



An Investigation on Influencing Factors of College Students' Use Behavioral of Chaoxing Learning Platform

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Abstract

Background and Aim: At present, the school where the researcher works has spent a lot of human, material, and financial resources to guide teachers and students to use the Chaoxing learning platform. The purpose of this article is to analyze the factors that affect students' use of the platform. Including connected classroom climate (CCC), performance expectancy (PE), social influence (SI), effort expectancy (EE), facilitating conditions (FC), behavioral intention (BI), and use behavioral (UB), and the relationship between these factors, such as PE and BI, SI and BI, FC and BI, CCC and PE, PE and SI, BI and UB. This research is a quantitative study. Data were collected by questionnaire, and through stratified sampling, a total of 500 students from three different majors at Zhanjiang University of Science and Technology of China were investigated. The results of the study are as follows: There is a significant relationship between these influencing factors. The purpose of this study was to determine the extent to which each variable affected the Chaoxing learning platform.

Materials and Methods: In this paper, a total of 486 data were collected through questionnaires, and data were analyzed using the Structural Equation Model.

Results: The results of the data analysis show that there are significant effects among the variables, and all hypotheses are verified. Among them, behavioral intention has the greatest impact on the use of behavior. It shows that behavioral intention is the key factor that directly drives individual behavior. At the same time, it also shows that these variables have a significant impact on students' use of the platform.

Conclusion: The study highlights the importance of behavioral willingness in students' use of the Chaoxing learning platform and suggests that enhancing the convenience of platform use may require more attention and support.

Keywords: Influencing factors; Use behavioral; Chaoxing learning platform

Introduction

At present, emerging information technologies such as artificial intelligence and big data are widely used and extended to the field of education. Innovation has become an inevitable trend in the development of the information age, and smart education drives innovative development in education and teaching (Zhu, 2016). In college, with the construction of innovative and entrepreneurial universities, it has become a trend to integrate technology in the classroom to promote and enhance student learning in this way. There are benefits to online learning: students have the flexibility to choose their study times, seek clarification when needed, and access course materials at their preferred speed (Tai & Lee, 2021). Schools are investing in technologies designed to provide educational value to students. So, in the researcher's school, the Chaoxing learning platform has been gradually used throughout the school.

However, providing quick and permanent access to professional knowledge and competencies necessitates the use of digital materials and mobile devices. In the use of the Shaoxing learning platform, learning is highly related to the use of mobile systems, which are conducive to students' learning knowledge and skill development. Utilizing technology for enhancing learning within universities has become a prevalent approach, primarily attributed to its capacity to mitigate temporal and spatial constraints inherent in conventional educational settings (Okeji & Alex-Nmecha, 2022). The objective of these systems is to develop solutions for mobile learning platforms that enable students to engage in searching, accessing, generating personal knowledge, collaborating on knowledge platforms, and overseeing them. Given the widespread adoption of mobile computing technology, mobile learning is poised to assume a pivotal role in the swiftly expanding e-learning sector. Educational institutions should

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promote the utilization of existing technology, empowering students to consistently enhance their intellectual capacities and accomplish their objectives while creatively elucidating technological concepts.

Introducing a theory by Harasim (2012), “online collaborative learning” directs its focus toward how internet features contribute to the construction of knowledge. Such as the integration of the Chaoxing learning platform into classroom management. The advantage of traditional face-to-face learning is that teachers provide a learning space free from any external interference, and students complete learning tasks in a relatively independent space. The hybrid classroom is a combination of virtual space and the traditional classroom model. Through this method, students can interact with teachers in both the real world and virtual classroom Spaces and student-to-student. However, the introduction of new technologies cannot be successful if students do not accept and use them. Therefore, this research discusses the factors that affect students’ use of the platform.

So, this study integrates the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003) with CCC (Dwyer et al., 2004) to expand understanding of the factors influence. The UTAUT model mainly explains the behavior of individuals adopting new technologies around four core dimensions, including PE, EE, SI, and FC. The innovation of this research lies in the fact that the Chaoxing Learning Platform has innovated the college education mode. Teachers use this learning platform to stimulate students' interest in learning, promote exchanges and cooperation between teachers and students or among students, and thus improve students' academic performance. Of course, some limitations should be recognized when considering the contribution of this study. The object of this study is a single cultural sample of Chinese college students, and future studies should explore the comparison of concepts between different ethnic cultures. In addition, this study only explores the relationship between students and teachers, and parents’ views on education may also be an important factor affecting young people’s acceptance.

