as the extent users believe using the system will improve their work performance. On the other hand, perceived ease of use is defined as the extent to which users believe that using the system does not require extra effort. Users believe that no extra effort is required to use the system (Davis, 1989).

Most studies on TAM have demonstrated that if users find technology easy to use, they will find it useful. If they find technology easy to use, they will perceive it as useful. In addition, if users find a technology both easy to use and useful, they will positively accept it (Davis, 1989; Huang et al., 2007, 2012). Accordingly, the following hypotheses proposed based on the above studies.

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

Davis (1989) defined perceived usefulness as “the extent to which a person thinks using the system or tool will improve his or her job performance.” Perceived usefulness is an important incentive for usage behavior and purpose (Davis et al., 1992). Perceived usefulness is the level to which the person believes technology will help him or her perform better at work or school (Akbar, 2013; Venkatesh et al., 2003). Based on Davis (1989), perceived usefulness is the level to which a person believes technology will improve job performance. Perceived usefulness has two aspects: perceived usefulness to the organization and the individual. The former concerns the financial benefits (product quality and savings in instructional costs) that an organization can gain by implementing new technology. For individuals, the benefits come from better job performance and incentives to use the technology (Robey & Dana, 1982). If a user perceives

that using technology will improve his or her job performance, then the application will be perceived as useful (Fan et al., 2021). Thus, hypotheses are stated as follow:
H3: Perceived usefulness has a significant impact on attitude.
H5: Perceived usefulness has a significant impact on behavioral intention.

2.3 Attitude

Attitude is a person's feeling or affection toward using technology (Davis, 1989). Attitude refers to how much students enjoy using the new technology for information sharing and completing feedback on group assignments (Cheng et al., 2019). Attitude is perceived usefulness, i.e., the degree to which a person believes using a new skill will improve job performance (Lourenco & Jayawarna, 2011). Attitude is an individual's positive or negative perception of a behavior (Tucker et al., 2020).

Attitude is a person's positive or negative feelings toward behavior or action (Ajzen, 1991; Ajzen & Fishbein, 2005). Individuals' attitudes toward using a system may be positive or negative, depending on the individual's perspective. An attitude is a person's first response to a behavior based on their beliefs (Alkhanak & Azmi, 2011). Several recent studies on the use of IT have shown that behavioral intention to use is influenced not only by perceived usefulness (Bhattacherjee, 2001; Lin et al., 2021) but also by factors like attitude (Lee & McLoughlin, 2010; Lin, 2011). Many researchers have used the IS continuity model to analyze behavioral intentions. The findings showed that users' satisfaction and perceived usefulness largely determined their intention to use (Bhattacherjee, 2001; Lin et al., 2021). Therefore, the next hypothesis is indicated:
H4: Attitude has a significant impact on behavioral intention.

2.4 Facilitating Conditions

Facilitating conditions refer to the extent to which someone trusts the facilitation of existing institutions and technical facilities to promote the application of new technologies (Venkatesh et al., 2003). Facilitation is defined as the training provided to users on new technologies when an organization tries to promote the use of new technologies. It can also mean the compatibility between old and new technologies (Teo & Noyes, 2014). FC interprets the facilities potential users believe will be available for using new technology in an organization. This relates to the organizational and technical infrastructure availability needed to use the scheduled technology (Ukut & Krairit, 2019).

Facilitation conditions mean the educational training that an organization provides users when trying to promote new technology. It also could refer to the compatibility between old and new technologies (Teo & Noyes, 2014). Thus, conveniences serve as key indicators for promoting a new technology since they help users learn to use the technology in a shorter period and minimize the problems they may encounter when using the technology.

FC means that users perceive that institutional support and infrastructure can assist in using the target technology (Venkatesh et al., 2012). Generally, technical support and infrastructure that assists in using the system are classified as FC. Facilitating conditions (FC) is the physical setting or environmental factors that convince individuals to do certain activities (Salloum & Shaalan, 2019). The environmental factor influences an individual's perception of the ease or difficulty of performing a task. It is the available external recourses needed to facilitate the performance of a particular behavior (Ajzen, 1991). Accordingly, based on the above studies, the hypotheses examined in this work are as follows:
H6: Facilitating conditions have a significant impact on perceived usefulness.
H7: Facilitating conditions have a significant impact on behavioral intention.

