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Drivers of Undergraduate Student Satisfaction with Smart Campus Technology: Insights from Chengdu

Li Zhaoyan*

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Abstract

Purpose: This study explores the primary factors affecting student satisfaction and continuance intention towards the Smart Campus at Xihua University in Chengdu, Sichuan. The conceptual framework interlinks system quality, information quality, service quality, perceived ease of use, perceived usefulness, user satisfaction, and continuance intention. **Research design, data, and methodology:** A quantitative approach was employed, involving a survey with 500 samples distributed among undergraduate students from four majors with strong IT literacy. The study utilized a multistage sampling technique, including Purposive and Convenience Sampling, to gather data. The analysis used Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM). Furthermore, the analysis included assessments of model fit, correlation validity, and reliability for each component. **Results:** The findings indicated that perceived usefulness and user satisfaction had the most significant direct effects on continuance intention (CI), with perceived ease of use showing the strongest indirect effect. The impact of system quality. service quality, perceived ease of use, perceived usefulness, and information quality on satisfaction diminished in a sequential manner. **Conclusions:** In order to make students realize the effectiveness and convenience of smart campuses, stakeholders such as Smart Campus enterprises, software developers, higher education institutions, school administrators, teachers, and IT workers should pay attention to the potential variables that have a significant impact on smart campus satisfaction and continued use intention.

Keywords: Smart Campus, User Satisfaction, Continuance Intention

JEL Classification Code: E44, F31, F37, G15

1. Introduction

Smart Campus, an advanced environment for education and daily living, is set to bring a wave of benefits to students. Leveraging Internet technology and application services (Mishalani et al., 2011), the Smart Campus integrates information and operational technology to modernize education (Alenezi, 2023). By utilizing advanced technologies, it creates an interconnected and interactive learning environment. The campus can connect various devices and systems to collect real-time data, providing valuable insights into campus operations and student behavior. Big data analytics processes this information to identify trends, predict needs, and improve decision-making. Cloud computing ensures that data and applications are accessible anytime and anywhere, facilitating seamless collaboration and resource sharing among students, teachers, and staff. Mobile technologies offer on-the-go access to educational content, campus services, and communication tools, enhancing flexibility and convenience. The ultimate goal is to establish a personalized learning ecosystem that not only boosts academic performance but also enhances the overall satisfaction and experience of everyone involved in the educational process. Through this innovative approach, the smart campus aims to transform traditional educational settings into dynamic and adaptive environments that cater to the individual needs of students, educators, and administrative staff. (Ahmed et al., 2020; Chagnon-Lessard et al., 2021; Mishalani et al., 2011; Sun, 2022). (Ahmed et al., 2020; Chagnon-Lessard et al., 2021; Mishalani et al., 2011; Sun, 2022). The platform facilitates convenient access to learning resources, efficient course management, and

1*Li Zhaoyan, Information Network Center, Xihua University, China. Email: 4973012@qq.com

precise campus administration (Li & Zhao, 2019). User satisfaction and continued usage intention are crucial for the Smart Campus's effectiveness, promising a future of enhanced learning and convenience for students.

Current research on factors influencing student satisfaction and continued usage intention of Smart Campus is limited. Understanding these factors is essential for improving services and supporting the sustainable development of Smart Campus. This research explores the connection between students' satisfaction with Smart Campus services and their intention to continue utilizing them. The objective is to offer valuable insights into Smart Campus projects' design, implementation, and assessment, thereby enriching the theoretical framework. (Sun, 2022).

By constructing and validating a Smart Campus satisfaction model, this study offers theoretical support for future research and practical guidance for developing Smart Campus in universities. It identifies key factors influencing satisfaction and proposes measures to enhance user satisfaction and continued usage, promoting sustainable development. Additionally, it serves as a reference for educational management and policymakers to develop effective policies for Smart Campus implementation. The significance of this study includes enhancing user experience by addressing problems and needs, promoting the sustainable development of Smart Campus through improved continued usage intention, driving wider adoption of Smart Campus, and optimizing resource allocation. Universities can benefit from Smart Campus construction by understanding user needs and improving resource utilization.