Objectives of the Study

The purpose of the study was to determine the influence factor analysis of each variable, including performance expectation (PE), social impact (SI), effort expectancy (EE), contributing factor (FC), connected topic climate (CCC), behavioral intention (BI) and use behavior (UB), on students' use of Chaoxing learning platform.

1. To determine the significant relationship between performance expectancy and college students’ behavioral intention of adopting the Chaoxing learning platform.
2. To determine the significant relationship between social influence and college students’ behavioral intention of adopting the Chaoxing learning platform.
3. To determine the significant relationship between effort expectancy and college students’ behavioral intention of adopting the Chaoxing learning platform.
4. To determine the significant relationship between facilitating conditions and college students’ behavioral intention of adopting the Chaoxing learning platform.
5. To determine the significant relationship between facilitating conditions and college students’ effort expectancy of adopting the Chaoxing learning platform.
6. To determine the significant relationship between connected classroom climate and performance expectancy.
7. To determine the significant relationship between connected classroom climate and social influence.
8. To determine the significant relationship between behavioral intention and use behavior.

Literature Review

Chaoxing Learning Platform



The Chaoxing learning platform is an online comprehensive platform based on network course resources, encompassing various digital resources related to education and teaching such as Chaoxing learning (APP), Chaoxing MOOCs (Massive Open Online Courses), and Chaoxing Library. This platform enables a teaching-aid system accessible through terminals like smartphones and PCs.

Connected Classroom Climate (CCC)

In the study by Ambrose et al., (2010), classroom climate was characterized as encompassing the cognitive, social, affective, and environmental surroundings within which students engage in learning. This viewpoint recognizes that the climate is influenced by a variety of influential factors, such as interactions between faculty and students, interactions among students, the instructional approach, potential biases, the composition of the student body, and the diversity of viewpoints embedded in the course material. It's important to highlight that the significance of CCC extends beyond conventional face-to-face classroom environments and encompasses the realm of online course teaching as well (Li et al, 2021). Numerous research endeavors have employed Dwyer et al., (2004) description of CCC to investigate student learning and instructor impact in in-person educational settings.

Ha1: Connected Classroom Climate has a significant influence on performance expectancy.

Ha2: Connected Classroom Climate has a significant influence on social influence.

Performance Expectancy (PE)

Performance expectancy is the expected impact of a technology's functional advantage even in uncertain conditions. Performance Expectancy measures the degree to which students perceive that university services can be easily accessed using the Chaoxing learning platform. Performance Expectancy (PE) is the degree to which an individual believes that using a system will help him to attain gains in job performance (Venkatesh et al, 2003).

Ha3: Performance expectancy has a significant influence on Behavioral intention.

Social Influence (SI)

Social Influence is—the degree to which an individual perceives that important others believe he or she should use the new system. Social influence significantly positively affected behavioral intention.

Ha4: Social influence has a significant influence on Behavioral intention.

Effort Expectancy (EE)

Effort expectancy is characterized by the level of simplicity linked to the utilization of the system (Venkatesh et al., 2003). Effort expectancy in the context of online learning concerns the ease of utilizing the system, including the factor of simplicity, along with the individual's perception of the system's contribution to enhancing work outcomes (Chao, 2019). This concept indicates that whether the architecture of information software or systems is easy for users to use, effort expectation has always been one of the important variables used in the field of information technology and system acceptance and use.

Ha5: Effort expectancy has a significant influence on Behavioral intention.

Facilitating Conditions (FC)

Facilitating Conditions can be understood as the extent to which an individual perceives the presence of organizational and technical infrastructure to support the utilization of the system (Venkatesh et al, 2003). Defined facilitating conditions as the learning support that the learners perceive in using a system from other individuals, institutions, and technical facilities. Furthermore, facilitating conditions provide a platform for users to use the new technology (favorable or unfavorable).

Ha6: Facilitating conditions have a significant influence on Behavioral intention.

Ha7: Facilitating conditions have a significant influence on effort expectancy.

Behavioral Intention (BI)

Behavioral intention to use pertains to the choice made by learners to either continue employing the technology or cease its usage, and this concept is considered a key factor influencing the adoption of the technology (Mahdi Mohammed Alamri, 2021). Behavioral intention signifies an individual's inclination to both initiate and sustain the utilization of technology, constituting a determining element in the utilization of said technology (Musa et al. (2017),

Use Behavioral (UB)

Davis (1989) defined behavioral intention represents the degree to which a person is prompted to accomplish certain behaviors.

