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Measuring Fourth-Year Undergraduates' Behavioral Intention to Use Chaoxing Learning Platform in The Post-Pandemic in Anhui, China

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Abstract

Purpose: This study investigates the factors that measuring undergraduates' behavioral intention to use Chaoxing learning platform in the post-pandemic 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 study's target population comprises 500 fourth-year undergraduate students who have a minimum of one year of experience using the Chaoxing Learning Platform. These students are drawn from three universities in Anhui, China, namely Anhui University of Finance and Economics, Bengbu University, and Tongling University. To assess validity, reliability, model fit, and test hypotheses, the researchers utilized statistical techniques such as Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM). **Results:** The results show that perceived usefulness is significantly impacted by perceived ease of use and facilitating conditions. Behavioral intention is significantly impacted by perceived usefulness, self-efficacy and subjective norm. Attitude is significantly impacted by self-efficacy and subjective norm. There are non-supported relationships between perceived usefulness, perceived ease of use attitude, facilitating conditions and behavioral intention. **Conclusions:** The recommendations focus on improving user experience, addressing concerns, leveraging social influence, and providing ongoing support, ultimately leading to increased intention and engagement with the platform.

Keywords : Attitude, Behavior Intention, Facilitating Conditions, Self-efficacy, Post-Pandemic

JEL Classification Code: E44, F31, F37, G15

1. Introduction

In early February 2020, China Ministry of Education issued the "Guidance on the organization and management of online teaching in general higher education institutions during the epidemic prevention and control period", which pointed out that all universities should rely on various online course platforms and on-campus online learning spaces to actively carry out online teaching activities such as online lectures and online learning to ensure the teaching progress and quality during the epidemic prevention and control period (Nicol & Bice, 2022). In recent years, China has attached great importance to the construction of education informatization and has formed a road of education informatization with Chinese characteristics through years of exploration, which provides strong and powerful support for online teaching during the epidemic prevention and control period (Guo et al., 2019). According to IiMedia Research (2020), China's online education market scale and user scale is growing rapidly, with China's online education market scale reaching 404.1 billion yuan in 2019, and China's online education market scale will reach 453.8 billion yuan in 2020; in terms of user growth, China's online education user scale reached 261 million in 2019.

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At present, Chaoxing has opened a multi-dimensional learning platform system for online teaching and learning, including a cloud platform centered on the learning platform, classroom PC software, mobile APP, and back-end management side data analysis system. These three ends correspond to classroom teaching, student self-learning and teaching management, which cover the whole process of daily teaching before and during the class (Bu, 2019).

The classroom PC software is course-centered, teacher-led and student-oriented, fully associated with the existing hardware in the classroom, covering a variety of classroom teaching modes, so that teachers can more conveniently sign in, select people, grab quizzes, teach in groups, discuss topics and other teaching activities, and fully dock with the learning platform to achieve real-time invocation of online courses and resources, turning the traditional classroom into a smart classroom (Buabeng-Andoh, 2018).

The mobile APP contains six sub-systems: "Mobile Classroom Interactive System", "Mobile Credit System", "Mobile Reading System", " mobile open course", "mobile teaching system", "mobile social system", using a variety of functions to perfectly connect before, during, after and outside the classroom. The management side provides a big data management and analysis system for teachers and teaching managers to monitor the teaching process data in real time (Bu, 2019).

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 fourth-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 was defined as the extent to which a person finds it effortless to use a technology (Lee, 2006). Cheng et al. (2019) interpreted the definition as “the degree to which students found it difficult to use the system”. Perceived ease of use refers to how easy users feel it is to use a new technology (Shi et al., 2015).

These positive correlations between perceived ease of use, perceived usefulness, and attitudes toward use have been validated by several other studies. For example, Huang et al. (2007) used TAM to study the attitudes of undergraduate and graduate students toward mobile learning. Their findings showed that perceived ease of use had a positive and significant effect on perceived usefulness, and that attitudes toward use were influenced by both perceived ease of use and perceived usefulness. Perceptual ease of use has a direct influence on perceived usefulness (Davis, 1989).

