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Influencers of the Postgraduate Students' Continuance Intention to Use E-learning at a Public University in Chengdu, China

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Abstract

Purpose: This study investigates how students intend to continue using e-learning at a public university in Chengdu, China. The conceptual framework of the study was built using the Technology Acceptance Model (TAM), the Information System Success Model (ISSM), and the Expectation-Confirmation Model (ECM). Computer self-efficacy, system quality, information quality, service quality, perceived usefulness, satisfaction, and continuance intention were examined their effects on continuance intention to use the e-learning platforms. **Research design, data, and methodology:** The data were collected from 492 postgraduate students from Xihua University. The researcher used a quantitative survey approach by distributing online questionnaires. The index of item-objective congruence (IOC) was applied and a pilot test (n=50) were conducted to evaluate the reliability using Cronbach's Alpha coefficient. Confirmatory factor analysis and structural equation modeling were employed in this study as statistical analysis tools to assess the data, the validity, reliability, factor loadings, and the path coefficient. **Results:** The data analysis showed that perceived usefulness had the strongest direct influence on continuance intention, consistent with the entire hypothesis. **Conclusions:** Administrators and educators should closely examine the variables influencing students' intention to use e-learning platforms. They should think about improving relevant teaching strategies going forward based on the findings of this study.

Keywords : E-Learning, Service Quality, Information Quality, Satisfaction, Continuance Intention

JEL Classification Code: E44, F31, F37, G15

1. Introduction

E-learning is now one of the most fascinating and rapidly evolving topics in contemporary society because of the ever-expanding Internet, which has made it available to individuals in corporations, governments, college and university settings, and other sectors (Chang, 2013). E-learning is becoming a more important tool for academic institutions and universities worldwide. It allows students access to a virtualized world to participate in several activities (Salloum et al., 2019).

With the current massive data, the "Internet of Things," and new information technology generations like mobile Internet applications and the depth of fusion of classroom teaching, online teaching development has recently focused on online learning as a new access point from the early education managing resources and customer support, to study management and interaction network teaching phase, to the massive open online course (MOOC) phase (Sun, 2016).

Internet-based online teaching has undergone four stages of development; the first stage involves creating, implementing, administrating, and supporting resources for online learning. The form of teaching is taken from the network at the second level. Teachers and students use network teaching platforms to actualize the flow of

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educational material and the procedure for knowledge production, exchange, and invention. The third level is a novel teaching service model that is nonlinear and generative and uses systematic courses with a comparatively given construct as the learning area (Li & Gao, 2020). The fourth phase has created an organic union between online learning and traditional classroom instruction, corrected issues brought on by the division of students and educators, and organically incorporated online learning and traditional classroom instruction in educational institutions (Liu, 2016).

Online education allows students to make the most of their limited time, which greatly promotes the growth of their capacity for independent study and the pursuit of secondary education or further education. Consequently, “Internet + education” integration has emerged as the primary educational and teaching transformation trend. (Zhang, 2020). The COVID-19 pandemic’s effects on the environment in 2020 have re-ignited interest in online education. According to iResearch’s China’s Online Education Industry Research Report 2020, the market size of China’s online education industry is projected to be 257.3 billion yuan in 2020, representing a CAGR of 34.5% over the preceding four years (iResearch, 2021).

Due to the pandemic of COVID-19, students and educators cannot return to regular lessons, so educational institutions have taken the required steps to ensure “School suspension without study suspension.” According to (Jiao et al., 2020), there are several typical schemes to consider when looking at the current school’s online education and counseling program, including online classes, network broadcasting teaching, students’ independent learning, TV classroom, etc. The widespread utilization of these educational tools has once again pushed online education to the public’s notice.

It is challenging to deliver uninterrupted online education in this setting, but it also offers a special opportunity. Although online learning is novel, independent, convenient, and effective, educators and students are aware of its drawbacks. Through research and investigation, we can comprehend teachers’ and students’ requirements, look into the factors that influence students’ online learning, suggest concepts for students their own and the creation of teaching platforms, maximize the effectiveness of teaching methods, and enable more students and educators to take advantage of online teaching, which is required to address the problems with online teaching. Therefore, the objective of this study is to investigate influencing factors of students’ continuance intention to use e-learning at a public university in Chengdu, China.

