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Exploring the Determinants of Satisfaction and Continuance Intention to Use E-Learning of University Students in Zhejiang, China

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Abstract

Purpose: This study aims to examine the factors impacting satisfaction and continuance intention to use e-learning of university students in Zhejiang, China. The conceptual framework proposes a causal relationship among course attributes, system attributes, instructor attributes, interactive attributes, social influence, user satisfaction, and continuance intention. **Research design, data, and methodology:** The target population and sample size are students (N=500) at five universities in Zhejiang, China. This study employs questionnaires as data collection tool of the quantitative method. For sampling techniques, purposive sampling is to select students from five universities. Then, stratified random sampling is to divide sample size into subgroups. Last, convenience sampling is to distribute online survey. Data analysis included model fit, reliability, and validity using Structural Equation Models and Confirmatory Factor Analysis. **Results:** Course attributes, instructor attributes, system attributes, and interactive attributes significantly impact user satisfaction. Continuance intentions are significantly impacted by user satisfaction. In contrast, social influence has no significant impact on continuance intention. **Conclusions:** Universities, educational institutions, and lecturers should provide a positive experience to improve user satisfaction with e-learning to build a favorable e-learning environment and recommendations among peers. In addition, building and retaining system attributes and instructor attributes is crucial for the students' continued intention to use e-learning.

Keywords: System Attributes, Social Influence, User Satisfaction, Continuance Intention, E-Learning

JEL Classification Code: E44, F31, F37, G15

1. Introduction

Information and communication technology (ICT) has made educational activities in the modern era a more dynamic experience. Innovations and improvements have emerged that have taken place in the world of technology and the world of telecommunications over the past decade. Due to the emergence of networks, cheaper storage, advanced computer efficiency, new equipment, including smartphones and tablet PCs, and the invention of other mobile devices, students can now experience a new digital experience and are changing their daily lives and learning habits. In the millennial generation, students are more dependent on technology and less tolerant of didactic teaching styles.

The definition of e-learning, as given by Siragusa et al. (2007), is that e-learning refers to the process through which students communicate with their professors, other students, and other educational resources through the Internet in order to be able to learn about their course material. There has been a rise in the popularity of e-learning over recent years.

The advent of the Internet has led to a change in communication methods, education styles, and social media. The term 'e-learning' refers to a system in which learning information is delivered electronically through electronic means. It has been defined by Rosenbaum (2012) as creating new learning experiences through e-learning technologies.

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With the ability for participants to access a virtual classroom from anywhere in the world, e-learning is an economical alternative to traditional teaching and learning methods. Al-Samarraie et al. (2018) found that e-learning provides users with several advantages, including the ability to study outside of a formal classroom and the flexibility to study at any time and place. Through e-learning, learners worldwide can interact and exchange knowledge with one another (Yilmaz, 2016). E-learning courses are available on about 60% of college and university campuses in the United States (Zhao, 2003). Two thousand eight hundred colleges and universities have a long-term strategic plan that includes e-learning, so faculty members are expected to be able to design and teach courses that incorporate e-learning as a critical component.

Due to COVID-19, the Ministry of Education had to end all classes, resulting in an unprecedented surge in e-learning customers. In over 3,000 colleges and universities across the country, the virus has infected approximately 30 million students. In response to the need for e-learning courses, over 1,400 colleges and universities have developed and provided online education courses, bringing the number of online courses to a new high.

It is estimated that 17.75 million students and 1,032 million lecturers offer e-learning courses worldwide. The Chinese higher education institutions offered MOOCs, teaching services, and data support to their universities in response to the COVID-19 pandemic. A pandemic-related increase in MOOC participation has been seen at Chinese universities. Over 1,200 Chinese universities now offer MOOCs, and over 60,000 instructors have taught 120,000 courses through MOOCs. On February 17th, 2020, Chinese universities offered MOOCs to more than 14 million students.

While studies on e-learning satisfaction and continuance intention exist in various contexts, there is a lack of research specifically focused on Zhejiang, China. Understanding the unique cultural, educational, and technological landscape of Zhejiang is crucial for tailoring e-learning platforms to meet the needs and preferences of local university students. Zhejiang is home to several technological hubs and innovative companies, providing students with exposure to cutting-edge technologies and digital trends. Understanding their experiences with e-learning can offer valuable insights into future trends and requirements in educational technology.