Ha8: Behavioral intention has a significant influence on Use behavior.

Conceptual Framework

A conceptual framework is an academic research framework evolved from previous research frameworks, as shown in Figure 1. There are 7 variables in this study, which are Connected Classroom Climate (CCC), Behavioral Intention (BI), Facilitating Conditions (FC), Effort Expectancy (EE), Social Influence (SI), Performance Expectancy (PE), Use Behavioral (UB).

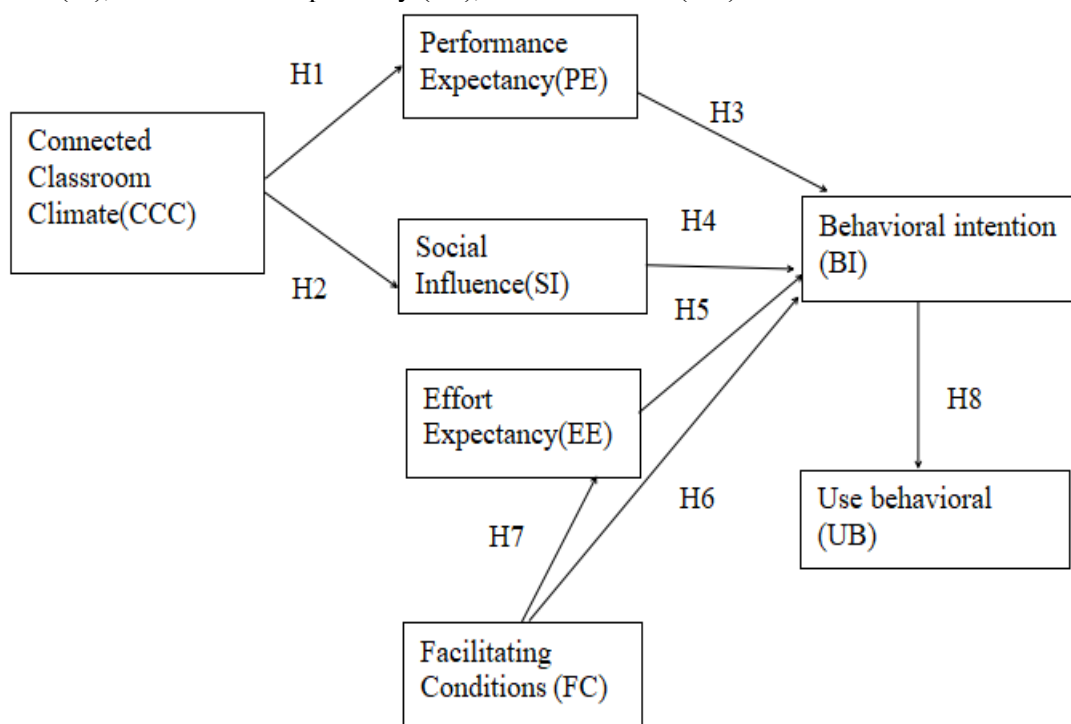


Figure 1 Conceptual Framework

Methodology

Research Instrument

The researcher used questionnaires to collect data, Use the questionnaire star to issue the questionnaire.

To evaluate the reliability questionnaire, the researcher selected some samples that were consistent with the characteristics of actual samples for testing. This study consists of 7 variables, with 27 questions for both variables. This included 4 items for Performance Expectancy (PE), 4 items for Facilitating



Conditions (FC), 4 items for Effort Expectancy (EE), 4 items for Social Influence (SI), 3 items for Behavioral Intention (BI), 4 items for Connected Classroom Climate (CCC), 4 items for Use Behavioral (UB). Seven independent variables were measured using a 5-point Likert scale, where 1 means "strongly disagree" and 5 means "strongly agree."

To measure the validity of the research instrument, the researcher will invite 3 experts to use IOC to score the questionnaire part of this study, 27 items, on three levels, suitable, not sure, and not suitable.

Population and Sample

Sophomore year students majoring in Accounting, Education, and English at Zhanjiang University of Science and Technology. These students come from different majors, including both male and female students, with ages ranging from 20 to 22 years old. They share the same educational level and are open to embracing new experiences.

There are 500 students majoring in accounting, English, and primary education in Zhanjiang University of Science and Technology.