Several researches have demonstrated that perceived ease of use impacts individuals' attitudes and behavioral intentions (Šumak et al., 2011; Teo, 2006; Wong & Teo, 2009). In addition, Van der Heijden (2003) also discovered that an understandable and easy-to-navigate system contributes significantly to the formation of positive attitudes towards the use of technology. A study by Moon and Kim (2001) concluded that perceived ease of use has a positive effect on the intention of Ghanaian students to use electronic library resources. Teo (2009) came to the conclusion that perceived ease of use had a significant effect on both perceived usefulness and attitudes. Also, Abramson et al. (2015) conducted a study using the extended TAM theory to examine the use of e-learning and the factors that influence users' BI with mobile learning. They found that perceived ease of use had a significant impact on attitudes. Therefore, the second hypothesis was formulated. Accordingly, based on the above studies, the hypotheses are proposed as follows.

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

Studies have shown that high levels of perceived usefulness often led to positive user performance relationships (Ong & Lai, 2006). More importantly, perceived usefulness was considered to be a significant predictor of course satisfaction in education (Teo, 2010). Perceived usefulness was defined as the degree to which a person considers that using a new technology will improve his or her task performance (Lee, 2006).

The higher the usefulness of the technology, the greater the propensity to adopt it. The perceived usefulness can be considered as an external motivation. This is because the expected benefits of using the system drive people to use or continue to use the system (Booker et al., 2012). Another study performed by Legris et al. (2003) concluded that about 12 to 14 studies investigating attitudes suggest perceived usefulness as an important factor in using technology. A study by Booker et al. (2012) found that perceived usefulness had a significant effect on students' attitudes. Also, Teo (2010) came to the conclusion that perceived usefulness had a meaningful effect on attitudes. Thus, the third and fifth hypothesis are stated as:

H3: Perceived usefulness has a significant impact on attitude.

H5: Perceived usefulness has a significant impact on behavioral intention.

2.3 Attitude

Attitude referred to the person's positive or negative feelings (evaluative emotions) toward performing the desired behavior (Fishbein & Ajzen, 1975, p. 216). Attitude (AT) refers to the degree to which users were satisfied or dissatisfied with the evaluation or judgment of the new technology. Attitude was an individual's perception of an object, such as whether he or she likes or dislikes it. In other words, people were more likely to accept behaviors that they agree with (Armitage & Conner, 2001). Attitudes were the level of interest users have in particular systems and have a direct impact on the intention to use those systems at a later date (Bajaj & Nidumolu, 1998).

Teo (2009) found that attitudes had a positive effect on teachers' behavioral intention. Okyere-Kwakye and Nor (2020) concluded that students' good attitudes towards e-library will have a positive and significant impact on their willingness to use e-library in their studies. Another study by Teo and Lee (2010) also concluded that pre-service teachers' attitudes have a positive effect on their behavioral intention. Therefore, the next hypothesis is stated as:

H4: Attitude has a significant impact on behavioral intention.

2.4 Facilitating Conditions

Facilitating conditions refers to the user's perception that there was agency support and infrastructure to assist in the use of the target technology (Venkatesh et al., 2012). It refers to the opinion of the degree to which the current organizational and technological structure provides support for using technology (Banerjee & Dey, 2013; Williams et al., 2011). Facilitating conditions were defined as providing support and assistance to the user to integrate technology. Here, it refers to factors in the setting that have an impact on a user's willingness to carry out a task. Researchers discovered that there were many barriers that prevent teachers from embedding technology in their instruction (Teo, 2010). In Teo (2010) study, facilitating condition was defined as the degree of technical support and assistance perceived by pre-service teachers in the e-learning process.

