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Factors Contributing to Undergraduate Students' Satisfaction and Continuance Intention of the Chaoxing Learning Platform in Yibin, China

Tao Yuezhen*

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Abstract

Purpose: This study identified key factors influencing undergraduate students' satisfaction and continuance intention to use the Chaoxing Learning Platform in Yibin, China. **Research design, data and methodology:** The researcher employed a quantitative approach (n=500) to distribute questionnaires to undergraduate students from the School of Mechanical Engineering at Sichuan University of Science & Engineering in Yibin, Sichuan Province, China. The study utilized non-probability sampling techniques, including judgmental sampling to select four target grades, quota sampling to determine the sample size, and convenience sampling for data collection and online questionnaire distribution. Data analysis was performed using structural equation modeling (SEM) and confirmatory factor analysis (CFA) to assess model fit, reliability, and construct validity. **Results:** The findings revealed that perceived usefulness ($\beta = 0.216$) and confirmation ($\beta = 0.215$) had the strongest effects on satisfaction, followed by information quality ($\beta = 0.175$) and service quality ($\beta = 0.168$). Satisfaction significantly influenced continuance intention ($\beta = 0.554$), as did subjective norm ($\beta = 0.332$). **Conclusions:** These results underscore the platform's usefulness and confirmation of expectations as critical satisfaction drivers. Platform developers and university administrators should enhance technical quality and tailor content to student needs while promoting instructor and peer endorsement. These strategies can increase student satisfaction and encourage continued usage with the platform in blended learning environments.

Keywords: Learning platform, Satisfaction, Continued Use Intention, Undergraduate, Yibin

JEL Classification Code: A22, I23, L86, O30

1. Introduction

Recent advancements in information technology have significantly transformed education, particularly through e-learning, which has reshaped traditional classroom dynamics and provided more flexible, accessible, and personalized learning experiences (Al-Samarraie et al., 2018; Suzianti & Paramadini, 2021). E-learning, leveraging ICT, enhances knowledge delivery and supports diverse learner needs, overcoming geographical and temporal barriers (Goldie, 2016). Its rapid evolution highlights the growing importance of e-learning in modern educational systems, especially in universities worldwide (Fauzi, 2022).

However, e-learning has limitations, such as a lack of direct interaction, which can hinder communication and reduce collaborative learning opportunities. Many students report feelings of isolation in fully online settings, leading to lower engagement and motivation (Martin & Bolliger, 2018). Additionally, e-learning demands strong self-discipline and time management, which some learners struggle with, resulting in lower completion rates (Francis et al., 2019). These challenges emphasize the need for better

1 *Tao Yuezhen, School of Mechanical Engineering, Sichuan University of Science & Engineering, China. Email：421300636@qq.com

support systems and solutions to optimize e-learning.

To address these issues, blended learning combines the benefits of e-learning with traditional face-to-face instruction (A. Kumar et al., 2021). By integrating online resources and in-person interactions, it fosters deeper engagement and collaboration, maintaining flexibility while improving teaching efficiency and learning experiences (Anthony et al., 2019). Studies show that blended learning, combining online media with traditional methods, is more effective than conventional e-learning (Yu et al., 2022) and enhances student satisfaction and learning outcomes (Anthony et al., 2022).

In recent years, China's higher education sector has undergone significant digital transformation, driven by advances in information technology (Xiao, 2019). National policies, such as the Education Informatization 2.0 Action Plan, have supported blended learning as a vital tool for modernizing education. This approach combines the benefits of physical classrooms with the flexibility of online platforms, improving access to resources and promoting personalized learning (Teng & Wang, 2021).

In China, the Chaoxing Learning Platform is a widely used e-learning tool in universities. Offering course management, resource sharing, online assessments, and interactive communication, Chaoxing supports various learning activities. Its user-friendly interface, mobile app, and extensive library of educational resources enhance learning flexibility, making it a key resource for advancing blended learning. Despite its growing integration into university teaching, limited empirical research has examined the specific factors influencing student satisfaction and their continuance intention toward Chaoxing in the context of blended learning. Prior studies have primarily focused on general e-learning adoption, often overlooking platform-specific attributes and contextual variables in Chinese universities.