The sampling method of this study is stratified sampling. By adopting this sampling method, the representativeness of the sample can be improved, the estimation accuracy can be enhanced, and the organization and implementation can be facilitated. Aim to select the same characteristics of the sample to portray the characteristics of the population. Each stratum will have different characteristics, but within the same strata, there is a similarity. In this study, according to the data provided by the educational administration system of Zhanjiang University of Science and Technology, there are a total of 3011 students majoring in accounting, English, and primary education. Accounting majors accounted for 40.9%, English majors accounted for 35.1%, and primary education majors accounted for 24%. The researcher will use a stratified sampling method, sampling a total of 500 people. In accounting major sample 205, English major sample 175, primary education major sample 120.

Table 1 Population and Sample Size

Major	Population Size Total=3011	Proportional sample Size Total=500
Accounting Major	1231	205
English major	1057	175
Primary education major	723	120

Data Collection and Analysis

During the research process, the researcher distributed questionnaires through the Questionnaire Star (online). Initially, a pilot test was conducted with 30 students who had previously used the Chaoxing learning platform. Conclusions were drawn based on Cronbach's Alpha coefficient, indicating that the 30 questionnaires distributed exhibited reliability. Subsequently, in the course of writing Chapter 5, questionnaires were administered to the study's sample. Upon data collection, questionnaire data was downloaded from the Questionnaire platform for analysis. Additionally, informed consent forms were obtained from the participants.

Researchers use SPSS to analyze the population information. Researchers use CFA and SEM to verify the conclusions. The research employed a confirmatory factor analysis (CFA) using AMOS to investigate the interrelationships among the constructs in the proposed model.

Results

Demographic Information

The researcher distributed 500 questionnaires through the questionnaire star, because there are 27 questions in the questionnaire and the answering time is not less than 3 minutes, according to the experience of the pre-survey, the researcher preliminarily cleaned some sample data whose answering



time is too short (less than 3 minutes), a total of 6 samples were cleaned. To further ensure the effectiveness of other questionnaires, we manually identified 8 samples with the same index answers and finally cleaned the sample data. From the 500 questionnaires, 486 valid data samples were obtained for empirical analysis, and the effective rate of questionnaire recovery was 97.2% and the participants were all sophomore students, distributed according to gender, among which 63% were female participants and 27% were male participants. According to the distribution of majors, accounting major students accounted for 41.3%, English major students accounted for 35.7%, and primary education major students accounted for 23%.

Table 2 Demographic Information of Samples

Variable	Category	Frequency	Percentage
Gender	Male	180	37.00%
	Female	306	63.00%
	Total	486	100.00%
Year of Study	Year 2	486	100.00%
	Accounting Major	201	41.30%
Major	English major	173	35.70%
	Primary education major	112	23.00%

Confirmatory Factor Analysis (CFA)

In Cho et al. (2020) study, a goodness-of-fit index (GFI) reaching 0.80 or higher is considered indicative of an exceptionally fitting model. Meeting this criterion aims to verify the consistency of the model (Ainur et al., 2017). The collected data underwent confirmatory factor analysis in this paper, evaluated against seven criteria. The comparative fit indices included the Comparative Fit Index (CFI), the Normed Fit Index (NFI), and the Tucker-Lewis Index (TLI). Absolute fit indices comprised Relative Chi-Square (CMIN/DF), Goodness of Fit Index (GFI), and Root Mean Square Error of Approximation (RMSEA).

Table 3 Fit Indices Results of the Confirmatory Factor Analysis

Categories	GOF Index	Criteria	Result
Incremental Fit indications	CFI	$CFI \geq 0.90$	0.919
	TLI	$TLI \geq 0.90$	0.906
	CMIN/DF	$CMIN/DF < 3.00$	2.316
Absolute Fit indications	GFI	$GFI \geq 0.80$	0.903
	RMSEA	$RMSEA < 0.08$	0.052

The findings from the research indicated favorable goodness-of-fit indices for the measurement model. According to the model fit test results of the figure 5.7, CFI is 0.919, greater than 0.80, TLI is 0.906, greater than 0.90, CMIN/DF is 2.316, less than 3.00, GFI is 0.903, greater than 0.90, RESEA is 0.052. Less than 0.08. It can be shown that the CFA model is a good fit.