Thus, conveniences serve as key indicators for promoting a new technology since they not only help users learn to use the technology in a shorter period of time, but also minimize the problems they may encounter when using the technology. Several studies have indicated that facilitating conditions positively and significantly affect perceived ease of use and perceived usefulness (Huang & Cai, 2015; Teo, 2009, 2011). Lai et al. (2013) found facilitating conditions for the adoption of a technology or a system may also affect a user's perceived usefulness. Teo (2009) demonstrated that facilitating conditions have a positive and significant impact on preservice teachers' perceived ease of use and perceived usefulness of a new technology; this is further supported by Teo (2011) study of in-service teachers.

Individuals perceive themselves as having FC when technology and organizational infrastructure are available to enhance FC, and from this perspective, individuals are incentivized to use e-learning systems. In the workplace context, the availability of training and the support provided to employees are considered part of FC (Tarhini et al., 2017). This study considers FC as a measure of the perception that students have access to the necessary resources and can receive adequate support to use Chaoxing learning platform. Personal assistance, use of training, availability of materials to improve knowledge and skills, and accessibility of e-learning systems are such facilitators (Salloum & Shaalan, 2019). Many researches (Teo, 2010) investigated the influence of FC on technology acceptance and it proved to influence the acceptance of e-learning systems (Sharma et al., 2016; Tarhini et al., 2015, 2017). 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

Compeau and Huff (1999) define perceived computer self-efficacy as "personal self-judgment of the ability to use computers in various IT environments". Self-efficacy was defined as self-perception of how easy it was to perform a particular behavior (Ajzen, 2002). Self-efficacy was defined as one' s overall confidence in one' s ability to carry out a task (Zolait, 2014). Zhang and Espinoza (1998) have ascertained that students' self-efficacy has a positive impact on their attitude of e-learning systems. Several studies have shown that a person's self-efficacy has a significant impact on their subsequent achievement (Bandura, 1977; Hill et al., 1987); Chow et al. (2012) discovered that self-efficacy has a significant impact on both perceived ease of use and perceived usefulness of students, which in turn affects their intention to utilize a technology.

This study concluded that students with higher self-efficacy were more willing to adopt Chaoxing learning platform to complete their courses study than students with low self-efficacy. Based on Waldman (2003), students who expressed interest in online learning had higher self-efficacy to use e-library resources. Ren (2000) argued that people are more interested in doing activities for which they have high self-efficacy. Therefore, it can be deduced that students who have a higher self-efficacy for e-libraries or searching for information for their homework on the web will be more likely to use what is around them (Wang & Duangekanong,

2022). Thus, the below hypotheses are proposed:
H8: Self-efficacy has a significant impact on attitude.
H9: Self-efficacy has a significant impact on behavioral intention.

2.6 Subjective Norm

The addition of subjective-norm constructions provided an important contribution to a researcher's comprehension of the way social factors influence behavior intention during times of stress (Maher & Mady, 2010). In Hu et al. (2015) study, they concluded that subjective norms, which were external perceptions, were defined as Chinese students' perceptions of social tensions and the impact of teachers, peers, or trusted friends on the use of behavioral performance.

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; Liao & Soltani, 2010; Lim & Dubinsky, 2005; Taylor & Todd, 1995). These findings provide support that normative beliefs can be incorporated through information from certain sources. Studies by Abramson et al. (2015), Peterson and Park (2009) and Teo et al. (2012) found that subjective-norm had a significant effect on attitudes and BI.
Therefore, we make the following hypothesis：

One could also argue that subjective norms are related to students' normative perceptions of what is expected of others (Lee & McLoughlin, 2010). In our paper, Chinese college students chose to Chaoxing learning platform if their teachers, classmates, and trusted friends used and recommended them. Park et al. (2012) found a relationship between the influence of subjective norms on the attitudes and behavioral intentions of college students. Hsu et al. (2014) also found that subjective norms on users' attitudes and behavioral use of information systems intention had a direct or indirect effect. Also, Abramson et al. (2015), Peterson and Park (2009) Studies found that subjective-norm had a significant effect on attitudes and behavioral intention. Therefore, we propose 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

Behavioral intention was defined as the probability that an individual plan to use the technology. It also shows a directed causal effect on real usage behavior (Ukut & Krairit, 2019). According to the theory of reasoned action (TRA), behavioral intention was the subjective probability that an individual will engage in a certain behavior (Hsiao & Tang, 2014). Behavioral intention refers to an individual's intention to use an e-learning system, from existing to future learning methods (Jaiyeoba & Iloanya, 2019).