This study addresses this gap by investigating the influence of system quality, information quality, perceived usefulness, confirmation, and subjective norm on student satisfaction and continuance intention to use Chaoxing. By applying structural equation modeling (SEM) to analyze student responses, this research contributes to the theoretical understanding of user engagement in blended learning environments and offers practical recommendations for enhancing platform design and implementation in higher education.

2. Literature Review

2.1 Factors Contributing to Undergraduate Students' Satisfaction and Continuance Intention

Petter and McLean (2009) defined system quality as the performance of an information system in areas like reliability, usability, functionality, and other relevant metrics. DeLone and McLean (2016) emphasized that system quality refers to the effectiveness of an information system's functionality, evaluating aspects like adaptability, availability, reliability, response time, and usability. Rui-Hsin and Lin (2018) suggested that system quality should also include metrics such as system inquiry, document transmission rate, feedback time, and access rates for software and hardware.

According to DeLone and McLean (2016), information quality is a key attribute for evaluating information systems, focusing on accuracy, timeliness, completeness, relevance, and consistency. Petter and McLean (2009) defined information quality as the characteristics of an information system's output, including accuracy, timeliness, and completeness. In e-learning, Chopra et al. (2019) regarded information quality as the quality of instructional content, such as PDFs, PPTs, audio, and video.

Davis (1989) defined perceived usefulness as the extent to which an individual believes that using a particular system will improve job performance. This construct is critical in predicting user acceptance of systems. Suzianti and Paramadini (2021) described perceived usefulness as cognitive beliefs shaping an individual's intentions, particularly regarding the adoption and continued use of a system. In education, Agudo-Peregrina et al. (2014) redefined it as the belief that an e-learning system enhances academic performance by supporting the learning process and task completion.

Bhattacherjee (2001) defined confirmation as the extent to which users perceive the actual performance of an information system (IS) or technology (IT) aligning with their expectations. Cheng (2014) described confirmation as the degree to which users feel a system meets their initial expectations during actual use, influencing satisfaction and continued use. In e-learning, Taghizadeh et al. (2022) linked confirmation to the alignment of online learning performance with students' initial expectations.

Ajzen (1991) defined subjective norm as the perceived social pressure to engage in or avoid a behavior. Ohanu et al. (2023) argued that subjective norm reflects how individuals perceive the influence of significant others, such as family and friends, on their behaviors. Kumar et al. (2020) emphasized the role of lecturers and peers in shaping students' decisions to engage in e-learning activities.

Bhattacherjee (2001) defined continuance intention as the intention to continue using a service after initial adoption. Chang (2013) characterized it as the likelihood of continuing to use e-learning systems in the future and recommending them to others. Sabah (2020) considered continuance intention as a direct extension of actions linked to the initial adoption of the system.

2.2 Research Hypothesis and Relationship between Variables

2.2.1 Relation between System Quality and Satisfaction

Lee-Post (2009) showed that high system quality, marked by user-friendly interfaces and dependable functionality, directly enhances user satisfaction in e-learning environments. Similarly, Roca et al. (2006) found that system quality positively influences both learners' satisfaction and their intention to persist with e-learning platforms. Al-Fraihat et al. (2020) highlighted that technical quality, such as system reliability and ease of use, significantly contributes to student satisfaction in blended learning contexts. Ozkan and Koseler (2009) emphasized that effective system quality, including accessibility and response time, improves overall satisfaction. Holsapple and Lee-Post (2006) further supported this, showing that robust system quality is crucial for fostering a positive user experience in online learning. DeLone and McLean (2003) extended their IS success model to e-learning, demonstrating that system quality is a key determinant of user satisfaction. Sun et al. (2008) observed that learners' perceptions of system quality, such as stability and speed, significantly impact satisfaction levels. Al-Fraihat et al. (2020) confirmed that high system quality is essential for achieving user satisfaction in e-learning platforms. Moreover, Hassanzadeh et al. (2012) stressed that elements of system quality, like reliability and ease of navigation, are critical for improving learner satisfaction. Additionally, Liu et al. (2009) found that superior system quality enhances students' learning satisfaction and engagement in e-learning environments. In the Chinese higher education context, where large-scale adoption of platforms like Chaoxing is common, maintaining robust system performance is vital to meet students' increasing expectations for seamless and mobile-first learning experiences. Therefore, the following hypothesis is proposed:

H1: System quality has a significant impact on satisfaction.