2. Literature Review

2.1 Courses Attributes

Regarding course attributes, the quality of data and course content have been considered (Agrawal et al., 2016; Chopra et al., 2019). In determining what drives effective e-learning, it has been identified that course attributes play an essential role in determining the quality of e-learning. Peltier et al. (2007) concluded that the content of e-learning courses is crucial to its effectiveness. Cho et al. (2009) posit whether e-learning design should be improved to enhance the quality of course content in an e-learning session. Furthermore, it has been pointed out that content designed for e-learning courses that meet the specific needs of students can also be used in conjunction with e-learning frameworks, as shown by Choi et al. (2007). If the content and data are easy to understand and have a straightforward layout, users are more likely to be satisfied with their learning (Choi et al., 2007; Lee, 2010; Liu et al., 2010).

Upon receiving the reminder from an academic, the activity needed to be completed. A video, quiz, and case study online training program for telecamera was designed for another study (Atack et al., 2004). A video and supporting material regarding telecamera equipment were shown during the session, and participants could recall any part of the video if they wanted more information. Video clips were useful to students, and they preferred them over written materials.

H1: Course attributes have a significant impact on user satisfaction.

2.2 System Attributes

E-learning systems, as defined by Hew and Kadir (2016), are platforms that integrate multimedia, dynamic presentations, and interactive elements. It has been shown that several factors determine the quality of information, such as its usability, understandability, consistency, reliability, accuracy, and relevance (Cidral et al., 2018). Several technical components of e-learning systems have been considered similar to those of information systems. As with any e-learning system, e-learning systems must be easy to use and provide user-friendly features for learners (Chopra et al., 2019). It has been shown that e-learning systems can provide useful educational tools through their interactive functionality (Cheng, 2012; Pituch & Lee, 2006), and students may find them useful (Cheng, 2012; Cho et al., 2009).

Unlike offline learning, E-learning systems can offer users adequate learning material, according to Lee (2006). It is also beneficial for the e-learning system for lecturers and students to exchange information in both directions. However, resistance to e-learning will negatively impact their performance (Fisher & Wesolkowski, 1999). E-learning systems at the school and those used by students may not be compatible, preventing students from using internet functionality and meeting assignment requirements. Providing or maintaining important information online might make students dissatisfied with it. It was pointed out by the authors of Goh et al. (2008) that technical requirements for delivering videos on any device were crucial to multimedia learning. Flipped classroom pedagogy and high-quality videos are essential to multimedia learning. For educational videos to be produced with high quality, background noise must be eliminated.

H2: System attributes have a significant impact on user satisfaction.

2.3 Instructor Attributes

Several factors affect the quality of e-learning, including the attributes of the instructor, which, in turn, affect students' satisfaction with it, according to Pham et al. (2019). In order to shape a tech-mediated learning environment, several factors must be considered, including the instructor, who is one of the most important, according to Webster and Hackley (1997). According to this study, a significant influencing factor of user happiness is the professor's characteristics (Daultani et al., 2020). DeLone and McLean (2003) define the instructor's quality as the consistency offered by the instructor's attributes.

Rosenbaum (2012) found that students' satisfaction is related to the professional competence of lecturers. Students' satisfaction with e-learning positively relates to instructors' attitudes towards it (Cidral et al., 2018; Sun et al., 2008). The use of these communication tools has been demonstrated in several studies as a method of engaging online learners and giving them the use of these communication tools has been demonstrated in several studies as a method of engaging online learners and giving them the feeling that they are part of a community of learners (Lee et al., 2005; Liu et al., 2010). According to Badia et al. (2014), students are encouraged to engage in multiple activities during teaching to maintain enthusiasm. It was more important for students to have access to the course materials than to see the teacher online, according to Chopra et al. (2019).

H3: Instructor attributes have a significant impact on user satisfaction.

2.4 Interactive Attributes

A learner's interactions with an instructor are described by interaction attributes, as defined by Baber (2022). As well as enhancing knowledge, Holland (2019) emphasized that interactive attributes empower learners. A study by Tang and Tsui (2018) found that interactive attributes in e-learning provide members with a platform for social interaction and reflect a shared lifestyle.

E-learning research has always considered three aspects: the value for money, the utility of the product, and students' satisfaction. In order to obtain internal or external control, facilitating conditions must be present. According to Neumann (1998), online learning could be improved if students and administrators interacted more and flaws in delivery techniques were identified. The efficacy of an interactive platform is also influenced by its intrinsic capabilities, according to Zhang et al. (2006). The provision of social-emotional forums and educational information through such portals proves to improve users' satisfaction, as Richardson and Swan (2003) demonstrate.