The government has emphasized that providing quality education that meets the needs of the people is fundamental to implementing strategies aimed at rejuvenating the nation through science and education, strengthening the country by cultivating talent and driving development through innovation. Delivering an education system that satisfies the public and accelerating the development of a strong educational framework is crucial for fulfilling the public's expectations for better education, as well as for ensuring national security and enhancing the well-being of the population. Creating a smart campus that meets the needs of students aligns not only with the researcher's professional responsibilities but also with their interests. This study, conducted at Xihua University in Chengdu, China, a key comprehensive university in Sichuan Province, underscores the integral role of educational management, policymakers, researchers, and professionals in the ongoing development of the smart campus. Xihua University is committed to the ongoing development of its smart campus and aims to establish a large-scale model of artificial intelligence education in the future. The university is focused on cultivating digital talent and advancing the digital transformation of education. Xihua University, which occupies nearly 4,000 acres and enrolls over 41,000 full-time students, is recognized as one of the first-class discipline construction universities in Sichuan Province and is a priority institution for the cultivation of new doctoral degree-awarding programs in the province. The university consists of 21 colleges offering 99 undergraduate majors, including 16 national first-class professional construction sites, 4 national characteristic majors, and 8 majors that have received engineering education professional certification. It also hosts 1 national "comprehensive reform pilot project" construction, 19 provincial first-class professional construction sites, and various provincial demonstration and characteristic majors, along with majors under the "Excellent Engineer Education and Training Program."With more than 60 years of undergraduate education and nearly 40 years of graduate education, Xihua University has developed a comprehensive academic structure, encompassing 10 disciplines such as engineering, science, management, law, economics, art, literature, education, agriculture, and interdisciplinary studies. The university also boasts 3 disciplines under the Sichuan Province "Double First-Class" Gongga Plan, 8 provincial key disciplines, and 39 master's degree authorization points.

This research qualitatively examined the main factors influencing college students' satisfaction with Smart Campus and their intention to keep using these services, incorporating the Technology Acceptance Model, Information Systems Success Model, and Technology Continuance Theory. Using questionnaire surveys and data analysis, five essential characteristics related to student satisfaction and intention to use continuous language were quantitatively evaluated at Xihua University in Chengdu, Sichuan Province.

2. Literature Review

2.1 System Quality

System Quality (SQ) pertains to the performance characteristics of an information system (IS) or IT. It encompasses accuracy, correctness, usability, efficacy, adaptability, trustworthiness, safety, and reactiveness of an IS or IT's functions. (Ali et al., 2022; Cheng, 2021; DeLone & McLean, 2003; Lin, 2007). SQ is characterized by the functionality of technology systems and the evaluation of technology user-friendliness while utilizing its services. (Dokhanian et al., 2022). System quality is one of the evaluation indicators of IS (Petter et al., 2013) and is the external manifestation of the software and hardware of IS (Bharati & Chaudhury, 2004); it relies on the requirements of users, as determined during the analysis and development of the system (Chang, 2013). According to the ISSM, SYQ is a crucial success factor that affects both US and COI. The effectiveness of an IS impacts students' inclination to utilize the system (DeLone & McLean, 2003). A subpar IS quality can result in dissatisfaction among students. When students encounter difficulties or inefficiencies with a system, their acceptance of it may diminish. (Perera & Abeysekera, 2022) SYQ is also a key determinant of user satisfaction. Factors such as visual appeal, technical effectiveness, latency, user-friendly navigation, data protection, and confidentiality play significant roles. (Chang, 2013), System quality positively influences perceived value and user satisfaction.

H1: System quality has a significant impact on user satisfaction.

2.2 Information Quality

Information Quality (IQ) pertains to the excellence of report contents and format the information system generates. It is gauged across various dimensions, including accuracy, accessibility, thoroughness, up-to-dateness, effectiveness, pertinence, extent, and promptness of information. (Cheng, 2020, 2021; DeLone & McLean, 2003; Kim & Lee, 2014; Lin, 2007; Nelson et al., 2005) It pertains to the caliber of information supplied by digital services. This assessment encompasses data accuracy, comprehensiveness, currency, and how the information is presented (Lin, 2007). Users perceive accurate and useful information as key indicators of information quality (Misra et al., 2023). The nature, level of detail, and range of information quality are usually established and refined during the design and development stages of the system. At the same time, aspects such as promptness, precision, and overall dependability result from the system's ongoing operational performance and maintenance. (Ahn et al., 2007). The information quality of a mobile website influences users' PU. Poor INQ may result in a decline in the US, as users anticipate obtaining high-quality information (Gao & Bai, 2014). In an e-learning environment, factors such as the accuracy of information, alignment with content needs, and timely delivery of information are essential for the system's effectiveness. Additionally, user feedback can reflect the quality of the information provided. (Jami Pour et al., 2022).

H2: Information quality has a significant impact on user satisfaction.