2.2.2 Relation between Information Quality and Satisfaction

Lee-Post (2009) found that high information quality, characterized by accurate, timely, and relevant content, enhances user satisfaction in e-learning environments. Similarly, Roca et al. (2006) demonstrated that the quality of information in e-learning systems is crucial for maintaining user satisfaction and encouraging continued use. Sun et al. (2008) emphasized that information quality, including content accuracy and completeness, significantly influences learners' satisfaction with e-learning platforms. Al-Fraihat et al. (2020) found that high-quality information improves user experiences and satisfaction in blended learning environments. They confirmed that information quality is a key determinant of user satisfaction in e-learning systems. Holsapple and Lee-Post (2006) highlighted that clear and concise content is essential for achieving high learner satisfaction. Ozkan and Koseler (2009) noted that effective information quality, including up-to-date and relevant content, significantly impacts students' satisfaction with e-learning courses. Hassanzadeh et al. (2012) found that high information quality enhances learners' satisfaction and engagement. Liu et al. (2009) demonstrated that superior information quality improves both student satisfaction and learning outcomes in e-learning environments. Additionally, Chiu et al. (2005) identified information quality as a crucial factor affecting learners' satisfaction and continued use of e-learning systems. Given China’s push for high-quality digital resources under the “Smart Education of China” initiative, ensuring rich, localized, and curriculum-aligned content on platforms like Chaoxing is becoming increasingly important for sustaining student satisfaction. Therefore, the following hypothesis is proposed:

H2: Information quality has a significant impact on satisfaction.

2.2.3 Relation between Perceived Usefulness and Satisfaction

Roca et al. (2006) found that learners' perceptions of an e-learning system's usefulness directly impact their satisfaction levels. This finding is supported by Holsapple and Lee-Post (2006), who identified perceived usefulness as a crucial determinant of user satisfaction in e-learning settings. Sun et al. (2008) observed that when learners perceive e-learning systems as useful, their satisfaction significantly increases. Al-Fraihat et al. (2020) emphasized that perceived usefulness positively influences learners' satisfaction and continued use of e-learning platforms. Holsapple and Lee-Post (2006) highlighted that perceived usefulness, particularly the system's ability to enhance learning performance, drives satisfaction. Al-Fraihat et al. (2020) also found that perceived usefulness is a key predictor of user satisfaction in blended learning environments. Further research by Ozkan and Koseler (2009) demonstrated that learners who find e-learning tools useful are more likely to be satisfied with their learning experiences. Hassanzadeh et al. (2012) found that perceived usefulness boosts satisfaction and engagement in e-learning environments. Liu et al. (2009) indicated that the usefulness of e-learning technologies is essential for achieving high satisfaction. Lastly, Chiu et al. (2005) showed that perceived usefulness significantly impacts satisfaction, leading to continued use of e-learning systems. In China's increasingly competitive academic environment, perceived usefulness is also linked to how well platforms like Chaoxing support students in achieving learning outcomes and preparing for assessments, making it a core element of platform satisfaction. Therefore, the following hypothesis is proposed:

H3: Perceived usefulness has a significant impact on satisfaction.

2.2.4 Relation between Confirmation and Satisfaction

Bhattacherjee (2001) emphasized that user satisfaction on e-learning platforms is strongly influenced by confirmation, which refers to the alignment of users' initial expectations with their actual experiences. Roca et al. (2006) further supported this, finding that meeting users' expectations is a critical factor in determining satisfaction with e-learning systems. Lin (2007) highlighted that when learners' expectations are confirmed, their satisfaction with the system increases, improving their overall learning experience. Similarly, Po-An Hsieh and Wang (2007) noted that confirmation positively affects satisfaction, leading to better engagement and learning outcomes. Lee (2010) demonstrated that the degree to which learners' pre-use expectations are met significantly influences their satisfaction in blended learning environments. A study by Wu et al. (2010) found that learners who perceive their expectations to be met by the system report higher satisfaction. Al-Fraihat et al. (2020) also showed that confirmation plays a pivotal role in shaping learners' satisfaction in e-learning settings. Furthermore, Ozkan and Koseler (2009) indicated that confirming expectations is crucial for achieving learner satisfaction in higher education e-learning courses. Chiu et al. (2005) confirmed that meeting learners' expectations is essential for their satisfaction and continued use of e-learning systems. Jo (2022) found that when students' experiences exceed their expectations, their satisfaction increases. In the context of Chinese universities, where students are often exposed to state-endorsed platforms with standardized features, the confirmation of expectations, especially regarding ease of use and academic alignment, is vital for ensuring satisfaction and continued use. Therefore, the following hypothesis is proposed:

H4: Confirmation has a significant impact on satisfaction.