The Chaoxing Learning Platform can be thought of as an information technology device that is only used when students believe that using the system will improve their learning performance. This improved performance can be measured in terms of learning productivity (or learning efficiency), effectiveness of learning, and improved grades. Therefore, in the context of e-learning, Chaoxing Learning Platform means the extent to which students perceive that using the Chaoxing learning platform will improve their learning performance. Thus, perceived usefulness affects their intention to accept and adopt Chaoxing Learning Platform either directly or indirectly (through perceived ease of use).

3. Research Methods and Materials

3.1 Research Framework

The theoretical framework of this study was constructed based on seven variables, categorized into two types: independent and dependent variables. Independent variables are those that explain the desired outcome variables (Hair et al., 2013) and have an impact on other variables (Clark-Carter, 2010). In this study, the independent variables include adoption, perceived ease of use, facilitating conditions, self-efficacy, and subjective norm. On the other hand, dependent variables are the variables that the research aims to investigate (Jackson, 2006; O'Leary, 2017). The dependent variables in this study are attitude, perceived usefulness, and behavioral intention. The conceptual framework, depicted in Figure 1, illustrates the relationships between these variables.

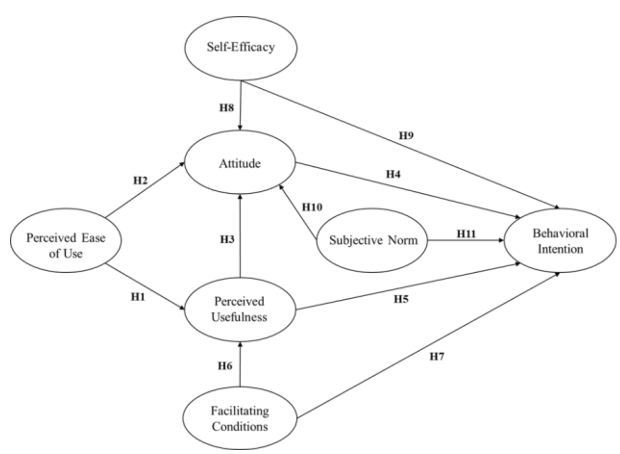

Figure 1: Conceptual Framework

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 research employs empirical analysis and quantitative methods to gather sample data through a web-based questionnaire. The main objective is to investigate the factors influencing college students' behavioral intention to use the Chaoxing online teaching platform in the post-epidemic era. The questionnaire, designed based on a quantitative research approach and informed by relevant theoretical literature and prior research, was distributed to fourth-year undergraduate students at three universities.

The questionnaire included screening questions, utilized a five-point Likert scale for measuring variables, and gathered demographic data from the respondents. Prior to data collection, the Item Objective Consistency Index (IOC) and a pilot test involving 50 participants were conducted to assess the reliability of the questionnaire. The IOC results, evaluated by a panel of three experts, indicated that all 30 scale items scored above 0.6, while the pilot test demonstrated excellent scale reliability with Cronbach's Alpha (CA) values exceeding 0.7 (Nunnally & Bernstein, 1994).

Following data collection, the study evaluated construct validity, encompassing both convergent and discriminant validity. Convergent validity examined the relationship between two tests measuring the same construct, while discriminant validity assessed the absence of correlation between two unrelated tests (Glen, 2015). Finally, the study utilized structural equation modeling (both measurement and structural models) to test hypotheses and assess the overall fitness of the model.