2. Literature Review

2.1 Computer Self-efficacy

Instead of reflecting simple component skills, computer self-efficacy might be regarded as a person’s ideas about their capacity to use computers to execute tasks (Ong et al., 2004). Computer self-efficacy is the capacity of an individual to carry out actions and use a computer in an environment of information technology use (Al-ammari & Hamad, 2008). Computer self-efficacy is utilizing a computer to achieve a particular activity. The degree of computer self-efficacy a person possesses substantially impacts their decision to use computers. People with low computer self-efficacy do not feel as confident and skilled in using computers. Thus, they require additional instructions and direction throughout the process (Mouakket & Bettayeb, 2015). In the information systems industry, the capacity to use computer capabilities to complete specific tasks is called computer self-efficacy (Roca et al., 2006). Computer self-efficacy refers to an individual’s perceptions of their inclination to use computers for information technology (Lee et al., 2014).

The considerable impact of computer self-efficacy on perceived usefulness has been empirically explored, and it has emerged as a favorable predictor of perceived usefulness (Ong & Lai, 2006). Lacking computer self-efficacy makes users significantly less confident. Thus, they need more guidance and explanations throughout the process (Gong et al., 2004). A person with high computer self-efficacy would view a platform as more useful. In contrast, a person with low computer self-efficacy would view a program as less beneficial (Yuen & Ma, 2008). It is possible to argue that a person’s perceived usefulness in an e-learning environment reflects their knowledge of or expectations for the task at hand, suggesting that computer self-efficacy may significantly influence perceived usefulness (Chau & Hu, 2001). Thus, a hypothesis is proposed:

H1: Computer self-efficacy has a significant effect on perceived usefulness.

2.2 System Quality

The system quality notion was measured using connection adaptability, interaction versatility, data adaptability, architecture flexibility, and modifiable suppleness (Samarasinghe, 2012). According to certain academics, system quality is how users judge a system as simple to use, understand, communicate with, and appreciate (Aldholay et al., 2018). System quality is the degree to which a system performs as intended, and it denotes a system’s accuracy, usability, profitability, flexibility, reliability, and responsiveness (Cheng, 2012). The system's technological features, usability, and functionality serve as benchmarks for its quality (Cidral et al., 2017). Technical proficiency, correctness, and the efficiency of the information system that produces information are all factors that affect system quality (Mohammadi, 2015).

According to various experts that have investigated the issue, there are positive relationships between system quality and user pleasure (Chiu et al., 2007; Hsieh & Wang, 2007). Hassanzadeh et al. (2012) assumed that user satisfaction rises as the technical quality of e-learning systems improves and supported it with actual data. The information system success model states that system quality significantly impacts satisfaction (Chopra et al., 2019). According to Almazán et al. (2017), system quality does have a significant beneficial impact on satisfaction. Hence, H2 is set:

H2: System quality has a significant effect on satisfaction.

2.3 Information Quality

The standards of the format and contents produced by the information system are called the information's quality. Its evaluation considers the data's accuracy, comprehensiveness, currency, effectiveness, relevance, extent, and timeliness (Cheng, 2012). Information quality, encompassing information's speed, coverage, relevance, and correctness, is related to the standard of a particular information system's output (Roca et al., 2006). Information quality is a term used to describe a system's ability to provide comprehensive and correct data for learning. It covers issues such as the accuracy, efficiency, security, usability, and timeliness of a system's information output (Kao & Lin, 2018). Exactness, consistency, currency, efficiency, dependability, scope, and timeliness are among the criteria that make up information quality measures (Cheng, 2014).