2.2.5 Relation between Satisfaction and Continuance Intention

Wu et al. (2010) found that student satisfaction in e-learning environments positively influences their intention to continue using these systems, as satisfied users perceive greater value and effectiveness in their learning experiences. Similarly, Lin (2007) highlighted that higher user satisfaction with online learning platforms strengthens intentions to continue use, emphasizing the importance of maintaining high satisfaction for sustained engagement. Bhattacherjee (2001) applied the Expectation Confirmation Model (ECM) and demonstrated that satisfaction is a key predictor of continuance intentions, suggesting that satisfied learners are more likely to persist in using e-learning systems. This was supported by Roca et al. (2006), who extended the Technology Acceptance Model (TAM) to show that user satisfaction significantly predicts continuance intentions in e-learning contexts. Lee (2010) observed that in blended learning environments, student satisfaction directly impacts their willingness to continue using the system, as positive experiences enhance their perception of the system's utility and effectiveness. Po-An Hsieh and Wang (2007) confirmed that satisfaction influences continuance intentions, with satisfied users showing a higher propensity to engage continuously with e-learning platforms. Sasono et al. (2023) further demonstrated that satisfaction, especially from engaging online learning with gamification, positively influences the intention to continue using MOOCs. Al-Fraihat et al. (2020) also noted that satisfaction drives continuance intentions, emphasizing that learners satisfied with e-learning systems are more likely to continue using them, ensuring long-term adoption. Chiu et al. (2005) highlighted the positive relationship between satisfaction and continuance intentions, stressing the importance of enhancing user satisfaction to achieve sustained use. Additionally, Ozkan and Koseler (2009) found that in higher education, student satisfaction with e-learning courses is a significant predictor of their intention to continue using these systems. In China's rapidly digitalizing higher education landscape, where national platforms like Chaoxing are integrated into curricula, sustained usage depends heavily on student satisfaction, which influences long-term adoption, policy compliance, and digital literacy development. Therefore, the following hypothesis is proposed:

H5: Satisfaction has a significant impact on continuance intention.

2.2.6 Relation between Subjective Norm and Continuance Intention

Subjective norm, which refers to the perceived social pressure to engage in or avoid a behavior, significantly impacts continuance intention in blended learning and e-learning contexts. Numerous studies support this relationship, highlighting subjective norm's role in shaping learners' intentions to continue using e-learning platforms. For example, Venkatesh and Davis (2000) found that subjective norm positively influences the intention to use a system when users perceive its use as mandatory. Chiu and Wang (2008) confirmed that subjective norm significantly affects students' intentions to persist in using e-learning systems, with social influences from peers and instructors promoting continued engagement. Similarly, Lee (2010) showed that encouragement and expectations from significant others, such as classmates and teachers, positively influence students' continuance intentions in e-learning environments. Yang and Su (2017) hypothesized that learners are more likely to stay engaged in MOOCs if they receive support from supervisors, friends, and peers. Sujood et al. (2023) suggested that subjective norm predicts students' intention to continue using digital libraries post-pandemic, with reinforcement from faculty and peers playing a crucial role. Hamad et al. (2024) indicated that subjective norm reflects students' perceptions of expectations from others, with classmates' encouragement driving engagement in blended learning. Cheung and Vogel (2013) emphasized that social pressure and normative beliefs from peers significantly affect learners' decisions to continue using blended learning platforms. Sun and Zhang (2006) supported this by showing that subjective norm positively influences learners' satisfaction and their continuance intention. Other studies, such as those by Yuen and Ma (2008), reinforced the importance of subjective norm, noting that approval and encouragement from influential figures lead to higher engagement and continued use of e-learning systems. Roca and Gagné (2008) concluded that subjective norm contributes to the development of positive attitudes toward e-learning, which fosters continuance intentions. In China, where collectivist cultural values emphasize the importance of group consensus and instructor authority, the influence of subjective norms from peers, faculty, and institutional expectations plays a pivotal role in encouraging students' continued engagement with platforms like Chaoxing. Therefore, the following hypothesis is proposed:

H6: Subjective norm has a significant impact on continuance intention.