2.5 Self-Efficacy

Self-efficacy refers to the level of confidence an individual has in his or her ability to perform specific actions (Bandura, 1986, 1997). Self-efficacy was defined as “believing oneself have the organizational and executive skills to meet future challenges” (Bandura, 1997). In other words, self-efficacy can be defined as “a person who believes that he or she can succeed in a given situation.” Compeau and Higgins (1995). Bandura developed the hypothesis that self-efficacy expectations impact the launching of an activity and the effort and persistence required to perform that activity (Bandura, 1986) successfully. Self-efficacy took on the power of self-motivation (Kankanhalli et al., 2005).

Self-efficacy refers to people’s beliefs about their ability to perform a task (Bandura, 1997). Self-efficacy is an examination of students’ ability to use computers to obtain access to Chaoxing learning platform resources. From the students’ perspective, Self-efficacy significantly impacts the use and adoption of the Chaoxing learning platform. Based on these statements, existing researchers state that about the impact of self-efficacy on computer technology attitude, Sam et al. (2005).

A person’s degree of effectiveness is associated with his/her willingness to adopt a particular technology. Therefore, a student’s level of efficacy will affect his/her willingness to use the Chaoxing learning platform. Chowdhury and Endres (2005) state that employees assess their environment and competencies before taking action. Therefore, students use the e-library portal when they determine that they have the necessary knowledge, skills, and competencies. This can be associated with Booker (2021) study, which concluded that students' anxiety decreases and their level of efficacy increases after having used electronic resources one or more times. Therefore, based on the above research, the hypotheses examined in this work are as follows.

H8: Self-efficacy has a significant impact on attitude.

H9: Self-efficacy has a significant impact on behavioral intention.

2.6 Subjective Norm

A subjective norm is an individual's perception that behavior should be performed by someone important to him or her (Ajzen & Fishbein, 1980; Pavlou & Fygenson, 2006). Subjective norms are the degree to which an individual perceives the people important to them (Jolaee et al., 2014). Subjective norm was "the perception that most of the people who were important to him consider that he should or should not do the act in issue (Fishbein & Ajzen, 1975)."

Persuasion theory suggests that persuasive communication affects a person's beliefs and attitudes by generating new ones (Eagly & Chaiken, 1993). In this sensation, people can internalize the opinions and suggestions of others and progressively change their original attitudes. Cognitive dissonance theory posits that when there is inconsistency, a person may change his/her decision or behavior in search of cognitive consistency (Festinger, 1957). Therefore, a person may vary his or her attitudes toward behavior in order to feel a connection to someone meaningful to that person. It is important to that person. There is also positive empirical evidence in business research that suggests a positive relationship between subjective norms and attitudes (Al-Rafee & Cronan, 2006; Chang, 1998; Lim & Dubinsky, 2005; Taylor & Todd, 1995).

The more important a person perceives the behavior that others think he or she should perform, the more effort he or she will make to perform it. Chinese students tend to be influenced by their peers and perceived significant others. According to Ajzen (1991), subjective norms, as an external perception, refer to Chinese students' perceived social pressure and the impact of teachers, classmates, or trusted friends on behavior. This research proposes the following hypothesis:

H10: Subjective norm has a significant impact on attitude.

H11: Subjective norm has a significant impact on behavioral intention.

2.7 Behavior Intention

Behavior intention is "the extent to which students were willing and continue to use the new technology to work with others in groups" (Cheng et al., 2019). Behavior intention refers to the participant's intention to use the new technology (Lourenco & Jayawarna, 2011). Behavioral intention is the degree to which an individual wants to carry out a particular behavior (Fishbein & Ajzen, 1975). Perceived usefulness is the degree to which individuals believe new technology will improve their task performance. Many empirical studies have supported the proposition that PU is a major predictor of IT use (Davis, 1989; Davis et al., 1992; Gefen et al., 2003; Gefen & Straub, 1997, 2000; Hsu & Lu, 2004; Igbaria et al., 1997; Ong et al., 2004; Venkatesh, 2000; Venkatesh & Davis, 2000). The study of Lin et al. (2021) showed that behavioral intention was influenced by perceived usefulness.

3. Research Methods and Materials

3.1 Research Framework

The conceptual framework of this study was developed based on seven variables. This study had two types of variables: independent and dependent. The independent variable is the variable that explains the outcome variables of interest (Hair et al., 2013). Clark-Carter (2010) stated that the independent variable is the variable that affects another variable. The independent variables for this study are adoption, perceived ease of use, facilitating conditions, self-efficacy, and subjective norm. Jackson (2006) and O'Leary (2017) stated that the dependent variable is the variable the research aimed to study. The dependent variable for this study is attitude, perceived usefulness, and behavioral intention. The conceptual framework of this study is presented in Figure 1.