H4: Interactive attributes have a significant impact on user satisfaction.

2.5 Social Influence

It has been proposed that as a means of measuring how much others' opinion has a significant impact on how much the use of a service is affected by it, a term known as "social influence" (SI) can be used (Venkatesh et al., 2003). In the study by Yassine et al. (2017), a crucial aspect of the effectiveness of e-learning can be seen in the role played by social influence. Furthermore, according to Lwoga and Komba (2015), social influence is connected to the degree to which individuals believe that e-learning platforms should continue to be used by students in the future. This includes colleagues, course lecturers, institutions, governments, and other entities contributing to the course. As Liaw (2008) and Smulowitz (2015) pointed out, many environmental and learner variables significantly affect user satisfaction.

In an early study, Jung et al. (2002) discovered that it has been shown that the outcomes of learners' educational process are positively impacted by the interactions that they have with their instructors throughout their online courses, as was the case in an earlier study. When learners interact with each other both during the course and at the final part of the course. It has been found that the exchange of content that is relevant to education on such online educational sites has been found to have a positive impact on the perception of learning and satisfaction among users, according to Richardson and Swan (2003). Depending on the type and accessibility of the information others have provided, it may be valuable to the decision-making process by providing either direct experience or information about the products or services offered, which may affect product and service selection (Sotiriadis & Van, 2013).

H5: Social influence has a significant impact on continuance intention.

2.6 User Satisfaction

The usability of e-learning technologies is primarily determined by user satisfaction, according to DeLone and McLean (2003). In addition to providing learners with the information they need, Kim and Malhotra (2005) suggest that users' satisfaction with an e-learning system is also influenced by the system's ability to provide them with the information they need. Using a user's experience, the experience, and the usefulness to the end user to measure customer satisfaction (Chiu et al., 2007). Weerasinghe and Lalitha (2018) suggest that student satisfaction during their learning process is a temporary sensation based on their educational background, learning services, and learning opportunities.

User satisfaction is directly linked to the level of satisfaction the user has with the learning environment on campus, including the campus amenities and the faculty and support staff members. Several factors can affect student satisfaction, such as course content, the effectiveness of the faculty, the accessibility of facilities, and the level of service provided, according to Hossain et al. (2018). Although these factors (interactivity, content of the course, and the design of the course quality) have been studied deeply (Cheng, 2020), little research has been conducted on their influence on learners' satisfaction and continuation intentions. User satisfaction with e-learning systems affects continuation intentions (Larsen et al., 2009; Lee, 2010; Lin & Wang, 2012).

H6: User satisfaction has a significant impact on continuance intention.

2.7 Continued Intention

The correspondence principle was also proposed by Ajzen and Fishbein (1977), stating that if one observes the correspondence principle, then the desire for someone to adopt a certain behavior in the future can be accurately predicted by the correspondence principle. It is explained by Cho et al. (2009) that continuous technology use is about using it in a continuous and long-term manner that is long-term and continuous. It has been suggested by Chiu and Wang (2008) that a person's willingness to continue to engage in e-learning could give a clue to their level of computer self-efficacy when it comes to their ability to use technology effectively. Two main factors influence continuation intentions towards e-learning, both of which are influenced by low interpersonal influence. The first factor is the low quality of information in our e-learning services, which is influenced by the second factor.

A study by Davis (1985) found that users who believe technology will improve their performance have more intentions of using technology and will be more likely to use it if they believe it will benefit them. Findings indicate that PU and intention to adopt e-learning are directly associated and significantly correlated. Participation in class plays a significant role in influencing the attitudes and behaviors of students and is one of the most significant influences on their behavior (Lee, 2010; Lee et al., 2005).

3. Research Methods and Materials

3.1 Research Framework

This conceptual framework was developed after a review of previous theoretical frameworks, which were based on a review of previous research. It is based on three different theoretical models from which it has been adapted. To begin with, Daultani et al. (2020) studied course attributes, system attributes, instructor attributes, and interactive attributes and how these attributes affect user satisfaction while using e-learning in higher education institutions. Secondly, Wang et al. (2017) proved that social influence on innovation continuance intention positively impacts innovative continuance intention. The final study was conducted by Cheng (2020), which focused on the involvement of satisfaction and continuance intentions. A conceptual framework for this study is presented in Figure 1.

