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Key Factors Influencing College Students' Satisfaction and Continuance Intention in E-Learning: A Study in Chengdu, China

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Abstract

Purpose: This paper investigates the variables influencing college students' e-learning satisfaction and usage in Chengdu, China, in the future. The conceptual framework suggests a causal relationship between System Quality, Perceived Ease of Use, Perceived Usefulness, Flow Experience, Satisfaction, and Continuity Intention. **Research design, data, and methodology:** Students at Chengdu, China's Sichuan Posts and Telecommunications College, answered a questionnaire survey administered by the researchers in a quantitative manner (n=500). Non-probability sampling comprises easy sampling, which gathers data and distributes questionnaires online; quota sampling, which establishes the sample size; and judgment sampling, which chooses students in four majors. The researchers carried out the data analysis, including model fit, reliability, and construct validity, using structural equation models (SEM) and confirmatory factor analysis (CFA). **Results:** The findings indicate that while flow experience has some bearing on satisfaction, system quality and validation have a major influence satisfaction as an intermediate variable affecting students' willingness to continue. Perceived usefulness also had a significant impact on students' intention to continue. Perceived ease of use had little effect on students' intention to continue. **Conclusions:** The statistical data suggests that the e-learning platform should improve user satisfaction, thereby improving the system's quality, confirmation, and flow experience so that students feel that they can learn useful knowledge.

Keywords: System Quality, Confirmation, Flow Experience, Satisfaction, Continuance Intention

JEL Classification Code: E44, F31, F37, G15

1. Introduction

The evolution of e-learning dates to the 1980s, when some colleges and universities began offering basic course materials online on campus. This form of e-learning is popular with many people because they can access learning resources anytime, anywhere. The global epidemic outbreak in 2020 has hindered offline education, and most offline education has shifted to online, and online education has gradually become a trend. Even after the epidemic ended, online work, life, and learning methods have remained deeply in everyone's hearts, further helping the development of e-learning. Many education professionals recommend fully integrating information technology and curriculum to help learners improve learning efficiency and quality (Nurkhin, 2020).

Bates (2001) believes that school education and training institutions use information technology to develop learning platforms, and the integration of curriculum content and network technology is called e-learning. It is very common for both students and ordinary people to use computers to learn; e-learning includes flexible learning, distance education, and so on (Conole, 2004). Since the 21st century, the popularity of mobile phones and computers has made it more and more convenient for people to learn, especially through online learning. The education department also attaches great importance to this way of learning and provides an official learning platform. Many schools incorporate e-learning into their educational practices and integrate it with various educational tools (Castro, 2019).

Over the past few decades, university students worldwide have been learning in various ways, such as in school, private

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tutors, and e-learning. E-learning is becoming increasingly popular because people can learn and repeat learning anytime, anywhere. In the field of modern education, information technology, as a new modern education paradigm, is widely used to transmit education and learning information (Sun et al., 2008). Scholars in different countries have different interpretations of e-learning. C.-H. Liu (2010) considers e-learning a formal teaching system with the help of electronic resources such as webinar tools or e-learning platforms. Outside of the classroom, computers and the Internet are important tools for using e-learning (Ratheeswari, 2018).

Computer and network technology are extensively utilized in school education and teaching within the educational setting, with electronic learning as a crucial component of contemporary education. (Sun et al., 2008). The popularization of network technology in learning is mainly reflected in providing learning information content services and network technology. In the process of e-learning, the quality of the course content in the information system greatly impacts learners' experience. Whether the network of the learning platform is smooth and whether the platform's operation is simple is very important (Nakamura et al., 2017).

Students can participate in school activities at home instead of school. This impact is critical to higher education, forcing a sudden transition to a full e-learning environment for all teaching and learning activities (Toquero, 2020). The coronavirus pandemic is rapidly changing teachers and students, affecting the way they traditionally learn and work. The education sector also needs to accelerate digital transformation to face the challenges of digital education and teaching. Adapt quickly and find the best way (Strauß & Rummel, 2020). The impact of this time on them is so great that it changes all normal teaching activities and student learning. For example, most of the classrooms, teaching seminars, and various examination activities in schools have been transferred from campus to online (Bao, 2020).