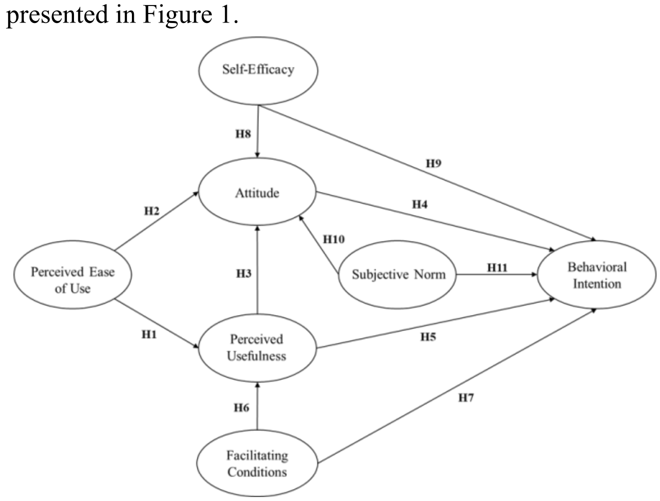

Figure 1: Conceptual Framework

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: Attitude has a significant impact on behavioral intention.
H5: Perceived usefulness has a significant impact on behavioral intention.
H6: Facilitating conditions have a significant impact on perceived usefulness.
H7: Facilitating conditions have a significant impact on behavioral intention.
H8: Self-efficacy has a significant impact on attitude.
H9: Self-efficacy has a significant impact on behavioral intention.
H10: Subjective norm has a significant impact on attitude.
H11: Subjective norm has a significant impact on behavioral intention.

3.2 Research Methodology

This study uses empirical analysis and quantitative methods to collect sample data using a web-based questionnaire to explore the factors influencing college students' behavioral intention to use the Chaoxing online teaching platform in the post-epidemic era. This study uses questionnaires as the research instrument and collects data from the target group by online survey method. The researcher developed the questionnaire using a quantitative research design in conjunction with the theoretical literature and prior research base related to this study. It was distributed to undergraduate students in their third year at three universities. The questionnaire designed for this study first designed screening questions, then used a five-point Likert scale to make relevant measurements of all variables, and finally determined the respondents' demographic data.

Before the data collecting, the Item Objective Consistency Index (IOC) and pilot test (n=50), using Cronbach's Alpha (CA) reliability test were implemented. In the case of the IOC's findings, a panel of three experts assessed a set of 30 scale items, concluding that all items scored above 0.6. The pilot test results for CA demonstrated values exceeding 0.7, which indicates excellent scale reliability (Nunnally & Bernstein, 1994).

Once the data were collected, this study assessed their construct validity, including convergent and discriminant validity. Convergent validity demonstrated the relationship between two tests that should test the same construct, and discriminant validity suggested that the two tests should not be correlated (Glen, 2015). Finally, structural equation modeling (measurement and structural models) was primarily used to test all hypotheses and the model's fitness.

3.3 Population and Sample Size

The target population for this study consists of 500 third year undergraduate students with a minimum of one year of experience using the Chaoxing Learning Platform. These students are enrolled at three universities in Anhui, China: Anhui University of Finance and Economics, Bengbu University, and Tongling University. The minimum sample size required by statistical calculator of Soper (n.d.) is 425. However, this study aims to collect 500 participants to ensure the effective data analysis of SEM.

3.4 Sampling Technique

Judgmental sampling was conducted to select third-year undergraduate students who have at least one year experience, using Chaoxing Learning Platform at three universities in Anhui, China, including Anhui University of Finance and Economics, Bengbu University, and Tongling University. Stratified random sampling was used to proportionate the sample size, as shown in Table 1. For convenience sampling, the questionnaires were created online through the website of China's online survey platform, Questionnaire Star, and distributed to respondents through WeChat and QQ by teachers of universities.