2.3 Service Quality

Service quality (SeQ) is the reliability provided by service providers, including usability, content usefulness, information adequacy, accessibility, and interaction. (Ahn et al., 2007; Cheng, 2020; DeLone & McLean, 2003; Kim et al., 2008) SeQ is often described as the consumer's assessment that arises from comparing their perception of the actual service delivery against their expectations of what the service should provide. It can also be described as a comprehensive evaluation or attitude regarding the excellence of the service (Kim & Lee, 2014). Service Quality refers to the support offered to users, including genuine concern and empathy in addressing their issues and answering their inquiries while using the IS. (W. DeLone & McLean, 2003). In the IS domain, IQ, SeQ, and SQ pertain to the quality of the results or characteristics of a particular IS. (Roca et al., 2006). Through correlation analysis, Masrek (2007) discovered that strong relationships exist between SeQ and satisfaction (Iqbal et al., 2022). Park and Kim (2003) observed that providing SeQ could enhance consumer satisfaction and contribute to maintaining a positive effect on customers. SEQ has a significant influence on PU and customer satisfaction. (Chang, 2013). SeQ substantially impacts use through User Satisfaction, indicating that SEQ operates through direct and indirect pathways (Iqbal et al., 2022).

H3: Service quality has a significant impact on user satisfaction.

2.4 Perceived Ease of Use

Perceived ease of use (PEU) is regarded as “the extent to which specified users can use a product to achieve specified goals with effectiveness, efficiency, and satisfaction in a specified context of use.” (Davis, 1989). The ISO 20000 defines ease of use as “the extent to which specified users can use a product to achieve specified goals with effectiveness, efficiency, and satisfaction in a specified context” (Mohammad et al., 2018). PEU is “the degree to which using technology is easy and does not need any specific effort” (Kumar et al., 2023). PEU denotes how effortlessly users can navigate and interact with a website and its interface (Saoula et al., 2023). PEU focuses on the simplicity with which users can interact with a system. It encompasses various aspects, including the intuitiveness of the interface design and ease of navigation. This concept also covers the convenience of operating the system’s interface, such as the clarity and consistency of design elements like icons, buttons, and menus. Perceived usefulness and PEU influence attitudes, whether positive or negative, that individuals develop based on their evaluation of performing specific behaviors, ultimately shaping their intention to use the technology. (Dokhanian et al., 2022). PEU positively influences perceived usefulness. When technology is intuitive and simple to master, users are more likely to perceive it as advantageous, leading to a favorable attitude toward its utilization (Foroughi et al., 2023). PEU is regarded as a key determinant of the overall US.

H4: Perceived ease of use has a significant impact on user satisfaction.

H5: Perceived ease of use has a significant impact on perceived usefulness.

2.5 Perceived Usefulness

Perceived usefulness is the subjective belief held by individuals or users regarding the extent to which using an IS to improve job performance can contribute to long-term advantages and positive outcomes in the future (Cheng, 2022a) and thus taps into the instrumental outcome's user associates with technology use (Karahanna et al., 2006). PU reflects whether someone perceives the technology as beneficial for their intended activities (Hossain et al., 2021). PU is a fundamental and central component of the Technology Acceptance Model. (Davis, 1989). PU is identified as a consistent factor predicting user behavior in both the initial adoption and continued use phases. In contrast, the impact of PEU tends to diminish and lose significance with greater usage experience. The positive impact of PU on continuance intention is clear. (Gao & Bai, 2014). with an increase in perceived usefulness leading to higher user satisfaction. (Dokhanian et al., 2022). User satisfaction plays a significant and positive mediating role in linking PU to the intention to use the application (Dokhanian et al., 2022).
H6: Perceived usefulness has a significant impact on user satisfaction.
H7: Perceived usefulness has a significant impact on continuance intention.

2.6 User Satisfaction

US, as the feelings users have about used specific computer applications, is strongly linked to the effectiveness of the system's design in addressing users' needs and expectations (Seddon & Kiew, 1996). The US is a user's emotional response resulting from interactions with the supplier organization or consumption of a product. The US is an amalgamation of science and art that plays a pivotal role in acquiring new users and retaining existing ones (Dokhanian et al., 2022). US as "the extent to which users believe the IS available meets their information requirements" (Hossain, 2016). User satisfaction reflects the alignment between users' perceptions and expectations. It assesses the efficiency of the interaction between an IS and its users, including their contentment with reports, web interfaces, and support services. (Jami Pour et al., 2022). User satisfaction denotes a complete technology assessment that echoes an emotion-driven response to the specific technology (Abdul Rahim et al., 2023). Satisfaction can be viewed as an individual's assessment and emotional response to the overall experience. IQ, SQ, and PU (Seddon & Kiew, 1996). Factors affecting student satisfaction include the system's simplicity, the quality of educational materials, internet connectivity, and interactive features (Chen et al., 2018). Moreover, the US with the IS/IT can contribute to their intention to continue using it (Cheng, 2020).
H8: User satisfaction has a significant impact on continuance intention.