In China, whether it is school students and teachers or people in society who need to receive continuing education, they are very fond of various e-learning platforms. Li et al. (2012) believe that information technology and higher education are closely linked, and e-learning provides the impetus for higher education teaching reform and guarantees for relieving teaching pressure and improving talent quality. The widespread adoption of e-learning systems in modern times is set to revolutionize all aspects of education and profoundly impact the future trajectory of learning, assuming an increasingly pivotal role. This paper examines the impact on students' satisfaction with e-learning and their willingness to continue using e-learning platforms at Sichuan Post and Telecommunication College in Chengdu.

There are many online learning platforms in China. An online learning platform was built by the Chinese government's education department. Many companies are building online learning platforms. For example, there are Chinese MOOCs, intelligent centers of vocational education, Wisdom Tree online education, and so on. These platforms are currently facing the challenge of student choice and many new changes, which require us to rethink online learning. The theoretical basis of the system quality, validation, process experience, perceived ease of use, usefulness, satisfaction, and continuation intention of the research learning platform must be further explored and studied. This paper takes the students of four majors at the Sichuan University of Posts and Telecommunications as the research object. This study explores factors affecting students' ability to continue learning through e-learning. It provides constructive suggestions for the next step in constructing and optimizing online learning platforms.

2. Literature Review

2.1 System Quality

DeLone and McLean (1992) found that the quality of the system and information directly influences users' satisfaction and continued usage intention. System quality refers to the information system running without problems and the smooth operation of the embodiment (Chen & Chen, 2010). The satisfaction of users' online shopping experience is contingent upon the specific requirements delineated during the analysis and development phases of the system. This crucial factor is influenced by various elements such as appearance, navigation, technological sophistication, latency, security, and privacy (Ahn et al., 2007). DeLone and McLean (2003) believe that the system's quality positively influences users' perceived value and satisfaction.

McGill et al. (2003) think the validation of the information systems developed by users with this model showed a strong correlation between information quality and satisfaction and between system quality and satisfaction. McGill et al. (2003) studied the study focused on network-based decision support systems and identified information and system quality as the primary determinants of satisfaction. Furthermore, it was found that network quality positively influences user satisfaction within e-learning systems in e-learning environments. (Roca et al., 2006). The hypotheses are as follows:

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

2.2 Confirmation

Learners have expectations before using the e-learning platform, and whether their expectations are met after use

will affect their satisfaction (Lee, 2010). If users derive the anticipated benefits from utilizing cloud computing services, evaluating their expectations for such services will be instrumental in gauging their satisfaction (Tan & Kim, 2015). Therefore, this study posits that the validation of college students' expectations for e-learning systems significantly impacts their overall satisfaction with said systems.

Extensive research has been conducted in e-learning to investigate confirmations that positively impact perceived usefulness and satisfaction (Cheng, 2020). In electronic learning, prior studies have indicated that utilizing information systems can yield favorable outcomes regarding perceived ease of use, usefulness, and overall satisfaction, aligning with anticipated benefits (Wu & Chen, 2017). The hypotheses are as follows:

H2: Confirmation has a significant impact on satisfaction.

2.3 Flow Experience

The electronic learning system can enhance users' intrinsic motivation, increasing their satisfaction with the system positively (Cheng, 2014). Therefore, this study hypothesizes that the flow experience elicited by the e-learning systems will affect college students 'satisfaction with them. Cheng (2021) thinks that flow experience comprises four concepts: cognitive concentration, perceptual control, enjoyment, and temporal separation.

Flow experience, as an intrinsic motivator, has become a valuable framework for studying how users use the system in online environments (Chang & Zhu, 2012). In e-learning, flow experiences include cognitive concentration, perceptual control, perceptual sensation, and temporal dissociation (Esteban-Millat et al., 2014). The flow experience is measured by four factors: perceptual enjoyment, cognitive concentration, perceptual control, and time separation (Shin, 2012). The hypotheses are as follows:

H3: Flow experience has a significant impact on satisfaction.