Table 1: Sample Units and Sample Size

Universities	Population Size	Proportional Sample Size
Anhui University of Finance and Economics	4332	160
Bengbu University	3982	147
Tongling University	5232	193
Total	**13546**	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

Table 2 reveals that the study involved 500 participants. The participants' demographic information, such as gender and frequency of using the Chaoxing Learning Platform, was collected. The questionnaire was distributed among 500 students in their third year. Of these respondents, 307 were females, accounting for 61.4 percent, while 193 were males, representing 38.6 percent. Regarding the frequency of using the Chaoxing Learning Platform, 106 or 21.2 percent of students reported using it 1-2 days a week, 151 or 30.2 percent reported using it 4-6 days a week, and 243 or 48.6 percent reported using it 7 days a week.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	193	38.6%
	Female	307	61.4%
Frequency Chaoxing Learning Platform	1-2 days a week	106	21.2%
	4-6 days a week	151	30.2%
	7 days a week	243	48.6%

4.2 Confirmatory Factor Analysis (CFA)

Confirmatory factor analysis (CFA) is one of the most common applications of structural equation models, first developed by Joreskog (1969). Hair et al. (2010) believed that CFA was a key starting point of SEM and played a key role in studying all potential variables in structural models (Alkhadim et al., 2019). It was often used to validate measurement models and helped understand the extent to which measurement items reflected potential variables (Khan & Qudrat-Ullah, 2021).

The CFA results for CA demonstrated values exceeding 0.7, which indicates excellent scale reliability (Nunnally & Bernstein, 1994).Factor loading criteria were established at 0.5, with P-value coefficients less than 0.05. Moreover, following the guidelines of Fornell and Larcker (1981), the cutoff points for Composite Reliability (CR) and Average Variance Extracted (AVE) were set at 0.7 and 0.5, respectively. Table 3 displays factor loading values exceeding 0.5, CR values above 0.7, and AVE values surpassing 0.4. These outcomes affirm the goodness of fit for the Confirmatory Factor Analysis (CFA) test and validate the reliability and validity of the data analysis results. Table 3 provides a comprehensive overview of the measurement model, displaying all the approved results.

Table 3: Confirmatory Factor Analysis Result, Composite Reliability (CR) and Average Variance Extracted (AVE)

Variables	Source of Questionnaire (Measurement Indicator)	No. of Item	Cronbach's Alpha	Factors Loading	CR	AVE
Perceived Ease of Use (PEOU)	Buabeng-Andoh (2018)	4	0.803	0.670-0.739	0.805	0.508
Perceived Usefulness (PU)	Buabeng-Andoh (2018)	4	0.808	0.675-0.778	0.808	0.514
Attitude (ATT)	Oertzen and Odekerken-Schröder (2019)	5	0.844	0.648-0.792	0.846	0.524
Facilitating Conditions (FC)	Buabeng-Andoh and Baah (2020)	4	0.778	0.657-0.726	0.781	0.472
Self-Efficacy (SE)	Sanchez et al. (2013)	4	0.824	0.665-0.814	0.826	0.544
Subjective Norm (SN)	Buabeng-Andoh (2018)	4	0.774	0.580-0.749	0.779	0.471
Behavioral Intention (BI)	Gao and Bai (2014)	5	0.910	0.766-0.883	0.912	0.674

The adequacy of the research model fit was assessed by examining the goodness-of-fit indices presented in Table 4. The statistical values of these indices were compared against the predetermined acceptance criteria. The calculated values for the indices were as follows: CMIN/DF = 1.655, GFI = 0.923, AGFI = 0.907, NFI = 0.911, CFI = 0.963, TLI = 0.958, and RMSEA = 0.036. Based on these results, it can be concluded that all the data met the acceptable standards. Therefore, the proposed conceptual framework demonstrated compatibility with the confirmatory factor analysis (CFA).

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 3.00 (Hair et al., 2006)	635.338/384 = 1.655
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.923
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.907
NFI	≥ 0.80 (Wu & Wang, 2006)	0.911
CFI	≥ 0.80 (Bentler, 1990)	0.963
TLI	≥ 0.80 (Sharma et al., 2005)	0.958
RMSEA	≤ 0.08 (Pedroso et al., 2016)	0.036
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

To evaluate discriminant validity, the square root of the Average Variance Extracted (AVEs) was calculated, following the approach proposed by Fornell and Larcker (1981). The results of this study indicate that the discriminant validity is greater than the inter-construct/factor correlations, as presented in Table 5. This finding strongly supports the notion of discriminant validity in the study.

Table 5: Discriminant Validity

	SE	PEOU	ATT	FC	SN	BI	PU
SE	**0.737**						
PEOU	0.138	**0.712**					
ATT	0.356	0.512	**0.724**				
FC	0.282	0.689	0.660	**0.687**			
SN	0.447	0.519	0.617	0.647	**0.687**		
BI	0.312	0.552	0.496	0.648	0.646	**0.821**	
PU	0.089	0.234	0.191	0.301	0.263	0.313	**0.717**

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

4.3 Structural Equation Model (SEM)

The SEM analysis after modification yielded satisfactory results, as indicated by CMIN/DF = 2.869, GFI = 0.868, AGFI = 0.844, NFI = 0.842, CFI = 0.891, TLI = 0.879, and RMSEA = 0.061. Thus, Table 6 showed that the modified SEM model had met the desired fit criteria.