3. Research Methods and Materials

3.1 Research Framework

This study is grounded in key theoretical models, including the Information System Success Model (ISSM) by DeLone and McLean (1992), the Expectation Confirmation Model (ECM) by Bhattacherjee (2001), and the Theory of Planned Behavior (TPB) by Ajzen (1991). Building on these theories, the researcher has developed a conceptual framework for the study, as shown in Figure 1.

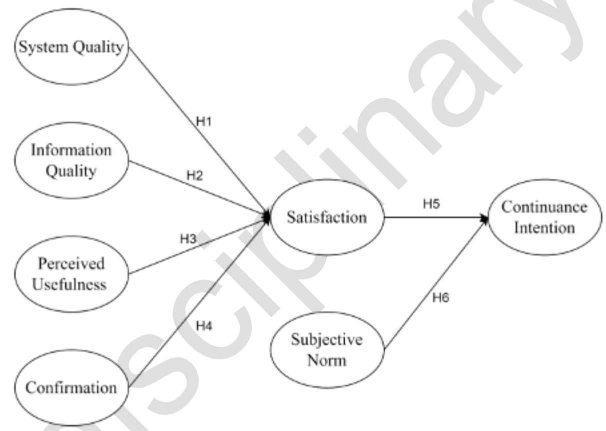

Figure 1: Conceptual Framework

The diagram illustrates a research model examining the factors influencing undergraduate students' satisfaction and continuance intention to use the Chaoxing Learning Platform. In the model, system quality, information quality, confirmation, and perceived usefulness are key antecedents of satisfaction. Satisfaction, along with subjective norm, affects students' continuance intention. The model indicates that both system-related and cognitive factors contribute to satisfaction, while social influence shapes long-term usage intentions.

3.2 Research Methodology

This study employs a quantitative approach with non-probability sampling to examine factors influencing undergraduate students' satisfaction and continuance intention to use the Chaoxing Learning Platform at the School of Mechanical Engineering, Sichuan University of Science & Engineering in Yibin, Sichuan Province, China. Questionnaires were distributed to undergraduate students with prior experience using the platform through an online platform. The collected data were analyzed to identify key factors impacting student satisfaction and continuance intention. The questionnaire was structured into three sections: the first contained screening questions to confirm participants' familiarity with the platform; the second, using a 5-point Likert scale, measured variables related to the six research hypotheses; and the final section gathered demographic information, such as gender and major.

To ensure reliability and validity, a pilot test with 50 participants was conducted before the full survey. The questionnaire achieved a satisfactory Item-Objective

Consistency Index (IOC) score after expert evaluation. Cronbach's Alpha confirmed that the questionnaire met validity and reliability standards. A total of 500 responses were collected, and the data were analyzed using SPSS AMOS. Confirmatory Factor Analysis (CFA) assessed the model's convergence accuracy and validation, confirming its fit. Structural Equation Modeling (SEM) was then used to investigate the causal relationships among the variables.

3.3 Population and Sample Size

The researchers used non-probability sampling methods, specifically judgmental and quota sampling, to select participants from four grades within the School of Mechanical Engineering at Sichuan University of Science & Engineering in Yibin, Sichuan Province, China. Questionnaires were distributed via an online platform, with the detailed sampling process presented in Table 1.

Table 1: Number of Questionnaire Distribution

School of Mechanical Engineering	Population Size	Proportional Sample Size
Freshman	636	124
Sophomore	552	107
Junior	647	126
Senior	735	143
Total	**2,570**	**500**

Source: Sichuan University of Science and Engineering, Academic Affairs Office (2024)

Between April and June 2024, a questionnaire survey was conducted. A data screening process was implemented to ensure the appropriateness of the target population, consisting of undergraduate students from the School of Mechanical Engineering at Sichuan University of Science & Engineering in Yibin, Sichuan Province, China.