The relationship between informative quality and user satisfaction that gave rise to the Information Systems Success model originally surfaced in DeLone and McLean's research (2003). It will be easier for users to enjoy the system if students believe that the course material offered by the e-learning system seems suitable for their needs (Cheng, 2012). The results of the empirical inquiry show that information quality is the most important precondition for user satisfaction (Almazán et al., 2017). Several studies demonstrate that information quality influences its usefulness and satisfaction in a positive way (Cidral et al., 2017). If the content offered by the e-learning system is regularly updated and sufficiently complete, users will find it easy to understand and feel more at ease utilizing the technology (Cheng, 2014). Accordingly, a following hypothesis is indicated:

H3: Information quality has a significant effect on satisfaction.

2.4 Service Quality

The usefulness of multiple communication channels for quickly assisting users in resolving usage-related difficulties is a key component of service quality (Cheng, 2012). Service quality metrics include the technical staff's perceived skill and attentiveness (Cidral et al., 2017). Service quality describes how well customers are supported by the information system, including through training and the help desk (Mohammadi, 2015). In online learning, the capacity to provide personalized information in a specific environment by understanding user preferences and wants in conjunction with individualized reciprocity is called service quality (Darawong & Widayati, 2021).

The level of learners' satisfaction with the learning system was influenced by service quality (Oliver, 1980; Rughoobur-Seetah & Hosanoo, 2021). Professional rates of participant acceptance and contentment with the e-learning experience will most likely result from top-notch support services (Cheng, 2014). Customers are satisfied when services are of higher quality, and past studies indicated a strong correlation between customer satisfaction and service quality (Brown & Chin, 2004; Zhu et al., 2002). Based on previous studies, a hypothesis is suggested:

H4: Service quality has a significant effect on satisfaction.

2.5 Perceived Usefulness

The degree to which academic success is predicted by scholars considering using online learning tools is referred to as perceived usefulness (Abbas, 2016). "Perceived usefulness" refers to how someone views the benefits of utilizing a technology (Salimon et al., 2021). Perceived usefulness is the inferred probability that a potential user of an application system would perform better while working in an organizational setting after using it (Yuen & Ma, 2008). Perceived usefulness is the degree to which one believes that utilizing the suggested system at work would maximize performance (Kanwal & Rehman, 2017). The term "perceived usefulness" refers to a user's conviction that using a system will improve work output (Mouakket & Bettayeb, 2015).

A reliable predictor of users' satisfaction with an e-learning platform is their perceived usefulness (Cheng, 2014, 2019). Users' continuance intention to utilize the system is influenced by their satisfaction with it and its perceived usefulness (Cheng, 2021; Limayem et al., 2007). Perceived usefulness affects students' satisfaction and intention to utilize the education program (Fan et al., 2021; Lee, 2010). Consequently, the research concludes below hypotheses:

H5: Perceived usefulness has a significant effect on satisfaction.

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

2.6 Satisfaction

When one's performance at work was evaluated, "satisfaction" was first employed to describe the positive emotional state that resulted (Hayashi et al., 2004). When a person believes using a service will make them feel good, it is described as satisfaction (Mouakket & Bettayeb, 2015). Satisfaction in an online course is outlined as the user's perceived degree of engagement and accomplishment (Chen et al., 2018). According to reports, it is also based on the satisfaction of online students with their choice to use it and how well it fits their requirements (Aldholay et al., 2018). A person is said to be satisfied when their wants and wishes are fulfilled, which is described as satisfaction (Darawong & Widayati, 2021).

The degree of satisfaction affected whether consumers intended to use online education, online commercial products, or electronic tax preparation in the future (Chang, 2013). The level of user satisfaction significantly affects whether they plan to continue utilizing the information system again (Chen et al., 2018; Joo et al., 2018). If users believe the products are sufficient, they are significantly more likely to continue using cloud-based computing systems (Cheng, 2019, 2021). According to the above assumptions, a hypothesis is developed:

H7: Satisfaction has a significant effect on continuance intention.

2.7 Continuance Intention

The term "continuation intention" refers to a person's readiness to use and encourage others to utilize an information system later (Mouakket & Bettayeb, 2015). An individual's chance to utilize the application is determined by their continuance intention to use (Hayashi et al., 2004). In MOOCs, learners' willingness to continue is known as continuance intention, irrespective of whether they complete a course throughout its entirety (Joo et al., 2018). The predicted future consumption of an information system or its output was characterized by Petter and McLean (2009) as continuance intention. Continuance intention refers to the users' willingness to utilize the learning management system in the future for their teaching activities. Users' satisfaction is crucial in determining an information system's intention to continue (Hussein et al., 2021).