Table 6: Goodness of Fit for Structural Model

Index	Acceptable	Statistical Values
CMIN/DF	< 3.00 (Hair et al., 2006)	1130.466/394 = 2.869
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.868
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.844
NFI	≥ 0.80 (Wu & Wang, 2006)	0.842
CFI	≥ 0.80 (Bentler, 1990)	0.891
TLI	≥ 0.80 (Sharma et al., 2005)	0.879
RMSEA	≤ 0.08 (Pedroso et al., 2016)	0.061
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 significance of each variable was assessed by examining its standardized path coefficient (β) and t-value, as detailed in Table 7.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-Value	Result
H1: PEOU→PU	0.105	1.921	Not Supported
H2: PEOU→ATT	0.333	6.110*	Supported
H3: PU→ATT	0.040	0.819	Not Supported
H4: ATT →BI	0.029	0.572	Not Supported
H5: PU →BI	0.121	2.630*	Supported
H6: FC →PU	0.243	4.240*	Supported
H7: FC→ BI	0.443	8.330*	Supported
H8: SE→ATT	0.189	3.828*	Supported
H9: SE→BI	0.072	1.639	Not Supported
H10: SN→ATT	0.440	7.316*	Supported
H11: SN→BI	0.448	7.658*	Supported

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

The significance of each construct in the research model was determined based on the Standardized Path Coefficient (β) and t-value, as presented in Table 7. The results of the hypothesis testing are as follows:

H1: The standardized path coefficient between perceived ease of use and perceived usefulness was 0.105 (t-value = 1.921). Therefore, no significant influence was found between perceived ease of use and perceived usefulness. Hence, H1 was not supported.

H2: The standardized path coefficient between perceived ease of use and attitude was 0.333 (t-value = 6.110*). Consequently, perceived ease of use has a significant impact on attitude. Thus, H2 was accepted.

H3: The standardized path coefficient between perceived usefulness and attitude was 0.040 (t-value = 0.819). Therefore, there is no significant influence found between perceived usefulness and Attitude. Hence, H3 was not supported.

H4: The standardized path coefficient between attitude and behavioral intention was 0.029 (t-value = 0.572). However, no significant influence was found between Attitude and Behavioral Intentions. Therefore, H4 was not supported.

H5: The standardized path coefficient between perceived usefulness and behavioral intention was 0.121 (t-value = 2.630*). Therefore, H5 was accepted, suggesting that perceived usefulness significantly impacts behavioral intention.

H6: The standardized path coefficient between facilitating conditions and perceived usefulness was 0.243 (t-value = 4.240*), demonstrating a significant impact of facilitating conditions on perceived usefulness. Therefore, H6 was accepted.

H7: The standardized path coefficient between facilitating conditions and behavioral intention was 0.443 (t-value = 8.330*), indicating a significant impact of facilitating conditions on behavioral intention. Consequently, H7 was accepted.

H8: The standardized path coefficient between self-efficacy and attitude was 0.189 (t-value = 3.828*), demonstrating a significant impact of self-efficacy on attitude. Therefore, H8 was accepted.

H9: The standardized path coefficient between self-efficacy and behavioral intention was 0.072 (t-value = 1.639). However, no significant influence was found between self-efficacy and behavioral intention. Therefore, H9 was not supported.

H10: The standardized path coefficient between subjective norm and attitude was 0.440 (t-value = 7.316*), indicating a significant impact of subjective norm on attitude. Consequently, H10 was accepted.

H11: The standardized path coefficient between subjective norm and behavioral intentions was 0.448 (t-value = 7.658*). Consequently, H11 was accepted, implying that subjective norm significantly impacts behavioral intentions.

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

This study assessed the behavioral intention to use the Chaoxing Learning Platform among third-year undergraduates in Anhui, China, in the post-pandemic period. Our analysis focused on several key factors, including perceived ease of use, perceived usefulness, attitude, behavior intention, facilitating conditions, self-efficacy, and subjective norm. Based on the findings, it was observed that perceived ease of use did not significantly impact perceived usefulness, contrary to our initial hypothesis. However, perceived ease of use significantly influenced attitude, indicating that when students perceived the platform as easy to use, it positively affected their attitude towards it. Furthermore, perceived usefulness significantly impacted both attitude and behavioral intention. This suggests that when students believed that the Chaoxing Learning Platform was useful, it influenced their attitude toward the platform and their intention to use it.