2.4 Satisfaction

If learners express Satisfaction with utilizing e-learning systems, their inclination to persist in utilizing them in subsequent instances will be heightened (Larsen et al., 2009). Suppose learning satisfaction is a necessary condition for sustained willingness. In that case, it can be anticipated that users who are content with cloud computing services are more inclined to demonstrate an intention to persist in utilizing said services (Tan & Kim, 2015). Therefore, this study hypothesizes that student satisfaction with e-learning systems influences their willingness to continue using them.

Spreng et al. (1993) argued that value should be related to user satisfaction, which means that when users of information systems feel the improvement in service value level, they will experience greater Satisfaction. Cronin et al. (2000) showed that the perceived value may influence Satisfaction and subsequently impact sustained intention. The determination of Satisfaction mediates the intentional relationship of perceived value continuation (Chang, 2013). Satisfaction is essential for electronic systems to provide continuous service willingness (Bhattacherjee, 2001). The hypotheses are as follows:

H4: Satisfaction has a significant impact on continuance intention.

2.5 Perceive Ease of Use

When users perceive the operation as effortless, their perceived ease of use is heightened, strengthening their acceptance and willingness to utilize these technologies (Humida et al., 2022). The more potential subscribers believe that an online learning platform will require minimal physical and mental effort to improve their academic performance, the stronger their behavioral willingness to use it (Nursiah, 2018). According to Chen and Tseng (2012), perceived ease of use of digital learning environments plays a critical role in shaping junior high school teachers 'preferences for e-learning platforms.

Al-Okaily et al. (2020) confirmed that students' confidence in effectively utilizing online learning platforms is pivotal in shaping their behavioral intentions. Perceived ease of use is considered an important precursor to teacher satisfaction with using technology in education (Islam et al., 2020). Perceived ease of use means learning to use a technology or system quickly and without much effort (Sharma & Srivastava, 2020). Bajaj et al. (2021) refer to the perceived ease of use and the simplicity with which individuals can acquire or operate existing technologies. The hypotheses are as follows:

H5: Perceived ease of use has a significant impact on continuance intention.

2.6 Perceive Usefulness

When students recognize the utility of e-learning platforms, it increases their motivation to exhibit positive behavior toward these platforms (Binyamin et al., 2019). Al-Aulamie et al. (2012) emphasize that the perceived utility of a technology exerts a positive and objective influence on user behavior, thereby regulating their willingness to engage with the technology. The usefulness of information technology is recognized by users, followed by a positive willingness to use it, and the perceived usefulness permeates into individual behavioral willingness (Budu et al., 2018).

The higher the perceived usefulness of an e-learning system by an individual, the more explicit their intention to use it becomes, and it directly impacts the adoption of the

system (Yang & Yoo, 2004). Users' behavioral willingness to e-learning is directly predicted by perceived usefulness, between accepting the intervention of perceived ease of use (Mohammadi, 2015). PU significantly impacted teachers 'willingness to adopt online teaching and continue teaching during the COVID-19 epidemic (Mehta, 2021). Mailizar et al. (2021) found that the utilization of PU does not substantially impact educators' inclination to adopt e-learning practices. The hypotheses are as follows:

H6: Perceived usefulness has a significant impact on continuance intention.

2.7 Continuance Intention

Bhattacherjee (2001) defines continuance intention as the behavior of users continuing to use services after receiving them. Loh et al. (2022) constructed that the study uses the cognitive-emotion-intention framework to explore the impact on the continued use of information systems by examining two kinds of emotions, positive and negative while using information systems. Regardless of intrinsic motivation, user beliefs may play a critical role in influencing the willingness of users to sustain their usage (Sørebø et al., 2009). Learners perceive gamification design as positive and a prerequisite for continued intent (Aparicio et al., 2019). The sustained adoption of e-learning systems is associated with favorable perceptions of their impact on learning outcomes (Lin, 2012).