3. Research Methods and Materials

3.1 Research Framework

The conceptual framework of this paper is based on previous academic investigation methods, and it mainly adopts three theories: the technology acceptance model (TAM), the information system success model (ISS), and the expectation confirmation model (ECM). Ong et al. (2004) state that perceived usefulness and computer self-efficacy are associated. The interconnection of system quality, information quality, service quality, satisfaction, and continuance intention were further shown by Chang (2013). Moreover, Cheng (2019) demonstrated a relationship between perceived usefulness, satisfaction, and continuing intention. Figure 1 illustrates how these theoretical frameworks create the conceptual framework.

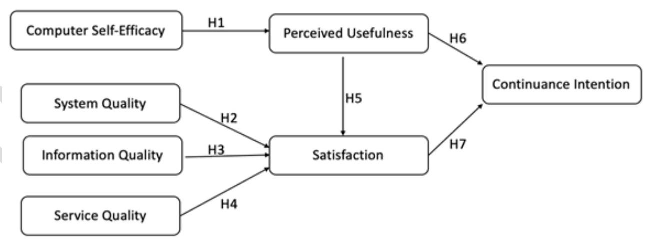

Figure 1: Conceptual Framework

H1: Computer self-efficacy has a significant effect on perceived usefulness.
H2: System quality has a significant effect on satisfaction.
H3: Information quality has a significant effect on satisfaction.
H4: Service quality has a significant effect on satisfaction.
H5: Perceived usefulness has a significant effect on satisfaction.
H6: Perceived usefulness has a significant effect on continuance intention.
H7: Satisfaction has a significant effect on continuance intention.

3.2 Research Methodology

The researcher used a probability sampling method and questionnaires among postgraduate students with at least one semester of online learning experience in the School of Architecture and Civil Engineering, Food and Biological Engineering, Law and Sociology, and Science of Xihua University in Chengdu, China. Observational data were aggregated and investigated to determine the factors influencing participants' intention to use e-learning platforms.

There were 3 components to the questionnaire. Secondly, according to Cooper and Schindler (2010), screening questions assist in identifying if respondents possess the skills or background required to participate in the research project. The characteristics of respondents are also crucial to the data collection procedure. Age, gender, educational attainment, and other basic data are required (Hammer, 2011). Last, employ the Likert scale, one of the most popular methods for assessing modern values (Salkind, 2012). Using a five-point scale, participants were asked to indicate whether they agreed or disagreed with a series of statements. Positive comments were rated on a scale of 1 to 5, with 5 denoting Strongly Agree and 1 indicating Strongly Disagree.

The index of item-objective congruence (IOC)'s results were assessed by three experts and deemed acceptable when scored at 0.60 or above. Subsequently, a pilot test involving 50 participants was conducted to evaluate the reliability using Cronbach's Alpha coefficient, which was considered satisfactory at a score of 0.7 or higher (Taber, 2018). To ascertain the measurement model's validity and reliability, confirmatory factor analysis (CFA) was employed. Additionally, the structural equation model (SEM) was utilized to assess the fitness of the structural model and conduct hypothesis testing.

3.3 Population and Sample Size

According to Boomsma (1985), appropriate structural equation modeling requires a sample size of at least 100 or 200. The sample size for this study is determined using the Danielsoper quantitative calculator. The calculated results indicate that at least 425 people should be included in the sample size for this empirical investigation. So, among 1,104 postgraduate students at the four target schools at Xihua University, the researchers chose a population sample of 500 students.

3.4 Sampling Technique

In the judgmental sampling, 990 postgraduates were chosen because, according to the author's analysis, some students do not have more than one semester of experience with e-learning. The researcher chose postgraduates from 4 levels as the quota sampling, with each postgraduate chosen in proportion to the sample size of about 500 individuals. 492 of the questionnaires were deemed valid once they were all collected.