2.7 Continuance Intention

Continuance intention (CI) is "the degree to which an individual is willing to use an information system in the future and to recommend it to others." (Chang, 2013).CI is described as the user's inclination to persist in utilizing a service following its initial acceptance (Bhattacherjee, 2001; Cheng, 2020, 2022a). In information systems, continuation intention is an endogenous variable that is defined as a behavioral pattern reflecting the continued use of a particular IS. (Hossain, 2016). According to the ECT, the COI using an information system is directly influenced by users' perceptions of its future usefulness and their satisfaction with previous experiences using the IS. (Ambalov, 2021), US significantly determines COI in IS (Bhattacherjee, 2001). Users are more likely to continue utilizing the IS/IT if they believe it substantially boosts their efficiency and productivity, providing added value and efficiency in their tasks., making perceived usefulness (PU) a precursor to continuance intention (Cheng, 2020). The US shapes COI, influenced by factors like perceived quality and PEU. Satisfaction, in turn, influences the likelihood that users will continue to engage with the system or technology, as their ongoing intention is closely linked to how well they perceive the SYQ and PEU. (Roca et al., 2006). COI is strongly influenced by users' PU and satisfaction (Cheng, 2022b). (Sharma et al., 2022)

3. Research Methods and Materials

3.1 Research Framework

The investigator has designed a theoretical model grounded in classic models and numerous previous research findings. The conceptual framework was formulated by integrating three core theories and drawing upon three established frameworks to build upon and expand the understanding of the topic. One of the foundational theories utilized is the TAM, originally formulated by Davis et al. (1989) (Davis, 1989). Additionally, the study draws on the TCT proposed by Liao et al. (2009) and referenced by Foroughi et al. (2023) (Foroughi et al., 2023). The first theoretical framework, introduced by Cheng (2022a), focused on three variables: PU, US, and COI. The second framework, developed by Iqbal et al. (2022), included four variables: SYQ, INQ, SEQ, and US. The third framework, proposed by Dokhanian et al. (2022), encompassed three variables: PU, US, and PEU. Figure 1 illustrates the conceptual framework of this study.

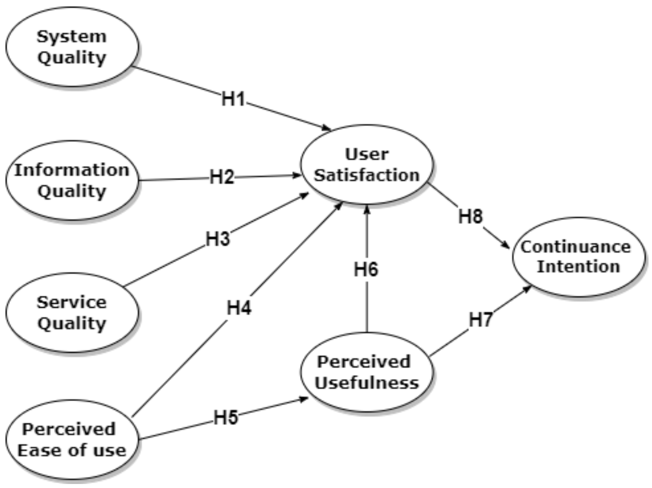

Figure 1: Conceptual Framework

H1: System quality has a significant impact on user satisfaction.
H2: Information quality has a significant impact on user satisfaction.
H3: Service quality has a significant impact on user satisfaction.
H4: Perceived ease of use has a significant impact on user satisfaction.
H5: Perceived ease of use has a significant impact on perceived usefulness.
H6: Perceived usefulness has a significant impact on user satisfaction.
H7: Perceived usefulness has a significant impact on continuance intention.
H8: User satisfaction has a significant impact on continuance intention.