3. Research Methods and Materials

3.1 Research Framework

Theoretical frameworks provide the theoretical basis and guidance for research, helping researchers explain phenomena, propose hypotheses, and carry out analysis (Qin et al., 2009). Before constructing their own conceptual framework, researchers need to draw on classical theoretical frameworks. A conceptual framework refers to the understanding and interpretation of concepts in research or analysis (Leshem & Trafford, 2007). Framing allows you to connect variables and observe correlations between them, which is the theoretical assumption of this study (Herek, 2011).

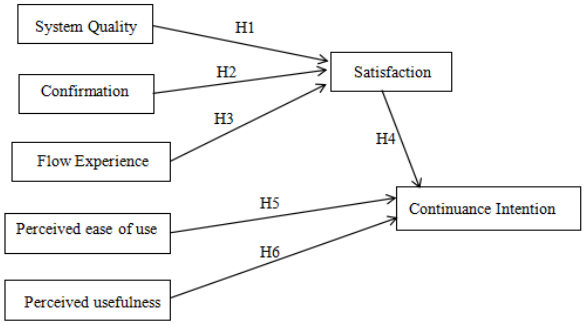

Figure 1: Conceptual Framework

H1: System quality impact has a significant impact on satisfaction.
H2: Confirmation has a significant impact on satisfaction.
H3: Flow experience has a significant impact on satisfaction.
H4: Satisfaction has a significant impact on continuance intention.
H5: Perceived ease of use has a significant impact on continuance intention.
H6: Perceived usefulness has a significant impact on continuance intention.

3.2 Research Methodology

This study used a quantitative method. The researchers selected the target group of four students from Sichuan Post and Telecommunication College in Chengdu, with a sample size of 500 people. The survey group's data was collected using a network questionnaire. The questionnaire must be tested before data analysis to ensure reliability and validity. Indexes of Item-Objective Congruence (IOC) ensures that the content is valid, and the results were that all items scored over 0.6. The pilot test results of 50 participants were acceptable at over 0.7.

The SPSS and JAMOVI statistical tools were used to sort out the data. Quantitative analysis is followed by empirical analysis to test the research's conceptual framework and hypothesis associations, using methods including CFA and SEM. The purpose of this study dictates that the main structure of this study includes an introduction, literature review of research variables, conceptual model construction and hypothesis formulation, questionnaire design and data collection, quantitative analysis, empirical testing, result analysis, formation of research conclusions, resolution of constraints encountered in the process of research, suggestions for improvement and prospects for the future.

3.3 Population and Sample Size

The formal distribution of questionnaires, 50 students in four majors were surveyed as a pilot test. Reliability was measured using Cronbach's alpha technique. The minimum sample size of structural equation modeling is 200, required by Hair et al. (2006). After data collection, 500 respondents were selected proportionally from four majors in college.

3.4 Sampling Technique

This paper's research object is the students of four majors at Sichuan Post and Telecommunication College in Chengdu. All of them have at least one year of online learning experience. To facilitate sampling, the researchers selected students from four majors at Sichuan Post and Telecommunication College. The electronic questionnaire was distributed to people who met three criteria: post-secondary students who were 19 years of age, in one of the four majors surveyed, and had at least one year of experience using online learning.

Table 1: Sample Units and Sample Size

Four Main Subjects	Junior College Students	Proportional Sample Size
Big data technology	195	88
Information safety	292	132
Computer network technology	372	168
Cloud computing	246	112
Total	**1105**	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

The data presents a comprehensive overview of the demographic and behavioral characteristics of 500 respondents. In terms of gender distribution, 56.4% are male and 43.6% are female, indicating a slightly higher proportion of males in the sample. Age-wise, nearly half (49.4%) of the respondents are between 19 and 20 years old, while 41.6% are aged 21 to 22 years, and a smaller percentage (9.0%) are over 23 years old. This suggests that most of the respondents are young adults, likely students, or early career professionals. Regarding academic standing, more than half (54.2%) are sophomores, 28.2% are freshmen, and 17.6% are juniors, highlighting a significant representation from second-year students.