Before using structural equation models (SEM) to test hypotheses, confirmatory factor analysis was used to assess the correlation between potential variables to assess the fit of the model. The use of CFA can help researchers analyze the degree of fit of project data that should be measured on a specific structure. As well as providing possible weaknesses in the project structure (Muller & Hancock, 2001). Table 4 shows the data results for all items of confirmatory factor analysis, composite reliability, and extracted mean variance.



On the premise that the CFA model has a good fit, the convergence validity (AVE) and combination reliability (CR) of each dimension of the scale will be further tested. The standardized factor load of each measurement item in the corresponding dimension is calculated through the established CFA model. Then, the convergence validity and combination validity of each dimension are calculated by the formula of AVE and CR. The researcher employed Hair et al. (2006) indices which are the Factor Loading greater than 0.5 and the Average Variance Extracted (AVE) greater than .50.

Table 4 The Results for Factor loading, Composite Reliability (CR), and Average Variance Extracted (AVE)

Observed Variable	Factor Loading	Cronbach's Alpha	CR	AVE
CCC1	0.594	0.802	0.810	0.520
CCC2	0.781			
CCC3	0.799			
CCC4	0.689			
PE1	0.634	0.778	0.800	0.503
PE2	0.717			
PE3	0.871			
PE4	0.579			
SI1	0.651	0.810	0.822	0.538
SI2	0.800			
SI3	0.807			
SI4	0.661			
EE1	0.565	0.786	0.804	0.513
EE2	0.733			
EE3	0.882			
EE4	0.645			
FC1	0.646	0.778	0.793	0.501
FC2	0.775			
FC3	0.836			
FC4	0.520			
BI1	0.808	0.768	0.774	0.534
BI2	0.712			
BI3	0.655			
UB1	0.670			
UB2	0.775	0.790	0.800	0.504
UB3	0.780			
UB4	0.597			

Discriminant Validity

Before structural equation model analysis, each concept needs to be tested for differential validity. According to Fornell and Larcker (1981), discriminant validity can be based on comparing the correlation coefficient of each structure with the square root of the Average Variance extraction (AVE). The result of the square root of AVE needs to be greater than the correlation coefficient of the construct to ensure the discriminant validity.



Table 5 Discriminant Validity

Correlation	CCC	PE	SI	EE	FC	BI	UB
CCC	0.721						
PE	0.319	0.709					
SI	0.249	0.288	0.734				
EE	0.132	0.144	0.270	0.716			
FC	0.083	0.145	0.080	0.209	0.708		
BI	0.238	0.302	0.288	0.316	0.271	0.728	
UB	0.250	0.408	0.379	0.299	0.146	0.492	0.710

Structural Equation Model (SEM)

The Structural Equation Model (SEM) was employed to test the hypotheses regarding causal relationships among the proposed variables. Structural Equation Modeling (SEM) is a statistical method used to assess and analyze complex relationships among multiple observed variables. It combines the measurement of causal relationships with structural modeling, allowing researchers to test causal relationships between variables while considering the effects of measurement errors and latent variables. This technique estimates the link between the observable variable and the latent variable (Bentler, 2010).

Table 6 Goodness of Fit for Structural Equation Modeling

Categories	GOF Index	Criteria	After Adjustment Values
Incremental Fit indications	CFI	CFI ≥ 0.9	0.911
	TLI	TLI ≥ 0.9	0.900
	SRMR	SRMR ≤ 0.08	0.066
Absolute Fit indications	CMIN/DF	CMIN/DF < 3.00	2.581
	GFI	GFI ≥ 0.80	0.896
	RMSEA	RMSEA < 0.08	0.054