3.2 Research Methodology

The researchers employed a probability sampling method and a descriptive research design to analyze the sample information statistically. Questionnaires were distributed to students majoring in fields with high digital literacy at Xihua University (Pickard, 2007). The quantitative research design was utilized to collect data and determine the basic characteristics of participants that significantly impact satisfaction and continuance intentions with smart campuses. Saunders et al. (2007) highlighted the importance of respondents reading and answering all questions in the questionnaire. The questionnaire was divided into screening questions, measurement variables, and demographic questions. First, validated screening items were used to classify participants with specific characteristics (Alessandro et al., 1988), such as having used the smart campus for more than one year and their majors. Second, demographic questions collected baseline information from respondents, including gender, age, grade, frequency of use, location of use, and favorite applications. Finally, a five-point Likert scale (Likert, 1932) was used to measure the variables.

To assess the accuracy of the goals proposed by the tool developers for this study, three experts in educational information technology with doctoral backgrounds were invited to conduct content validity testing of item-objective consistency (IOC). To test the tool's reliability, 30 target participants took part in a pre-test, and Cronbach's Alpha was used to evaluate the internal consistency reliability of the questionnaire. The IOC results are passed at above 0.6. The pilot test presented Cronbach’s alpha results over 0.7.

After confirming the validity and reliability of the tool, the questionnaire was distributed online to the target population, yielding 500 valid responses. The researchers utilized AMOS (28) to perform confirmatory factor analysis (CFA) and structural equation modeling (SEM) for data evaluation. CFA was employed to assess factor loading, t-values, composite reliability (CR), average variance extracted (AVE), and discriminant validity. SEM was used to test the hypotheses and evaluate the latent structural associations' direct, indirect, and overall effects.

3.3 Population and Sample Size

This study examines four prestigious majors at Xihua University, known for their longstanding educational excellence and students' advanced information technology skills. These majors are e-commerce, intelligent science and technology, computer science and technology, and telecommunications engineering. Using relevant theoretical frameworks, the research sample size was meticulously calculated to be 425 individuals, considering the number of variables and measurement queries. Initially, an online survey was conducted with 1,197 students enrolled in these majors. After a rigorous screening, filtering process, and quota-based selection, a final cohort of 500 students was chosen as the study sample.

3.4 Sampling Technique

The researchers employed a multi-stage sampling method divided into two parts. Initially, they used judgment sampling to select 1,197 students from the four majors based on specific criteria. Subsequently, they applied quota sampling to choose 500 respondents from the survey data, ensuring proportional representation from each of the four majors, resulting in the final sample.

Table 1: Sample Units and Sample Size

Subject	Population Size	Proportional Sample Size
E-commerce	150	63
Intelligent Science and Technology	391	163
Computer Science and Technology	465	194
Telecommunications engineering	191	80
Total	**1197**	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

Table 2 provides a detailed summary of the demographic information of the 500 respondents. Male respondents comprised 60.40% of the sample, while female respondents made up 39.60%. Regarding age distribution, 78.00% of the respondents were 18-21, 21.40% were 22-24, and 0.60% were older than 25. Regarding grade distribution, sophomores accounted for 25.40%, juniors 45.00%, and seniors 29.60%. Concerning usage frequency, 80.60% of respondents used the smart campus more than seven times a week.

Table 2: Demographic Profile

Demographic and Behavior Data (N=500)		Frequency	Percentage
Gender	Male	302	60.40%
	Female	198	39.60%
Age	18-21	390	78.00%
	22-24	107	21.40%
	Above 25	3	0.60%
Grade	sophomore	127	25.40%
	junior	225	45.00%
	senior	148	29.60%
Weekly frequency	0	0	0.00%
	1 time	3	0.60%
	2-3 times	15	3.00%
	4-6 times	79	15.80%
	Above 7	403	80.60%

4.2 Confirmatory Factor Analysis (CFA)

Confirmatory factor analysis (CFA) confirmatory factor analysis (CFA) was utilized to evaluate whether the number of elements and the highest levels of each measured variable align with theoretical expectations (Malhotra et al., 2007). Tenenhaus et al. (2005) recommended using the goodness-of-fit (GOF) approach for evaluating CFA and SEM. The GOF approach measures how well a model fits the data by defining the relationship between the model's structure and a set of observed measurements.

The convergent validity of the conceptual model was assessed through factor loading, average variance extracted (AVE), and composite reliability (CR) (Hair et al., 2013). In this analysis, all variables exhibited factor loadings exceeding 0.5 and p-values less than 0.05, demonstrating adequacy (Hair et al., 2013). Moreover, all variables had CR values above 0.8 and AVE values over 0.6, which was deemed sufficient (Table 4). Discriminant validity is established when the square root of AVE is greater than the correlation coefficients between related constructs (Fornell & Larcker, 1981).