Behaviorally, the frequency of e-learning usage shows a strong engagement among respondents. A substantial 45.0% use e-learning platforms more than six times per week, with 26.2% using them 3-4 times per week. In contrast, only a small fraction (2.6%) does not use e-learning platforms at all. When it comes to preferred locations for e-learning, 41.4% of respondents use computers, making it the most common choice. Electronic classrooms are used by 27.4%, while 21.0% prefer mobile phones, and 10.4% use other locations. This indicates a clear preference for computers and electronic classrooms over mobile devices for e-learning activities.

Table 2: Demographic Profile

Demographic and Behavior Data (N=500)		Frequency	Percentage
Gender	Male	282	56.4%
	Female	218	43.6%
age	19-20 years old	247	49.4%
	21-22 years old	208	41.6%
	more than 23	45	9%
grade	Freshman year	141	28.2%
	Sophomore year	271	54.2%
	Junior year	88	17.6%
Number of times per week	0 times	13	2.6%
	1-2 times	77	15.4%
	3-4 times	131	26.2%
	5-6 times	54	10.8
	more than 6 times	225	45%
Use e-learning locations	Mobile phone	105	21%
	Computer	207	41.4%
	Electronic classroom	136	27.4%
	Others	52	10.4%

4.2 Confirmatory Factor Analysis (CFA)

Jöreskog (1969) found that confirmatory factor analysis (CFA) explained correlations between variables. The measurement model specifies potential variables using CFA support (Suhr, 2006). CFA is commonly used in scale research and item relationship testing (Kline, 2023). Confirmatory factor analysis (CFA) is important in test size relationships (Oran et al., 2018). Bandalos and Finney (2018) mention that CFA is recommended to test scale relationships when factors and items are known. In addition, researchers often use CFA to evaluate some value of a variable, such as reliability and validity (Byrne, 2013).

Confirmatory factor analysis (CFA) was utilized in this study to measure every variable in the conceptual framework. The measurement's findings demonstrated the significance of each scale item for every variable. Furthermore, each scale item's factor loading values were within acceptable bounds, suggesting that the study's conceptual framework was a suitable fit. For this investigation, all construct reliabilities were greater than 0.70, all mean extracted variances were greater than 0.50, all p-values were less than 0.05, and all factor loading values were greater than 0.30. Every one of these estimates was noteworthy. These data are all displayed in Table 3.

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)	Chang (2013)	4	0.847	0.508-0.976	0.851	0.608
Confirmation (Conf)	Cheng (2021)	3	0.888	0.823-0.872	0.888	0.726
Flow Experience (FE)	Cheng (2021)	4	0.925	0.744-0.966	0.923	0.753
Perceived ease of use (PEOU)	(Kumar et al., 2023)	4	0.863	0.522-0.995	0.864	0.634
Perceived usefulness (PU)	(Kumar et al., 2023)	4	0.871	0.706-0.847	0.873	0.634
Satisfaction (SA)	Chang (2013)	4	0.851	0.727-0.825	0.853	0.592
Continuance Intention (CI)	Cheng (2021)	4	0.836	0.718-0.773	0.837	0.563

This study employed GFI, AGFI, NFI, CFI, TLI, and RMSEA as measures of model fit in the CFA test.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/df	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	741.943/303 or 2.449
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.899
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.874
NFI	>0.9 (Hair et al., 2006)	0.927
IFI	>0.9 (Arbuckle, 1995)	0.956
TLI	>0.9 (Hair et al., 2006)	0.948
CFI	>0.9 (Hair et al., 2006)	0.956
RMSEA	< 0.08 (Pedroso et al., 2016)	0.054
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, IFI = Incremental Fit Indices, TLI = Tucker Lewis index, CFI = comparative fit index and RMSEA = root mean square error of approximation

The square roots of the extracted level differences are shown in Table 5, and these values suggest that all of the study's variables have suitable correlations.