Table 1: Sample Units and Sample Size

Educational Background	Grade Level	Population	Proportional Sample Size
Postgraduate	Architecture and civil engineering	220	111
	Food and bioengineering	341	172
	Law and Sociology	203	103
	Science	226	114
Total		**990**	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

Table 2 summarizes the demographic details of the 492 respondents. 29.47% of respondents were male, 70.53% were female, 1.63% were between the ages of 21 and 22, 64.63% were between the ages of 23 and 24, 30.49% were between the ages of 25 and 26, and 3.25% were over the age of 26. Tencent Conference and Super Star platforms are the two e-learning platforms respondents use most frequently, and 46.14 percent of these respondents utilize them four to seven times per week.

Table 2: Demographic Profile

Demographic and General Data (N=492)		Frequency	Percentage
Gender	Male	145	29.47%
	Female	347	70.53%
Age	21-22	8	1.63%
	23-24	318	64.63%
	25-26	150	30.49%
	More than 26	16	3.25%
Number of e-learning sessions per week	1 time	23	4.67%
	2-3times	149	30.28%
	4-7times	227	46.15%
	More than 7times	93	18.90%
Name of the most used e-learning platform	Superstar	170	34.55%
	MOOC	17	3.46%
	WeChat	6	1.22%
	Tencent Conference	190	38.62%
	Ding Talk	7	1.42%
	Rain Class	24	4.88%
	Wisdom Tree	3	0.61%
	Bili Bili	57	11.59%
	Others	18	3.65%

Source: Constructed by author

4.2 Confirmatory Factor Analysis (CFA)

To check whether each observed variable's number of variables and load circumstances match those predicted by the viability of the hypotheses, confirmatory factor analysis was used (Malhotra et al., 2004). The results of the factor loading analysis and the proper values for each observed variable proved the inquiry matrix's goodness of fit.

Table 3 displays that Cronbach's Alpha coefficient was considered satisfactory at a score of 0.7 or higher (Taber, 2018), the composite reliability (CR) was over 0.70 (Hair et al., 2021), the average extracted variance (AVE) values were all larger than 0.50 (Hair et al., 2020), and the factor loading values were all greater than 0.50. (Byrne, 2001).

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
Computer Self-efficacy (CSE)	Salloum et al. (2019)	5	0.899	0.737-0.822	0.896	0.632
System Quality (SYQ)	Salloum et al. (2019)	5	0.916	0.724-0.761	0.861	0.553
Information Quality (IQ)	Salloum et al. (2019)	5	0.869	0.761-0.809	0.887	0.611
Service Quality (SQ)	Cheng (2014)	3	0.877	0.731-0.817	0.809	0.587
Perceived Usefulness (PU)	Salloum et al. (2019)	4	0.918	0.741-0.837	0.877	0.640
Satisfaction (SAT)	Cheng (2014)	4	0.952	0.735-0.793	0.851	0.588
Continuance Intention (CI)	Cheng (2014)	4	0.913	0.764-0.811	0.868	0.623

Furthermore, Table 4 displays and demonstrates that all applicable criteria for such absolute fit indicators, such as CMIN/DF, GFI, AGFI, and RMSEA, as well as the incremental fit measurements, such as CFI, NFI, and TLI, fulfill the specifications. The goodness of fit metrics applied in the CFA evaluation were all legitimate.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 3.00 (Hair et al., 2010)	1.206
GFI	≥ 0.90 (Hair et al., 2010)	0.940
AGFI	≥ 0.80 (Segars & Grover, 1993)	0.928
RMSEA	< 0.08 (Pedroso et al., 2016)	0.020
CFI	≥ 0.90 (Hu & Bentler, 1999)	0.990
NFI	≥ 0.90 (Bentler & Bonett, 1980)	0.943
TLI	≥ 0.90 (Hu & Bentler, 1999)	0.988
Model Summary		**In harmony with empirical data**

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = Goodness-of-fit index, AGFI = Adjusted goodness-of-fit index, RMSEA = Root mean square error of approximation, CFI = Comparative fit index, NFI = Normed fit index, and TLI = Tucker–Lewis index.