3.3 Population and Sample Size

This study focuses on a target population of 500 fourth-year undergraduate students who have at least one year of experience using the Chaoxing Learning Platform. These students are currently studying at three universities in Anhui, China: Anhui University of Finance and Economics, Bengbu University, and Tongling University. According to the statistical calculator by Soper (2023), the minimum required sample size is 425. However, to ensure effective data analysis for Structural Equation Modeling (SEM), the study aims to collect a sample of 500 participants.

3.4 Sampling Technique

In this study, the selection of participants involved a combination of judgmental sampling and stratified random sampling methods. The targeted group consisted of fourth-year undergraduate students who had at least one year of experience using the Chaoxing Learning Platform, and they were chosen from three universities in Anhui, China: Anhui University of Finance and Economics, Bengbu University, and Tongling University. The sample size was proportionately distributed among the strata, as presented in Table 1. To facilitate the data collection process, convenience sampling was employed. The researchers created online questionnaires using China's online survey platform, Questionnaire Star, and distributed them to the participants via WeChat and QQ through university teachers' assistance.

Table 1: Sample Units and Sample Size

Universities	Population Size	Proportional Sample Size
Anhui University of Finance and Economics	3852	158
Bengbu University	3456	142
Tongling University	4895	200
Total	**12203**	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

According to Table 2, the study included a total of 500 participants. Demographic information, including gender and frequency of using the Chaoxing Learning Platform, was collected from these participants. The questionnaire was distributed to students in their fourth year, and out of the total respondents, 317 were females, accounting for 63.4 percent, while 183 were males, representing 36.6 percent of the sample. In terms of the frequency of using the Chaoxing Learning Platform, 63 students reported using it 1-2 days a week, 284 reported using it 4-6 days a week, and 153 reported using it 7 days a week.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	183	36.6%
	Female	317	63.4%
Frequency Chaoxing Learning Platform	1-2 days a week	63	12.6%
	4-6 days a week	284	56.8%
	7 days a week	153	30.6%

4.2 Confirmatory Factor Analysis (CFA)

Confirmatory factor analysis (CFA) can generally be used for four purposes: one is to analyze the validity of maturity scales, including structural validity, aggregation (convergence validity) and discrimination validity; Second, confirmatory factor analysis can be used to analyze the combination reliability; Third, confirmatory factor analysis can also be used for common method deviation CMV test; Fourth, confirmatory factor analysis was used to calculate the weight (Byrne, 2010). Confirmatory factor analysis (CFA) was used to validate the measurement model, including reliability, convergent validity, and discriminant validity (Anderson & Gerbing, 1988); and then structural equation modeling (SEM) was used to clearly analyze the role of individual indicators on the aggregate and the interrelationships among individual indicators.

The Confirmatory Factor Analysis (CFA) results for CA indicated excellent scale reliability, with values exceeding 0.7, as recommended by Nunnally and Bernstein (1994). The factor loading criteria were set at 0.5, with P-value coefficients less than 0.05. Additionally, according to the guidelines of Fornell and Larcker (1981), the cutoff points for Composite Reliability (CR) and Average Variance Extracted (AVE) were established at 0.7 and 0.5, respectively.

Table 3 presents a comprehensive summary of the measurement model, showing factor loading values surpassing 0.5, CR values above 0.7, and AVE values exceeding 0.4. These results confirm the goodness of fit for the CFA test and validate the reliability and validity of the data analysis. Table 3 serves as a valuable resource, providing an overview of all the approved findings from the measurement model.

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	0.827	0.693-0.796	0.830	0.551
Perceived Usefulness (PU)	Buabeng-Andoh (2018)	4	0.774	0.650-0.715	0.777	0.466
Attitude (ATT)	Oertzen and Odekerken-Schröder (2019)	5	0.873	0.655-0.813	0.874	0.583
Facilitating Conditions (FC)	Buabeng-Andoh and Baah (2020)	4	0.804	0.640-0.784	0.806	0.512
Self-Efficacy (SE)	Sanchez et al. (2013)	4	0.758	0.558-0.737	0.767	0.454
Subjective Norm (SN)	Buabeng-Andoh (2018)	4	0.900	0.792-0.872	0.901	0.694
Behavioral Intention (BI)	Gao and Bai (2014)	5	0.823	0.669-0.715	0.824	0.483