Table 5: Discriminant Validity

	SQ	Conf	FE	PEOU	PU	SA	CI
SQ	**0.780**						
Conf	0.438	**0.852**					
FE	0.402	0.644	**0.868**				
PEOU	0.155	0.224	0.199	**0.796**			
PU	0.422	0.385	0.344	0.109	**0.796**		
SA	0.592	0.477	0.419	0.167	0.448	**0.769**	
CI	0.315	0.306	0.215	0.029	0.314	0.332	**0.750**

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

4.3 Structural Equation Model (SEM)

Awang (2012) recommended that the Chi-square/degrees-of-freedom (CMIN/DF) ratio for model fit measures was less than 5.00, a criterion also supported by Al-Mamary and Shamsuddin (2015). Sica and Ghisi (2007) suggested a GFI greater than 0.85. Sica and Ghisi (2007) suggested AGFI greater than 0.80. Hair et al. (2006) suggested that the NFI, TLI, and CFI were greater than 0.90. Arbuckle (1995) suggested that the IFI was greater than 0.90. Pedroso et al. (2016) suggested that the RMSEA was less than 0.08.

The researchers modified the model using SPSS AMOS version 27 for the SEM computations. This study's fit index results showed a good fit. The degree of freedom to the chi-square value ratio (CMIN/DF) is 3.219. These were the group's chi-square statistical results: Tucker-Lewis index (TLI) = 0.921, comparative fitting index (CFI) = 0.929, standardized fitting index (NFI) = 0.901, adjusted goodness-of-fit index (AGFI) = 0.830, Tucker-Lewis index (GFI) = 0.858, and approximate root mean square error (RMSEA) = 0.067.

Table 6: Goodness of Fit for Structural Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/df	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	1013.904/315 or 3.219
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.858
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.830
NFI	>0.9 (Hair et al., 2006)	0.901
IFI	>0.9 (Arbuckle, 1995)	0.929
TLI	>0.9 (Hair et al., 2006)	0.921
CFI	>0.9 (Hair et al., 2006)	0.929
RMSEA	< 0.08 (Pedroso et al., 2016)	0.067
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, IFI = Incremental Fit Indices, TLI = Tucker Lewis index, CFI = comparative fit index and RMSEA = root mean square error of approximation

4.4 Research Hypothesis Testing Result

Through the obtained values, the regression weight of the variable and the variance of R2 can be calculated to obtain the significance of the research model.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: SQ→SA	0.420	9.003*	Supported
H2: CONF→SA	0.352	7.310*	Supported
H3: FE→SA	0.124	2.859*	Supported
H4: SA→CI	0.301	5.558*	Supported
H5: PEOU→CI	-0.061	-1.303	Not Supported
H6: PU→CI	0.223	4.368*	Supported

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

These results supported all the hypotheses of this study. System Quality influenced Satisfaction (β=0.420), Confirmation influenced Satisfaction (β=0.352), Flow experience influenced Satisfaction (β=0.124), Satisfaction influenced Continuance Intention (β=0.301), Perceived ease of use influenced Continuance Intention (β=-0.061) and Perceived usefulness influenced Continuance Intention (β=0.223).

With a criteria coefficient value of 0.420 in its structural route, the researcher concluded that establishing H1 suggested that system quality was one of the major drivers of Satisfaction. These findings are shown in Table 6. According to the establishment of H2, with a criteria coefficient value of 0.352 in its structural path, Confirmation was one of the major drivers of Satisfaction. According to the establishment of H3, flow experience—which had a structural path criterion coefficient value of 0.124—was one of the major drivers of Satisfaction. The development of H4 demonstrated that, with a criteria coefficient value of 0.301 in its structure path, contentment was one of the major drivers of continuance intention. H6's structure route revealed that perceived utility was one of the main factors influencing continuing intention, as evidenced by its standard coefficient value of 0.223. However, the construction of H5, with a standard coefficient value of -0.061 in its structural route, showed that perceived ease of use was not one of the major drivers of continuance intention.

5. Conclusion and Recommendation

5.1 Conclusion

This paper takes four Sichuan Post and Telecommunication College students as the research object. All participants possess over one year of experience in e-learning. Through survey research, the researchers analyzed pertinent factors, encompassing student satisfaction with e-learning and their inclination to continue utilizing e-learning platforms. The conceptual framework of this study is grounded in three fundamental theories embraced by the researchers. The seven variables in the conceptual framework are system quality, confirmation, flow experience, perceived ease of use, perceived usefulness, satisfaction, and continuance Intention. The mediator is satisfaction, and the dependent variable is continuation intention.