4. Results and Discussion

4.1 Demographic Profile

When investigating user behavior (e.g., satisfaction and continuance intention), demographic information such as gender, academic year, and major are typically used to analyze behavioral variations across different groups (J. C. Sun & Rueda, 2012). The demographic profile of the respondents is summarized as follows: Out of the 500 participants, the majority were male, accounting for 84.2 percent (421), while female respondents made up 15.8 percent (79). This gender distribution reflects the typical composition of students in the School of Mechanical Engineering at Sichuan University of Science & Engineering, where male students generally outnumber female students due to the nature of engineering disciplines. Regarding academic major, the distribution was as follows: 26.4 percent (132) were enrolled in Process Equipment and Control Engineering, 28.6 percent (143) in Mechanical Design, Manufacture, and Automation, 20 percent (100) in Mechanical and Electronic Engineering, and 25 percent (125) in Vehicle Engineering.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	421	84.2
	Female	79	15.8
Major	Process Equipment and Control Engineering	132	26.4
	Mechanical Design, Manufacture and Automation	143	28.6
	Mechanical and Electronic Engineering	100	20.0
	Vehicle Engineering	125	25.0

4.2 Confirmatory Factor Analysis (CFA)

This study employed confirmatory factor analysis (CFA) to evaluate the conceptual framework. The measurement results indicated that most variables met reliability and validity criteria, with factor loading values generally falling within an acceptable range. These results supported the structural integrity of the conceptual framework. The reliability and validity of the constructs were assessed using Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE). As shown in Table 3, most constructs exhibit adequate levels of reliability and convergent validity.

Table 3 presents the results of the Confirmatory Factor Analysis (CFA), including Composite Reliability (CR) and Average Variance Extracted (AVE) for the study variables. The Cronbach's Alpha values for all constructs range from 0.750 to 0.917, indicating acceptable internal consistency. Factor loadings for the measurement indicators fall between 0.620 and 0.973, demonstrating satisfactory item reliability. The CR values, ranging from 0.751 to 0.919, exceed the recommended threshold of 0.7, confirming construct reliability. Additionally, the AVE values, ranging from 0.501 to 0.694, meet the minimum requirement of 0.5, indicating adequate convergent validity (Fornell & Larcker, 1981). These findings confirm that the measurement model exhibits strong reliability and validity.

The results presented in Table 4 indicate that the measurement model demonstrates an acceptable and good fit. The CMIN/df value of 2.371 falls within the acceptable range (<5.00), suggesting a reasonable model fit. The GFI (0.913) and AGFI (0.888) exceed their respective thresholds (≥0.85 and ≥0.80), indicating a satisfactory level of fit. Additionally, the NFI (0.916), CFI (0.949), and TLI (0.940) all surpass the recommended cut-off values, reflecting a strong model fit. The RMSEA value of 0.052 is below the acceptable threshold (<0.08), confirming a low error of approximation. Collectively, these indices suggest that the measurement model exhibits a satisfactory fit, providing a solid foundation for further structural equation modeling (SEM) analysis.

Table 5 presents the discriminant validity results based on factor correlations. The square roots of the Average Variance Extracted (AVE) are shown along the diagonal in bold, with values ranging from 0.709 to 0.833, all exceeding the corresponding inter-construct correlations. This confirms that each construct shares more variance with its own indicators than with other constructs, indicating satisfactory discriminant validity. The correlation coefficients between constructs range from 0.108 to 0.509, demonstrating that the constructs are related yet distinct. These results confirm that the measurement model meets the criteria for discriminant validity.

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

Variable	Source of Questionnaire (Measurement Indicator)	No. of Item	Cronbach's Alpha	Factor Loading	CR	AVE
System Quality (SQ)	Mirabolghasemi et al. (2021)	5	0.869	0.622-0.973	0.893	0.635
Information Quality (IQ)	Mirabolghasemi et al. (2021)	5	0.917	0.764-0.926	0.919	0.694
Perceived Usefulness (PU)	Roca et al. (2006)	3	0.767	0.677-0.797	0.770	0.528
Confirmation (COF)	Roca et al. (2006)	3	0.751	0.620-0.806	0.755	0.509
Subjective Norm (SN)	Lee (2010)	3	0.750	0.669-0.738	0.751	0.501
Satisfaction (SAT)	Roca et al. (2006)	3	0.771	0.674-0.744	0.752	0.504
Continuance Intention (CI)	Roca et al. (2006)	3	0.863	0.754-0.877	0.859	0.671