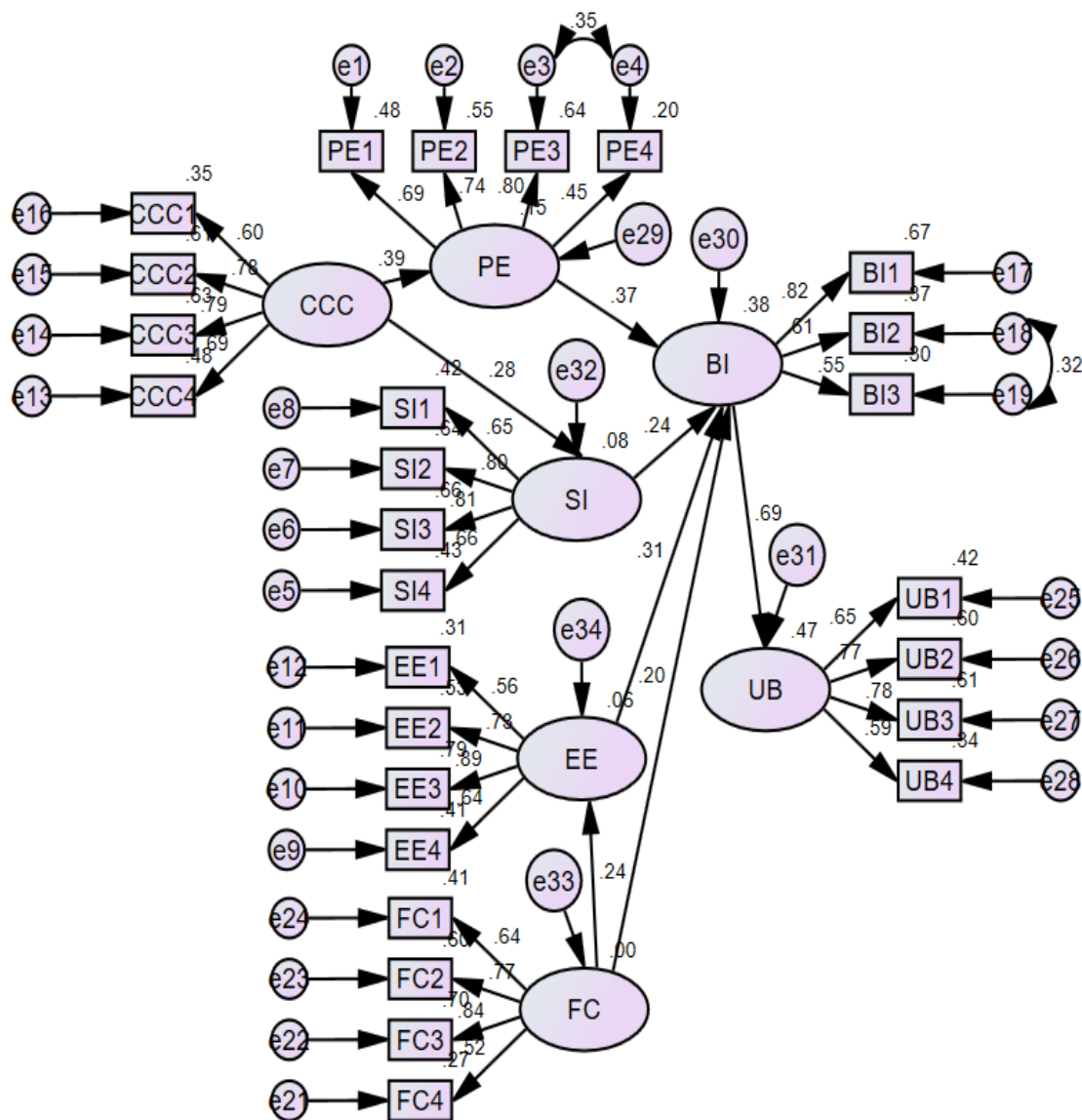


Figure 2 Structural Equation Model (SEM)

Research Hypothesis Testing Result

The SEM parameter estimates table (Table 7) shows the hypotheses testing for each of the hypotheses stated in the study. Research hypotheses are forecasts of research outcomes, typically focusing on the relationships between variables. The quantitative study utilized the Amos 23.0 software program for path analysis.



Table 7 Hypothesis Results

Hypotheses	path	Standardized Path Coefficient (β)	T-Value	Tests Result
Ha1	PE \leftarrow CCC	0.391	6.522***	Supported
Ha2	SI \leftarrow CCC	0.281	4.941***	Supported
Ha3	BI \leftarrow PE	0.374	6.760***	Supported
Ha4	BI \leftarrow SI	0.236	4.573***	Supported
Ha5	BI \leftarrow EE	0.307	5.679***	Supported
Ha6	BI \leftarrow FC	0.198	3.663***	Supported
Ha7	EE \leftarrow FC	0.244	4.206***	Supported
Ha8	UB \leftarrow BI	0.686	9.675***	Supported

As shown in Table 5.7, all eight hypotheses are supported.

Ha1: The first hypothesis proposes that Connected Classroom Climate has a significant influence on performance expectancy. There is a significant influence between the two variables. The standardized path parameter was 0.391, and the t-value was 6.522, the p-value was $p < 0.001$. Therefore, the null hypothesis is rejected.