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
System Quality (SQ)	Iqbal et al. (2022)	4	0.912	0.836 - 0.868	0.913	0.723
Information Quality (IQ)	Iqbal et al. (2022)	4	0.917	0.825 - 0.895	0.917	0.735
Service Quality (SeQ)	Iqbal et al. (2022)	3	0.893	0810 - 0.894	0.895	0.740
Perceived Ease of Use (PEU)	Rezvani et al. (2022)	6	0.948	0.850 - 0.879	0.948	0.752
User Satisfaction (US)	Harsasi and Sutawijaya (2018)	4	0.872	0.777 - 0.807	0.872	0.631
Perceived Usefulness (PU)	Cheng (2022a)	4	0.868	0.778 - 0.811	0.869	0.624
Continuance Intention (CI)	Cheng (2022a)	4	0.861	0772 - 0.789	0.861	0.607

Table 4 shows that the thresholds for chi-square to the degree of freedom (CMIN/DF), goodness-of-fit index (GFI), adjusted goodness-of-fit index (AGFI), comparative fit index (CFI), normalized fit index (NFI), Tucker-Lewis index (TLI), and root mean square error of approximation (RMSEA) were all within acceptable ranges. Thus, these goodness-of-fit measures confirm the appropriateness of the CFA testing in this study. The goodness-of-fit indices in Table 3 are reported as follows: CMIN/DF = 1.989, GFI = 0.914, AGFI = 0.895, NFI = 0.931, CFI = 0.964, TLI = 0.959, and RMSEA = 0.045.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	<3 (Hair et al., 2006)	1.989
GFI	≥0.85 (Sica & Ghisi, 2007)	0.914
AGFI	≥0.80 (Sica & Ghisi, 2007)	0.895

Fit Index	Acceptable Criteria	Statistical Values
NFI	>0.90 (Arbuckle, 1995; Hair et al., 2006)	0.964
TLI	>0.90 (Hair et al., 2006)	0.931
CFI	>0.90 (Arbuckle, 1995; Hair et al., 2006)	0.959
RMSEA	<0.08 (Pedroso et al., 2016)	0.045
Model Summary		**Acceptable Model Fit**

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 = normalized fit index, TLI = Tucker Lewis index, CFI = comparative fit index and RMSEA = root mean square error of approximation

As shown in Table 5, all coefficients between any two latent variables are below 0.80, and the square roots of all AVE values are higher than the correlations among constructs in this study, thus confirming discriminant validity for the measurement model (Table 5).

Table 5: Discriminant Validity

	SQ	IQ	SEQ	PEU	US	PU	CI
SQ	**0.850**						
IQ	0.126	**0.857**					
SEQ	0.151	0.125	**0.860**				
PEU	0.136	0.166	0.219	**0.867**			
US	0.296	0.191	0.269	0.233	**0.794**		
PU	0.212	0.223	0.191	0.311	0.294	**0.790**	
CI	0.194	0.216	0.25	0.234	0.35	0.489	**0.779**

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

4.3 Structural Equation Model (SEM)

Structural equation modeling (SEM) is a sophisticated mathematical technique to explore and quantify the relationships between observable and latent variables (Beran & Violato, 2010). SEM allows researchers to test complex theoretical models and assess the direct and indirect effects between variables, providing a comprehensive framework for understanding the underlying relationships in data. Table 6 presents the goodness-of-fit indices for the structural equation model (SEM). The statistical values reported are CFI = 0.955, RMSEA = 0.049, CMIN/DF = 2.211, TLI = 0.950, GFI = 0.900, AGFI = 0.882, and NFI = 0.921, all of which fall within acceptable limits. Consequently, the SEM's goodness of fit has been confirmed.

Table 6: Goodness of Fit for Structural Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	<3 (Hair et al., 2006)	2.211
GFI	≥0.85 (Sica & Ghisi, 2007)	0.900
AGFI	≥0.8 (Sica & Ghisi, 2007)	0.882
NFI	>0.9 (Arbuckle, 1995; Hair et al., 2006)	0.955
TLI	>0.9 (Hair et al., 2006)	0.921
CFI	>0.9 (Arbuckle, 1995; Hair et al., 2006)	0.950
RMSEA	<0.08 (Pedroso et al., 2016)	0.049
Model Summary		**Acceptable Model Fit**

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 = normalized fit index, TLI = Tucker Lewis index, CFI = comparative fit index and RMSEA = root mean square error of approximation