The findings of the investigation and display of the discriminant validity are shown in Table 5. The amount diagonally displayed is the AVE square root of the AVE. The discriminant validity was established using these numerical measures.

Table 5: Discriminant Validity

	CSE	SYQ	IQ	SEQ	PU	SAT	CI
CSE	**0.795**						
SYQ	0.283	**0.744**					
IQ	0.334	0.386	**0.782**				
SEQ	0.240	0.201	0.323	**0.766**			
PU	0.361	0.259	0.336	0.436	**0.800**		
SAT	0.258	0.305	0.380	0.489	0.487	**0.767**	
CI	0.267	0.196	0.329	0.446	0.446	0.502	**0.789**

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

Source: Created by the author.

4.3 Structural Equation Model (SEM)

In this study, the structural equation model (SEM) verification came after the CFA evaluation. Researchers can utilize empirical models to test the viability of theories since SEM provides a flexible framework for developing and analyzing complex interactions between many variables. (Beran & Violato, 2010). Table 6 demonstrates that even after being rectified using the statistical software, the combined values of CMIN/DF, GFI, AGFI, CFI, NFI, TLI, and RMSEA were all above the permissible limits. The outcomes demonstrate that the goodness of fit of the SEM was established.

Table 6: Goodness of Fit for Structural Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 3.00 (Hair et al., 2010)	1.920
GFI	≥ 0.90 (Hair et al., 2010)	0.902
AGFI	≥ 0.80 (Segars & Grover, 1993)	0.884
RMSEA	< 0.08 (Pedroso et al., 2016)	0.043
CFI	≥ 0.90 (Hu & Bentler, 1999)	0.953
NFI	≥ 0.90 (Bentler & Bonett, 1980)	0.907
TLI	≥ 0.90 (Hu & Bentler, 1999)	0.948
Model Summary		**In harmony with empirical data**

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = Goodness-of-fit index, AGFI = Adjusted goodness-of-fit index, RMSEA = Root mean square error of approximation, CFI = Comparative fit index, NFI = Normed fit index, and TLI = Tucker–Lewis index.

4.4 Research Hypothesis Testing Result

The results shown in Table 7 show that perceived usefulness had an immediate, significant impact on continuance intention. With a standardized path coefficient of 0.434 (t-value of 8.527***), this effect was the most significant in this quantitative method. With the β at 0.420 (t-value at 7.696***) and the effect of service quality on satisfaction as the second-powerful significant interaction. Computer self-efficacy also significantly influenced perceived usefulness with the β at 0.356 (t-value at 7.046***). At the same time, satisfaction significantly impacted continuance intention with the β at 0.353 (t-value at 6.790***) and perceived usefulness significantly impacted satisfaction with the β at 0.341 (t-value at 6.875***). Also, it was shown that information quality significantly impacted satisfaction with a β of 0.189 (t-value of 4.070***). In this measurable analysis, system quality consequently had the least significant impact on satisfaction, as measured by the β of 0.149 (t-value at 3.118**).

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-Value	Result
H1: CSE→PU	0.356	7.046***	Supported
H2: SYQ→SAT	0.149	3.118**	Supported
H3: IQ→SAT	0.189	4.070***	Supported
H4: SEQ→SAT	0.420	7.696***	Supported
H5: PU→SAT	0.341	6.875***	Supported
H6: PU→CI	0.434	8.527***	Supported
H7: SAT→CI	0.353	6.790***	Supported

Note: *** p<0.001, ** p<0.01
Source: Created by the author

With a normalized path parameter threshold for this structural approach of 0.356, the results in **H1** show that computer self-efficacy is a significant determinant for perceived usefulness. According to prior studies, a person's inclination to use technology based on its perceived utility is greatly influenced by their level of computer self-efficacy (Agarwal et al., 2000).

With a standardized path coefficient of 0.149, the analysis of **H2** demonstrates that system quality impacts satisfaction, but this effect is the least important of all the hypotheses. Many investigations have shown that system quality significantly impacts satisfaction (Petter & McLean, 2009).