Ha2: The second hypothesis proposes that Connected Classroom Climate has a significant influence on social influence. There is a significant influence between the two variables. The standardized path parameter was 0.281, and the t-value was 4.941, the p-value was $p < 0.001$. Therefore, the null hypothesis is rejected.

Ha3: The third hypothesis proposes that Performance expectancy has a significant influence on Behavioral intention. There is a significant influence between the two variables. The standardized path parameter was 0.374, and the t-value was 6.760, the p-value was $p < 0.001$. Therefore, the null hypothesis is rejected.

Ha4: The fourth hypothesis proposes that social influence has a significant influence on Behavioral intention. There is a significant influence between the two variables. The standardized path parameter was 0.236, and the t-value was 4.573, the p-value was $p < 0.001$. Therefore, the null hypothesis is rejected.

Ha5: The fifth hypothesis proposes that Effort expectancy has a significant influence on Behavioral intention. There is a significant influence between the two variables. The standardized path parameter was 0.307, and the t-value was 5.679, the p-value was $p < 0.001$. Therefore, the null hypothesis is rejected.

Ha6: The sixth hypothesis proposes that facilitating conditions have a significant influence on Behavioral intention. There is a significant influence between the two variables. The standardized path parameter was 0.198, and the t-value was 3.663, the p-value was $p < 0.001$. Therefore, the null hypothesis is rejected.

Ha7: The seventh hypothesis proposes that facilitating conditions have a significant influence on Effort expectancy. There is a significant influence between the two variables. The standardized path parameter was 0.244, and the t-value was 4.206, the p-value was $p < 0.001$. Therefore, the null hypothesis is rejected.

Ha8: The eighth hypothesis proposes that Behavioral intention has a significant influence on Use behavior. There is a significant influence between the two variables. The standardized path parameter was 0.686, and the t-value was 9.675, the p-value was $p < 0.001$. Therefore, the null hypothesis is rejected.

Discussion

Based on statistical analysis of questionnaire data, the researcher found a relationship between performance expectancy and behavioral intention, with performance expectancy significantly influencing behavioral intention, with a T-value of 6.760***, previous literature studies have indicated that



performance expectancy has an impact on behavioral intention Feng et al., (2015); Venkatesh et al. (2003). Therefore, the research findings align with the existing literature.

Based on statistical analysis of questionnaire data, the researcher found a relationship between social influence and behavioral intention, with social influence significantly influencing behavioral intention, with a T-value of 4.573***, previous literature studies have indicated that social influence has an impact on behavioral intention Musa et al. (2017), Lukwago et al., (2017), Masa'deh et al., (2016), Tai & Lee (2021). Therefore, the research findings align with the existing literature.

Through statistical analysis of questionnaire data, the researcher identified a significant relationship between effort expectancy and behavioral intention, with effort expectancy exerting a significant influence on behavioral intention (T-value = 5.679***). Previous literature studies, including those by Musa et al. (2017), Feng et al. (2015), Venkatesh et al. (2003), and Masa'deh et al., (2016), have also indicated the impact of effort expectancy on behavioral intention. Hence, the research findings are consistent with existing literature.

Through statistical analysis of questionnaire data, the researcher established a significant relationship between facilitating conditions and behavioral intention, with facilitating conditions exerting a notable influence on behavioral intention (T-value = 3.663***). Previous literature studies, including those by Feng et al. (2015), Venkatesh et al. (2003), and Brandford Bervell & Valentina Arkorful (2020), have also highlighted the impact of facilitating conditions on behavioral intention. Therefore, the research findings align with existing literature.

Through statistical analysis of questionnaire data, the researcher established a significant relationship between facilitating conditions and effort expectancy, with facilitating conditions exerting a notable influence on effort expectancy (T-value = 4.206***). Previous literature studies, including those by Kuciapski, M. (2016) and Brandford Bervell & Valentina Arkorful (2020), have also emphasized the impact of facilitating conditions on effort expectancy. Therefore, the research findings are in line with existing literature.

The researcher confirmed a significant relationship between connected classroom climate and performance expectancy, with connected classroom climate exerting a notable influence on performance expectancy (T-value = 6.522***). Previous literature studies, including those by Yang et al. (2019), Li et al. (2021), and Prisbell, M et al., (2009), have also underscored the impact of connected classroom climate on performance expectancy. Therefore, the research findings align with existing literature.