To assess the adequacy of the research model fit, the goodness-of-fit indices presented in Table 3 were examined. These indices were compared against predetermined acceptance criteria. The calculated values for the indices were as follows: CMIN/DF = 1.518, GFI = 0.929, AGFI = 0.915, NFI = 0.918, CFI = 0.970, TLI = 0.966, and RMSEA = 0.032. 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)	583.040/384 = 1.518
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.929
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.915
NFI	≥ 0.80 (Wu & Wang, 2006)	0.918
CFI	≥ 0.80 (Bentler, 1990)	0.970
TLI	≥ 0.80 (Sharma et al., 2005)	0.966
RMSEA	≤ 0.08 (Pedroso et al., 2016)	0.032
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 assess discriminant validity, the square root of the Average Variance Extracted (AVEs) was calculated using the approach suggested by Fornell and Larcker (1981). The results of this study, as presented in Table 5, demonstrate that the discriminant validity is higher than the inter-construct/factor correlations. This finding provides strong evidence in support of discriminant validity within the study.

Table 5: Discriminant Validity

	SE	PEOU	ATT	FC	SN	BI	PU
SE	**0.674**						
PEOU	0.614	**0.743**					
ATT	0.276	0.183	**0.763**				
FC	0.582	0.357	0.260	**0.715**			
SN	0.655	0.471	0.301	0.395	**0.833**		

	SE	PEOU	ATT	FC	SN	BI	PU
BI	0.522	0.501	0.242	0.265	0.522	**0.695**	
PU	0.670	0.625	0.248	0.371	0.660	0.631	**0.683**

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 modified structural equation modeling (SEM) analysis produced satisfactory results, as evidenced by the following values: CMIN/DF = 2.980, GFI = 0.859, AGFI = 0.833, NFI = 0.834, CFI = 0.883, TLI = 0.870, and RMSEA = 0.063. Therefore, it can be concluded from Table 6 that the modified SEM model 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)	1173.963/394 = 2.980
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.859
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.833
NFI	≥ 0.80 (Wu & Wang, 2006)	0.834
CFI	≥ 0.80 (Bentler, 1990)	0.883
TLI	≥ 0.80 (Sharma et al., 2005)	0.870
RMSEA	≤ 0.08 (Pedroso et al., 2016)	0.063
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. The findings of this study confirmed the substantial impact of H1, H2, H3, H4, H5, H6, H7, and H8.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-Value	Result
H1: PEOU→PU	0.593	9.346*	Supported
H2: PEOU→ATT	-0.013	-0.182	Not Supported
H3: PU→ATT	0.078	1.074	Not Supported
H4: ATT →BI	0.065	1.279	Not Supported
H5: PU →BI	0.484	7.617*	Supported
H6: FC →PU	0.204	4.056*	Supported
H7: FC→ BI	-0.068	-1.310	Not Supported
H8: SE→ATT	0.114	2.133*	Supported
H9: SE→BI	0.165	3.079*	Supported
H10: SN→ATT	0.213	4.258*	Supported
H11: SN→BI	0.225	4.446*	Supported

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

The results for **H1** indicated a coefficient of 0.593, with a t-value of 9.346. These findings are consistent with previous studies on the support relationship between perceived ease of use and usefulness. For **H2,** the coefficient was -0.013, with a t-value of -0.182. This result requires further support. Similarly, for **H3,** the coefficient was 0.078, with a t-value of 1.074. Additional support is needed for this result as well. **H4** yielded a coefficient of 0.065, with a t-value of 1.279. However, this result is not supported by previous studies. In contrast, **H5** showed a coefficient of 0.484, with a t-value of 7.617, which supports previous research (Oliver, 1980). **H6** had a coefficient of 0.204, with a t-value of 4.056, supporting previous studies. On the other hand, **H7** had a coefficient of -0.068, with a t-value of 6.904, indicating that it is not supported. **H8** had a coefficient of 0.114, with a t-value of 2.133, providing support for H8. Similarly, **H9** had a coefficient of 0.165, with a t-value of 3.079, indicating support for H9. **H10** had a coefficient of 0.213, with a t-value of 4.258, which was also supported. Finally, **H11** had a coefficient of 0.225, with a t-value of 4.446, and the standardized path coefficient supported the hypothesis.