Note: CR = Composite Reliability, AVE = Average Variance Extracted

Table 4: Goodness of Fit for Measurement Model

Index	Criterion	Statistical Value
CMIN/DF	< 5.00 (Awang, 2012)	2.371
GFI	≥ 0.85 (Wu & Wang, 2006)	0.913
AGFI	≥ 0.80 (Wu & Wang, 2006)	0.888
NFI	≥ 0.80 (Wu & Wang, 2006)	0.916
CFI	≥ 0.80 (Bentler, 1990)	0.949
TLI	≥ 0.80 (Sharma et al., 2005)	0.940
RMSEA	< 0.08 (Sica & Ghisi, 2007)	0.052

Note: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI = normalized fit index, CFI = comparative fit index, TLI = Tucker Lewis index and RMSEA = root mean square error of approximation

Table 5: Discriminant Validity

Variable	Factor Correlations						
	SQ	IQ	PU	COF	SN	SAT	CI
SQ	**0.797**						
IQ	0.509	**0.833**					
PU	0.177	0.113	**0.727**				
COF	0.192	0.276	0.242	**0.713**			
SN	0.310	0.324	0.108	0.262	**0.709**		
SAT	0.314	0.284	0.232	0.224	0.133	**0.710**	
CI	0.200	0.277	0.229	0.426	0.340	0.497	**0.819**

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

4.3 Structural Equation Model (SEM)

The results in Table 6 assess the overall model fit for the structural equation model (SEM). The CMIN/df value of 3.580 falls within the acceptable range (<5.00), indicating an adequate model fit, although not as strong as the CFA model. The GFI (0.861) and AGFI (0.832) exceed their respective thresholds (≥0.85 and ≥0.80), suggesting an acceptable level of model fit. The NFI (0.865) and CFI (0.898) are close to the commonly recommended 0.90 threshold, reflecting a moderate to good fit. However, the TLI (0.887) is slightly below the ideal cut-off of 0.90, indicating that some model refinements may be beneficial. The RMSEA value of 0.072 is below 0.08, signifying an acceptable error of approximation and a reasonable model fit.

Table 6: Goodness of Fit for Structural Model

Index	Criterion	Statistical Value
CMIN/DF	< 5.00 (Awang, 2012)	3.580
GFI	≥ 0.85 (Wu & Wang, 2006)	0.861
AGFI	≥ 0.80 (Wu & Wang, 2006)	0.832
NFI	≥ 0.80 (Wu & Wang, 2006)	0.865
CFI	≥ 0.80 (Bentler, 1990)	0.898
TLI	≥ 0.80 (Sharma et al., 2005)	0.887
RMSEA	< 0.08 (Sica & Ghisi, 2007)	0.072

Note: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI = normalized fit index, CFI = comparative fit index, TLI = Tucker Lewis index and RMSEA = root mean square error of approximation

4.4 Research Hypothesis Testing Result

This section presents the hypothesis testing results using Structural Equation Modeling (SEM). The relationships between system quality (SQ), information quality (IQ), perceived usefulness (PU), and confirmation (COF) on satisfaction (SAT), as well as the impact of satisfaction (SAT) and subjective norm (SN) on continuance intention (CI), were examined. The hypotheses were tested based on standardized path coefficients (β), standard errors (S.E.), t-values, and significance levels. Table 7 presents the results of the calculations.

Table 7: Hypothesis Testing Result of Structural Model

Hypothesis	Standardized path coefficients (β)	t-value	Test Result
H1: SQ → SAT	0.168	3.336*	Supported
H2: IQ → SAT	0.175	3.449*	Supported
H3: PU → SAT	0.216	3.794*	Supported
H4: COF → SAT	0.215	3.773*	Supported
H5: SAT → CI	0.554	9.436*	Supported
H6: SN → CI	0.332	6.296*	Supported

Note: *=p-value<0.05

According to the results in Table 7, student satisfaction with the Chaoxing Learning Platform is primarily influenced by system quality, information quality, perceived usefulness, and confirmation. Among these factors, perceived usefulness (β=0.216) and confirmation (β=0.215) have the strongest effects, indicating that students are more likely to be satisfied when they find the platform useful and when their actual experiences align with their expectations. Satisfaction is the strongest predictor of continuance intention (β=0.554), suggesting that students who are satisfied with the platform are more likely to continue using it. Subjective norm (β=0.332) also plays a significant role, indicating that social influences from peers, instructors, or other relevant individuals notably affect students' decisions to continue using the platform.