The researcher established a significant relationship between connected classroom climate and social influence, with connected classroom climate exerting a notable influence on social influence (T-value = 4.941***). Previous literature studies, including those by Yang et al. (2019), Li et al. (2021), and Prisbell, M et al., (2009), have also highlighted the impact of connected classroom climate on social influence. Therefore, the research findings are consistent with existing literature.

The researcher established a significant relationship between behavioral intention and use behavior, with behavioral intention exerting a notable influence on use behavior (T-value = 0.686***). Previous literature studies, including those by Musa et al. (2017), Lukwago et al., (2017), and Masa'deh et al., (2016). Tai & Lee (2021), have also emphasized the impact of behavioral intention use behavioral. Therefore, the research findings align with existing literature.

Implications for Practice

This study examines the factors influencing students' usage of the Chaoxing learning platform, including Effort Expectancy, Performance Expectancy, Facilitating Conditions, Connected Classroom Climate, Social Influence, Behavioral Intention, and Use Behavioral. The research findings reveal significant effects, such as Connected classroom climate on Performance expectancy, connected classroom climate on social influence, Performance expectancy on Behavioral Intention, Social Influence on Social Influence, Effort expectancy on Behavioral Intention, Behavioral Intention on Behavioral



Intention, Facilitating Conditions on Effort expectancy, and Behavioral Intention on Use Behavioral. These findings have various implications for future practices:

Firstly, instructional design and implementation: Educators can utilize the research findings to design and implement teaching strategies that promote students' usage of the Chaoxing learning platform. They can develop course content and teaching activities based on these influencing factors to enhance students' positive attitudes and intentions toward the platform.

Secondly, technical support and training: Schools and educational institutions can provide technical support and training tailored for both teachers and students to help them better utilize the Chaoxing learning platform. This may include guidance on utilizing platform features, troubleshooting technical issues, and accessing teaching resources.

Thirdly, classroom management and atmosphere creation: Educators can foster a connected classroom climate to encourage collaboration and interaction among students, and leverage facilitating conditions to support students' usage of the learning platform. This can contribute to creating a positive learning environment, fostering students' motivation, and enhancing their behavioral intentions.

Fourthly, instructional assessment and improvement: Educational institutions can use these influencing factors to assess students' usage of the Chaoxing learning platform and make improvements based on feedback. Regular surveys and evaluations can help understand students' satisfaction and needs, allowing timely adjustments to teaching strategies and platform functionalities to meet students' learning requirements.

In summary, the research findings imply that educators can optimize instructional design, provide technical support, foster classroom management, and utilize assessment information for continuous improvement. These efforts can better facilitate students' effective usage of the Chaoxing learning platform and enhance learning outcomes.

Recommendations for Future Research

The researcher proposes the following future research directions on students' usage of the Chaoxing learning platform:

Firstly, due to limitations in research time, this study solely analyzed the influencing factors of the use of the Chaoxing learning platform among 486 students from three different majors at Zhanjiang University of Science and Technology. In future research, it is necessary to understand the long-term usage and effects of the Chaoxing learning platform among all students in the university, including its impact on learning outcomes, academic achievements, and learning motivation.

Secondly, cross-cultural comparative research: compare students from different cultural backgrounds and different majors regarding their attitudes toward and influencing factors on the usage of the Chaoxing learning platform to understand the cultural factors influencing platform usage.

Thirdly, research on integrating new technologies: investigate how to integrate the Chaoxing learning platform with other new technologies such as artificial intelligence and virtual reality to enhance students' learning experiences and effectiveness.

Fourthly, research on the role of teachers: explores the role and influence of teachers in facilitating students' usage of the Chaoxing learning platform, including teachers' technical support, guidance, and motivation.

Fifthly, research on differences among student groups: research the differences and influencing factors of students' usage of the Chaoxing learning platform among different age groups, genders, academic backgrounds, and learning abilities.

Sixthly, research user experience, and gain a deeper understanding of students' usage experiences with the Chaoxing learning platform, including their perceptions and feedback on interface design, functionality, and usability.

Additional, research on data analysis and predictive modeling: utilize big data analysis techniques and predictive models to study the relationship between students' usage behavior and learning outcomes



with the Chaoxing learning platform, aiming to predict students' learning behavior and results. These research directions can further deepen the understanding of students' usage of the Chaoxing learning platform and promote the development of educational technology and continuous improvement in teaching practices.

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