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

Based on the results from the group of fourth-year students, several important findings emerge that shed light on the factors influencing their adoption and intention to use the Chaoxing learning platform.

Firstly, the results reveal that perceived usefulness is significantly impacted by two key factors: perceived ease of use and facilitating conditions (Šumak et al., 2011; Teo, 2006; Wong & Teo, 2009). Perceived ease of use refers to how user-friendly and effortless students perceive the platform to be. The positive relationship with perceived usefulness suggests that when the Chaoxing learning platform is perceived as easy to use, students are more likely to find it valuable and useful for their learning needs. Additionally, the presence of facilitating conditions, such as access to resources and technical support, further enhances students' perception of the platform's usefulness (Venkatesh et al., 2012).

Secondly, the study demonstrates that behavioral intention is significantly influenced by perceived usefulness, self-efficacy, and subjective norm (Jaiyeoba & Iloanya, 2019; Maher & Mady, 2010; Zolait, 2014). Perceived usefulness continues to play a pivotal role, indicating that when students perceive the platform as valuable and beneficial, they are more likely to intend to use it for their educational purposes. Self-efficacy, which reflects students' confidence in their ability to use the platform effectively, also positively impacts behavioral intention. Furthermore, the subjective norm, representing the influence of social factors on students' intentions, plays a significant role in shaping their intention to use the platform.

Additionally, the findings suggest that attitude towards the Chaoxing learning platform is significantly impacted by self-efficacy and subjective norm. This implies that when students have higher levels of self-efficacy and perceive positive support from their social environment, they are more likely to hold a favorable attitude towards the platform (Wang & Duangekanong, 2022).

However, the study also identifies non-supported relationships between perceived usefulness, perceived ease of use, attitude, facilitating conditions, and behavioral intention. These non-supported relationships indicate that these factors may not be significant predictors of behavioral intention among fourth-year students in this particular context.

These findings have implications for educational institutions aiming to promote the adoption and utilization of the Chaoxing learning platform among fourth-year students. By focusing on enhancing perceived ease of use and providing facilitating conditions, institutions can increase students' perception of the platform's usefulness. Moreover, fostering self-efficacy and leveraging the subjective norm can positively influence students' behavioral intention to use the platform. Understanding the non-supported relationships is also essential, as it highlights that these factors may not be the primary drivers of intention in this specific group of fourth-year students.

Overall, this study contributes to understanding the factors influencing the behavioral intention to use the Chaoxing learning platform among fourth-year undergraduates in the post-pandemic period in Anhui. It provides valuable insights that can inform educational institutions and policymakers in promoting the effective adoption and utilization of technology-based learning platforms.

5.2 Recommendation

In the study that measured fourth-year undergraduates' behavioral intention to use the Chaoxing learning platform in the post-pandemic period in Anhui, the findings and discussions have yielded several recommendations to enhance the platform's adoption and utilization among students.

Firstly, it is crucial to prioritize user-friendliness and ease of navigation. This can be achieved through user interface improvements, providing clear instructions, and incorporating intuitive features. By making the platform more accessible and user-friendly, students will feel more comfortable and confident using it.

Secondly, highlighting the benefits and advantages of the Chaoxing learning platform is vital. Emphasizing its potential for improving learning outcomes, resource access, collaboration, and overall educational experiences can motivate students to engage more actively with the platform.

Additionally, continuous monitoring and improvement of the platform are necessary. Regular content updates, ensuring technical reliability, and promptly addressing student concerns will contribute to a positive user experience. Gathering student feedback and making necessary adjustments based on their satisfaction levels will further enhance their engagement with the platform.