The Unified Theory of Technology Acceptance and Use (UTAUT), the theory of planned behavior (TPB), and the Technology Acceptance Model (TAM) are the two theoretical frameworks that are integrated in this study in addition to the conceptual framework of the classical model. The statistical analysis of the collected data was carried out using a quantitative method. Firstly, the judgment sampling method selects students from four Sichuan Post and Telecommunication College majors. The next stage is to adopt a stratified random sampling technique, and the sample size of each specialty is determined according to the proportion of the number of different specialties. The third step adopts the method of convenient sampling to issue online questionnaires to the target population and collect survey data. Obtaining data through questionnaires is a common method. In December 2023, questionnaires were sent to students of four target majors in Sichuan Post and Telecommunication College. These target groups are all eligible students. To ensure the reliability and consistency of items in the scale, the researchers initially tested 50 samples. After correcting the tests, the researchers distributed 500 more questionnaires to eligible students.

The questionnaire's data returns are sorted out, giving quantitative research a strong starting point. With seven hypotheses put out, the main goal of this study is to investigate the causal links between variables. Confirmatory factor analysis (CFA) and structural equation modeling (SEM) were used to examine the relationship between the two factors. The investigation's findings demonstrate the consistency of the following: factor load, mean square extraction analysis, convergence validity, composite reliability, and discriminant validity. The data was analyzed using the JAMOVI scale and SPSS.

Additionally, the conceptual framework satisfies the requirements of the AMOS test methodology. This study's data fit the data quite well. CFA evaluated the study's factor structure and confirmed the model's suitability.

The study presents seven possibilities. Satisfaction is greatly impacted by System Quality and confirmation. Experience in Flow has a big influence on Happiness. The degree to which something is deemed easy to use influences the intention to continue. The intention to continue is significantly influenced by perceived usefulness. Continuance Intention was significantly impacted by satisfaction.

The findings suggest that to improve students' satisfaction with e-learning, the system quality, confirmation, and flow experience of learning platforms need to be improved. Students will only continue using learning

platforms when satisfied and can learn useful knowledge from them. Students need to attach more importance to the simplicity of the platform's operation, which has little impact on whether they continue using the learning platform in the later stage.

The study results offer a comprehensive insight into students' satisfaction with e-learning and the determinants impacting their sustained online education adoption. It can help students learn to improve their teaching methods. It has reference value for introducing and constructing teaching platforms in schools. Help education platform development companies improve their online education platforms and launch online learning platforms more conducive to post-secondary students' learning. At the same time, it also provides a useful research path for the research and development of online learning.

5.2 Recommendation

Based on the research results of this paper, we propose the following suggestions. First, the quality of the learning platform's construction is very important. To improve students' satisfaction, we must pay attention to the quality of the platform. For example, the learning video plays smoothly without quality problems.

Second, we propose to enhance the confirmation of the learning platform. When using the learning platform, students can immerse themselves in the learning atmosphere, eliminate irrelevant affairs, and feel relaxed and happy (Csikszentmihalyi & Csikszentmihalyi, 1992). Students' satisfaction with the learning platform will be greatly improved.

Finally, the learning platform enriches the content, and the content can bring benefits to learners. Students of different majors can find new knowledge on the platform to improve their learning content. Students will continue to use the learning platform in the future. Learning platform companies will have more users.

5.3 Limitation and Further Study

The test data in this study came from the Sichuan University of Posts and Telecommunications in Chengdu, which was limited by time and space. The content of these data is related to students' personal preferences. Different individual differences will lead to different data research results. The researchers used statistical strategies to assess this effect (Podsakoff et al., 2012), and the results showed that the effect was modest. Although there are some limitations in the investigation process, the final result is consistent with the theoretical inference. Similar variables can be studied in future studies, and the group of data collected in the study can be expanded to more professional students, which will contribute to the further development of the study.

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