The information quality hypothesis is supported by observable statistical findings in **H3,** where the standard coefficient value of 0.189 is just marginally higher than the influence of system quality on satisfaction in H2. One of the major factors influencing satisfaction and actual use is information quality, which has a big impact on satisfaction (Petter & McLean, 2009).

H4 demonstrates that service quality significantly affects satisfaction; the expected value is 0.420, greater than the effects of system quality and information quality. More customer satisfaction will result from higher service quality, claim Parasuraman et al. (1985) that early research revealed a strong relationship between customer satisfaction and service excellence.

With a common coefficient value of 0.341, the findings of the observable statistics for **H5** confirmed the hypothesis that perceived usefulness had a considerable impact on satisfaction. Previous research has demonstrated that users' perceived usefulness of an information system positively correlates with their satisfaction when using a platform and their intention to continue using it (Limayem et al., 2007; Lin et al., 2005).

The largest significant influence in this quantitative investigation was identified for **H6,** where we discovered a significant association between perceived usefulness and continuance intention. The standard coefficient value for this relationship was 0.434. Also, a significant portion of information organization theories concentrates on how behavioral continuance intention is impacted by perceived usefulness (Ong et al., 2004).

H7 has determined that satisfaction significantly influenced the continuance intention with a final statistical score of 0.353 on the standard coefficient of the active influence. According to several research, student satisfaction has been linked to the continued use of an e-learning system (Samarasinghe, 2012). User satisfaction substantially impacts users' intention to persist with an online study platform (Hayashi et al., 2004; Petter & McLean, 2009).

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

In this study, which was conducted at Xihua University, a public university located in the Chinese province of Sichuan, the goal was to pinpoint the factors that had a major impact on postgraduate students' intention to continue their online education. The seven hypotheses that explain how computer self-efficacy, perceived usefulness, system quality, information quality, service quality, satisfaction, and continuance intention interact with one another were displayed in the conceptual framework. In order to determine whether there was any interaction between these variables, 492 postgraduate students with at least one semester of experience in e-learning participated in the survey.

According to the study's findings, perceived usefulness has the most significant impact on continuance intention. Service quality had a substantial impact on satisfaction. Moreover, lower standardized route coefficients for information and system quality impacted satisfaction. Moreover, perceived usefulness and satisfaction are both influenced by computer self-efficacy, respectively. Finally, satisfaction has a direct impact on the continuance intention.

5.2 Recommendation

The researchers give the following useful recommendations for future e-learning for postgraduate students based on the findings of this research collection.

The results of this study indicate that perceived usefulness has the biggest impact on students' continuance intention of using e-learning platforms. Many students feel that whether e-learning platforms are useful directly impacts whether they will use them again. In order to help students, acquire useful knowledge or skills through e-learning, help them develop into talents, and encourage more students to accept e-learning platforms, school teaching units should fully clarify the teaching objectives, start with the improvement of student's abilities, and help students acquire useful knowledge or skills through e-learning.

Second, customer satisfaction is significantly directly impacted by service quality. Two more potential factors, system, and information quality, can also impact student satisfaction. For learners to recognize that the various learning operations of an e-learning platform are much relatively simple, much more understandable, and considerably more convenient than traditional classroom teaching, teaching units should focus on further optimizing the program design of an e-learning platform and providing the corresponding instructional documents and manual assistance. As a result, this recommendation will significantly increase students' satisfaction with using an e-learning platform.

Additionally, teachers should offer good lessons on the e-learning platform to help students become more proficient computer users. This will increase students' confidence when using the platform and help them conclude that it can provide useful knowledge and information.

Students will keep using e-learning once they are satisfied with the experience. Therefore, to encourage students to continue using the e-learning platform, teachers should create reasonable learning plans that align with their teaching needs, set reasonable learning objectives, and implement mechanisms for evaluating their learning performance.

5.3 Limitation and Further Study

This study's shortcomings can be broken down into two categories. First, given the purpose, it would be preferable if more majors could participate in the research, which is currently restricted to the four offered majors. Second, only six potential factors that could affect how sustainably e-learning is used were considered in the analysis, and some concepts that other researchers believed to have significant observational value were included when the conceptual framework for this study was developed.

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