All six hypotheses were supported, confirming the importance of system quality, information quality, perceived usefulness, and confirmation in shaping students' satisfaction. Additionally, satisfaction and subjective norm significantly contribute to students' continuance intention. These findings highlight the key determinants of students' engagement with the Chaoxing Learning Platform and provide valuable insights for enhancing user experience and retention.

5. Conclusions and Recommendation

5.1 Conclusions

The purpose of this study was to provide a comprehensive analysis of the factors influencing undergraduate students' satisfaction and continuance intention to use the Chaoxing Learning Platform at Sichuan University of Science & Engineering. The rapid adoption of blended learning platforms in higher education, especially after the pandemic, has led to an increased reliance on such tools for academic engagement. Given the importance of understanding the factors that drive student satisfaction and their intention to continue using these platforms, it was essential to conduct an in-depth investigation into the key determinants, such as system quality, information quality, perceived usefulness, confirmation, and subjective norms. This study proposed six hypotheses, examining the relationships between these factors and their influence on student satisfaction and continuance intention.

The target population of this study was undergraduate students from the School of Mechanical Engineering at Sichuan University of Light and Chemical Industry. A survey was conducted among students from four different grades within the School of Mechanical Engineering. Questionnaires were distributed to 500 students who actively used the Chaoxing Learning Platform. The data collected from these questionnaires were analyzed to evaluate the factors influencing student satisfaction and continuance intention.

The findings support the Information System Success Model (DeLone & McLean, 2003) and the Expectation-Confirmation Model (Bhattacherjee, 2001), which emphasize that system quality, information quality, perceived usefulness, and confirmation influence user satisfaction, while satisfaction is the key determinant of continuance intention. The study also highlights the significant role of subjective norm in students' continuance intention, indicating that social factors (e.g., recommendations from instructors and peer influence) play a crucial role in students' continued use of the Chaoxing Learning Platform.

5.2 Recommendations

Based on the findings, several strategies are recommended to enhance student satisfaction and continuance intention toward the Chaoxing Learning Platform. Firstly, improving both system and information quality is essential for a better user experience. The platform should focus on ensuring system stability, responsiveness, and ease of navigation to provide a seamless learning process. Additionally, ensuring that learning materials are accurate, well-organized, and regularly updated will help meet students' expectations and increase their perception of the platform's value. Secondly, enhancing the perceived usefulness of the platform is crucial for boosting student engagement. This can be achieved by expanding the range of high-quality learning resources, incorporating interactive features, and leveraging AI-driven recommendations tailored to students' learning progress and preferences. Personalizing content to fit individual needs will make the learning experience more effective and engaging, leading to higher satisfaction and greater willingness to continue using the platform. Finally, social influence, including instructor encouragement and peer interactions, plays a key role in fostering students' continuance intention. Encouraging instructors to integrate the platform into their teaching and actively recommend its use will motivate students and build trust in the platform. Additionally, facilitating peer engagement through collaborative tools like discussion forums and group activities can create a supportive learning environment, further reinforcing students' commitment to using the platform long-term. Implementing these strategies can lead to higher satisfaction, better learning outcomes, and greater likelihood of continued usage of the Chaoxing Learning Platform.

5.3 Limitation and Further Study

This study has several limitations. First, the sample was drawn from four grades within the School of Mechanical Engineering at Sichuan University of Science & Engineering, which may limit the generalizability of the findings to other disciplines. Future studies should include a more diverse sample from different faculties to improve external validity. Second, while factors such as system quality, information quality, and satisfaction were examined, other potential influences, like technological self-efficacy and learning motivation, were not considered. Future research could explore these additional variables. Finally, this study used a cross-sectional design, capturing students' perceptions at a single point in time. A longitudinal approach could provide insights into how satisfaction and continuance intention evolve over time. Addressing these limitations in future research will provide a more comprehensive understanding of students' engagement with the Chaoxing Learning Platform.

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