Additionally, facilitating conditions significantly impacted both perceived usefulness and behavioral intention. This implies that when students had access to favorable conditions that facilitated their use of the platform, such as technical support or resources, it positively influenced their perception of usefulness and intention to use. Moreover, self-efficacy was found to significantly impact attitude, highlighting the importance of students' confidence in their ability to use the platform. However, no significant influence was found between self-efficacy and behavioral intention, indicating that self-efficacy alone may not directly determine students' intention to use the platform.

Lastly, the subjective norm was found to impact both attitude and behavioral intention significantly. This suggests that the influence of social norms and the opinions of others play a role in shaping students' attitudes toward the platform and their intention to use it.

5.2 Recommendation

Based on the findings of the assessment of the behavioral intention to use the Chaoxing Learning Platform among third-year undergraduates in Anhui, China, in the post-pandemic period, the following recommendations can be made to enhance the adoption and usage of the platform:

Improve Perceived Ease of Use: Although perceived ease of use did not significantly impact perceived usefulness, it is still important to focus on improving the ease of use of the Chaoxing Learning Platform. This can be achieved by conducting user experience studies, gathering student feedback, and making necessary improvements to the platform's interface, navigation, and overall user-friendliness.

Enhance Perceived Usefulness: To increase students' perception of the platform's usefulness, educational institutions should emphasize the benefits and advantages of using the Chaoxing Learning Platform. This can be done through effective communication and training sessions highlighting the platform's features, functionalities, and how it can enhance students' learning outcomes.

Foster Positive Attitudes: Since attitude was influenced by perceived ease of use, perceived usefulness, facilitating conditions, and self-efficacy, efforts should be made to create a positive attitude towards the Chaoxing Learning Platform. This can be achieved by providing students with positive experiences, showcasing success stories, and addressing concerns or challenges.

Provide Facilitating Conditions: Educational institutions should ensure that students have access to necessary resources, technical support, and training to facilitate their use of the Chaoxing Learning Platform. This can include providing reliable internet connectivity, offering technical assistance, and organizing workshops or tutorials to help students navigate and maximize their platform use.

Build Self-efficacy: While self-efficacy impacted attitude significantly, it did not directly influence behavioral intention. To enhance self-efficacy, educational institutions can provide training and support programs that help students develop the necessary skills and confidence to use the platform effectively. This includes offering online tutorials and step-by-step guides and fostering a supportive learning environment.

Promote Subjective Norms: Given the influence of subjective norms on attitude and behavioral intention, educational institutions should encourage positive word-of-mouth and create a supportive learning environment that promotes using the Shaoxing Learning Platform. This can be achieved by showcasing success stories, organizing peer-to-peer learning activities, and involving faculty members and mentors in promoting the platform's benefits.

Continuous Evaluation and Improvement: It is important for educational institutions to continuously evaluate the effectiveness and user satisfaction of the Chaoxing Learning Platform. This can be done through regular feedback surveys, focus groups, and monitoring usage data. By actively seeking and incorporating student feedback, the platform can be improved to better meet the evolving needs and expectations of the users.

In conclusion, by implementing these recommendations, educational institutions can enhance the adoption and usage of the Chaoxing Learning Platform among third-year undergraduates in Anhui, China. This will ultimately improve students' overall learning experience and support their academic success in the post-pandemic era.

5.3 Limitation and Further Study

One aspect that can be explored in further studies is the concept of imitation. In assessing the behavioral intention to use the Chaoxing Learning Platform, imitation refers to the influence of observing others' behavior on an individual's intention to use the platform. While the current study focused on perceived ease of use, usefulness, attitude, facilitating conditions, self-efficacy, and subjective norm, imitation can be an additional factor.

Research has shown that individuals are often influenced by the behavior of others, particularly if they perceive the behavior to be successful or socially desirable. In the case of using the Chaoxing Learning Platform, observing peers or influential figures who have had positive experiences and outcomes through the platform may positively influence an individual's intention to use it as well. Therefore, investigating the role of imitation and its impact on behavioral intention can provide valuable insights into the social dynamics surrounding the adoption of online learning platforms.

By conducting further studies in these areas, researchers can gain a more comprehensive understanding of the factors influencing the behavioral intention to use the Chaoxing Learning Platform and identify strategies to enhance its effectiveness and user satisfaction.

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