Furthermore, encouraging positive word-of-mouth and peer recommendations can significantly influence students' intention to use the platform. Engaging professors and instructors to endorse and actively use the platform in their teaching can create a supportive and collaborative learning environment.

To mitigate perceived risk associated with using the platform, providing clear information about data privacy, security measures, and technical support is essential. Offering training sessions or tutorials to familiarize students with the platform's features and addressing concerns can alleviate their perceived risk.

Comprehensive training and support services for students are crucial to enhance their skills and knowledge using the platform. Workshops, online tutorials, and readily available technical assistance can boost students' confidence and competence in utilizing the Chaoxing learning platform.

To create awareness among students, targeted marketing campaigns are recommended. Utilizing various communication channels, such as social media, email newsletters, and campus events, can inform and engage students effectively. Sharing success stories and testimonials from students who have benefited from using the platform can also help generate interest and encourage adoption.

Regularly assessing students' satisfaction, usage patterns, and feedback regarding the platform will be instrumental in making necessary improvements and adapting to students' evolving needs and preferences. This iterative approach ensures the Chaoxing learning platform remains relevant and effective in supporting students' learning experiences.

By implementing these strategies, educational institutions in Anhui can enhance the adoption and utilization of the Chaoxing learning platform among fourth-year undergraduates in the post-pandemic period. Focusing on improving user experience, addressing concerns, leveraging social influence, and providing ongoing support will ultimately lead to increased intention and engagement with the platform.

5.3 Limitation and Further Study

The study measuring fourth-year undergraduates' behavioral intention to use the Chaoxing learning platform in the post-pandemic period in Anhui has several limitations that should be acknowledged. The study may have limitations in terms of the representativeness of the sample. The participants included in the study were fourth-year undergraduates from a specific region (Anhui). Therefore, the findings may need to be more generalizable to a broader population of undergraduates or other regions. The specific characteristics and context of the sample may influence the results.

The study relied on voluntary participation, which may introduce self-selection bias. Students who chose to participate may have different characteristics or motivations than those who did not. This could impact the generalizability of the findings and limit the ability to conclude the larger population.

As with any self-report study, participants may have responded in a socially desirable manner. They might have provided answers that they believed were expected or favorable, which could impact the accuracy and reliability of the data. This bias may lead to overestimating positive attitudes and intentions towards the Chaoxing learning platform.

The study relied solely on self-report questionnaires to collect data. While self-report measures are commonly used in research, they are subject to limitations such as recall bias, response bias, and subjective interpretation. Additional methods, such as observation or interviews, could provide a more comprehensive understanding of students' behavioral intentions and usage of the Chaoxing learning platform.

The study employed a cross-sectional design, which captured data at a single point in time. This design limits the ability to establish causal relationships between variables and understand the dynamics of behavioral intention over time. A longitudinal design that tracks students' intention and usage of the platform over an extended period would provide more robust insights.

The study focused on specific variables such as The study focused on specific variables such as perceived ease of use, perceived usefulness, attitude, behavior intention, facilitating conditions, self-efficacy and subjective norm. While these variables are important for understanding behavioral intention, other factors such as individual characteristics, institutional support, and technological infrastructure may influence students' intention to use the platform. The exclusion of these variables may limit the comprehensiveness of the findings.

The post-pandemic study may have influenced students' attitudes and intentions toward the Chaoxing learning platform. The unique circumstances of the pandemic, such as the shift to online learning, may have affected students' perceptions and usage patterns. Therefore, the findings may not be applicable in non-pandemic contexts or during different educational circumstances.

In summary, while the study provides insights into the behavioral intention to use the Chaoxing learning platform among fourth-year undergraduates in the post-pandemic period in Anhui, it is important to recognize its limitations. Future research should address these limitations to enhance the validity and generalizability of the findings and provide a more comprehensive understanding of the factors influencing behavioral intention in different contexts.

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