4.4 Research Hypothesis Testing Result

Table 7 reveals that PU exerted the most substantial direct effect on CI, marked by a standardized path coefficient (β) of 0.534 (t-value of 9.383***). US was the next significant factor, influencing CI with a β of 0.254 (t-value of 5.327***). Regarding impacting the US, SQ had the highest direct influence, reflected by a standardized path coefficient (β) of 0.249 (t-value of 5.199***). SeQ was the next key factor, with β at 0.203 (t-value of 4.253***), followed by PU (β = 0.190, t-value = 3.622***), PEU (β = 0.178, t-value = 2.273*), and IQ (β = 0.113, t-value = 2.406*). Additionally, PU had the most significant overall impact on CI, with a standardized path coefficient (β) of 0.534 (t-value of 9.383***). PEU was the second most influential on PU, registering a β of 0.344 (t-value of 7.005***).

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: SQ→US	0.249	5.199***	Supported
H2: IQ→US	0.113	2.406*	Supported
H3: SeQ→US	0.203	4.253***	Supported
H4: PEU→US	0.178	2.273*	Supported
H5: PEU→PU	0.344	7.005***	Supported
H6: PU→US	0.190	3.622***	Supported
H7: PU→CI	0.534	9.383***	Supported
H8: US→CI	0.254	5.327***	Supported

Note: *** p<0.001, * p<0.05
Source: Created by the author

Based on the findings in Table 7, researchers propose the following extensions:

Our research, as indicated by H1 and the findings in Table 7, underscores the pivotal role of system quality in determining user satisfaction. The standardized path coefficient of 0.249 in this structural model further emphasizes the significance of system quality. This factor is not only essential in influencing user satisfaction but also in shaping usage behavior intentions (Cheng, 2014). The empirical study by Gao and Bai (2014) and the partial validation of DeLone and McLean's IS Success Model by Seddon and Kiew (1996) both confirm the substantial impact of system quality on user satisfaction (Chang, 2013; Seddon & Kiew, 1996).

Our analysis for H2 brings to light the significant contribution of information quality to user satisfaction, with a standardized path coefficient of 0.113. This finding underscores the crucial role of information quality in user satisfaction, highlighting the direct relationship between the quality of information and user satisfaction (Iqbal et al., 2022). The provision of high-quality information not only motivates learners to continue using an e-learning system but also enhances their overall satisfaction (Cheng, 2014).

Our results for H3 provide strong confirmation that service quality significantly influences user satisfaction, with a standardized coefficient of 0.203. This finding underscores the notable positive effect of service quality on instructors' satisfaction with Learning Management Systems (LMSs) (Hussein et al., 2021). The study by Harsasi and Sutawijaya (2018) further supports this, showing that effective technological support in online university education greatly improves student satisfaction. Lin (2015) also reinforces that service quality is a strong predictor of overall user satisfaction.

Regarding H4, findings showed that perceived ease of use (PEU) significantly affects user satisfaction, with a standardized coefficient of 0.178. PEU is crucial for customer retention (Saoula et al., 2023) and is a major determinant of user satisfaction, as technology that eases user effort encourages continued use (Rafique et al., 2021). Hong et al. (2013) also emphasized that PEU plays a significant role in students' satisfaction with educational systems.

In H5, the study established that perceived ease of use (PEU) strongly influences perceived usefulness, with a standardized coefficient of 0.344. In ATM technology, anticipated effort directly impacts PEU and perceived usefulness (Dokhanian et al., 2022). User-friendly technology enhances perceived usefulness and fosters a favorable attitude toward its use (Foroughi et al., 2023). Hong et al. (2013) also found that PEU significantly impacts students' perceived usefulness of software tools.

H6 demonstrated that perceived usefulness contributes positively to user satisfaction in this study, with a standardized coefficient of 0.190. Perceived usefulness significantly influences user satisfaction, with higher levels leading to greater satisfaction (Dokhanian et al., 2022). It also positively impacted user satisfaction and continued use intentions (Mandari & Koloseni, 2023). Within the Technology Acceptance Model (TAM), perceived usefulness is the primary driver of users' intentions to adopt technology (Hu & Zhang, 2016).

H7 confirmed that perceived usefulness significantly influences continuance intention, reflected in a standardized coefficient of 0.534. Perceived usefulness, a central aspect of TAM, represents users' beliefs about the system's ability to enhance their performance and productivity, driving their intent to continue using it. Continuance intention is greatly influenced by perceived usefulness (PU) and user satisfaction, with PU being a precursor to ongoing technology use (Cheng, 2022a).

Lastly, H8 showed that user satisfaction significantly impacts continuance intention, with a standardized coefficient of 0.254. Continuance intention refers to users' plans to use information technology (Bhattacherjee, 2001). In Information Systems, it denotes the ongoing use of a system (Hossain, 2016). Satisfaction with an e-learning system strongly predicts continuance intention (Cheng, 2014, 2020). Studies consistently show that user satisfaction is a robust predictor of continuance intention in IS.

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

This study aimed to comprehensively identify and analyze the primary factors affecting Xihua University students' satisfaction with the smart campus and their intention to continue using it. The survey framework was meticulously developed based on ISSM, TCT, TAM theories, and extensive relevant literature. The potential variables assessed for their impact on satisfaction and continuance intention included system quality, information quality, service quality, perceived usefulness, and perceived ease of use. The intricate relationships between these seven variables were clarified by rigorously testing eight hypotheses. A quantitative research design was systematically applied to analyze the relationships among the research variables. Content validity was rigorously established through evaluations by three experts, and the reliability of the questionnaire was thoroughly tested using item-goal consistency and pre-testing before distribution, ensuring the accuracy of our research. Confirmatory factor analysis and structural equation modeling were employed to comprehensively assess model fit, correlation validity, and the reliability of each component. Upon completing the hypothesis testing, all hypotheses were fully supported.

The findings revealed that PU and US had the most significant and direct effects on CI, while PEU emerged as the variable with the most substantial indirect effect. The effects of SYQ, SEQ, PU, PEU, and INQ on the US decreased sequentially, which aligns well with the ISSM model. Consistent with the technology acceptance model (TAM), PEU exhibited the greatest and most positive influence on PU in this study, highlighting the robust and dynamic interplay between these critical variables.

5.2 Recommendation

This paper examines the factors influencing student satisfaction and continuance intention with the smart campus at Xihua University. Based on data from this quantitative survey, the study highlights the importance of considering the relationships between system quality, information quality, service quality, perceived ease of use, perceived usefulness, satisfaction, and continuance intention. To improve the smart campus, enhance the digital literacy of teachers and students, and support the digital transformation of education, the following recommendations are proposed:

Perceived usefulness is a critical factor for student satisfaction and continuance intention. Student needs should drive the development of the smart campus. The smart campus should encompass all aspects of college life. For instance, a welcome system can be implemented to allow students to join classes and handle administrative matters online before entering school. After admission, systems for teaching, student services, one-card access, online learning, and thesis management should be provided, covering all academic, research, and personal life aspects. After graduation, an alum system can help students stay connected with the school and support its development. Enhancing the perceived usefulness of the smart campus can increase student engagement and foster a sense of belonging.

User Satisfaction: Satisfaction is a crucial factor for continuance intention and is influenced by perceived usefulness, system quality, service quality, perceived ease of use, and information quality. The smart campus must address students' needs, such as checking class schedules, grades, available classrooms, and consumption records, and handling service needs like applying for scholarships, course selection, and paying fees. The information system must be accurate, convenient, efficient, flexible, reliable, secure, and responsive to achieve this. High service quality is essential, with multiple channels available for problem resolution, such as real-time help via phone, WeChat, QQ, or asynchronous methods like email and knowledge bases. User issues should be tracked and addressed, with unresolved problems leading to system upgrades and iterations. The information system should be user-friendly and straightforward. In the digital age, mobile terminals are commonly used for information processing. Users will abandon the system if obtaining simple enough information is complex. Therefore, the system must be intuitive and easy to navigate. The quality of information should be concise and clear, with applications combining icons and brief text to avoid overwhelming users. Simple operations encourage continued use of the system. While information quality is less critical for satisfaction compared to other factors, it remains important. Mobile applications should present information clearly and concisely to facilitate ease of use. Simplifying operations will promote ongoing engagement with the information system.

5.3 Limitation and Further Study

This study's limitation is that the research population and sample are confined to Xihua University. The sample is not representative enough and may not capture the diversity of the entire student body, affecting the findings' generalizability. Additionally, the sample is drawn primarily from specific majors, which could limit the applicability of the results. The conceptual framework includes only seven variables, which may not encompass all factors influencing satisfaction and continuance intention.

Future research should focus on two main directions. First, expanding the sample size, improving data collection methods, and adopting longitudinal research designs would enhance the representativeness and robustness of the findings. This approach would allow for developing a more comprehensive smart campus theoretical framework with broader applicability and value. Second, integrating additional information technology and educational theories would support a more complete and nuanced research framework, providing deeper insights into the factors influencing satisfaction and continuance intention.

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