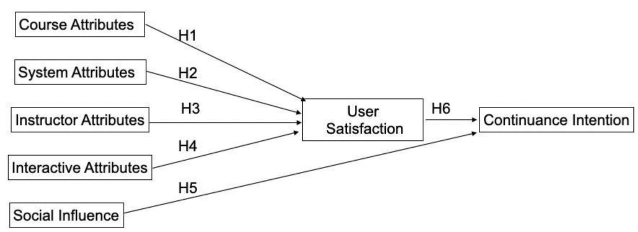

Figure 1: Conceptual Framework

H1: Course attributes have a significant impact on user satisfaction.
H2: System attributes have a significant impact on user satisfaction.
H3: Instructor attributes have a significant impact on user satisfaction.
H4: Interactive attributes have a significant impact on user satisfaction.
H5: Social influence has a significant impact on continuance intention.
H6: User satisfaction has a significant impact on continuance intention

3.2 Research Methodology

To achieve the objective of this study, the researcher employed a nonprobability sampling method for the quantitative approach, employing both online and paper questionnaires distributed to five selected university students. A comprehensive analysis of the collected data has been performed, and several factors that affect the Satisfaction and Continuance Intentions of University students regarding e-learning have been identified. The survey is divided into three parts, each of which has its purpose. First of all, screening questions are used to determine the participants' characteristics. The second step was to use a five-point Likert scale to measure the level of agreement for each of the four hypotheses. At the end of the analysis, we used a 5-point Likert scale to present the results. In addition, the demographic question concerns the gender, age, and educational background of the applicant. A pilot test was conducted on 30 respondents to assess the 'index of item-objective congruence' (IOC) and the pilot test.

The validity and reliability of Cronbach's Alpha were tested using the Cronbach's Alpha approach. To evaluate the reliability of the questionnaire, 500 responses were accepted following the reliability test before the questionnaire was distributed to a target group of respondents. The researcher used an SPSS AMOS 26.0 program to analyze the collected data. Confirmatory Factor Analysis (CFA) was employed to test the accuracy of convergence and validate the model. The model fit measurement was calculated in conjunction with the overall test to evaluate whether the model matched the data or not to verify its validity and reliability. Furthermore, to investigate the significance of variables in the subject matter of the study, the researcher employed a Structural Equation Model (SEM).

3.3 Population and Sample Size

Students enrolled in five selective universities in the Zhejiang province of China are the main target population for this paper. A sample size of at least 200 respondents was recommended in the literature for Structural Equation Models (Kline, 2016), which is the recommendation for this study. A total of 550 respondents were surveyed as part of this survey. In this study, 500 responses from the survey were used after they had been screened for data quality.

3.4 Sampling Technique

To select students from five universities in Zhejiang, the author has used a non-probability sampling method based on purposive sampling. Then, stratified random sampling was used to determine the sampling quotas for each university. The proportions of the distribution are shown in Table Furthermore, convenience sampling was used to distribute online and survey to collect data.

Table 1: Sample Units and Sample Size

Universities	Population Size	Proportional Sample Size
Jiaxing University	15600	115
Jiaxing Nanhu University	7700	57
Wenzhou University	16754	123
Taizhou University	15000	110
Lishui University	13000	95
Total	**68054**	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

The demographic profile of the study targets 500 participants. Table 2 shows that 56.4% (282) of participants were females, while 43.6% (218) were males. According to the educational background of respondents, 97.2% had undergraduate degrees (486), and 2.8% had graduate degrees (14). Under the age of 20 represented 68.8% (344) of the total sample in this study, followed by 21-29 years of age, which accounted for 31.2% (156). As for e-learning experience, the largest group was those who began 2018-2019 (256), followed by those who began 2020-2021 (196), followed by those who began pre-2015 (11.2%), followed by those who began 2016-2017 (13.6%). There were 38.4% (192) traditional courses, 27.8% (139) hybrid courses, and 33.8% (169) hybrid courses among respondents as to the type of course offered at universities.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	218	43.6%
	Female	282	56.4%
Education background	Graduate	14	2.8%
	Undergraduate	486	97.2%
Age	Under 20 years old	344	68.8%
	21-29 years old	156	31.2%
	30-39 years old	0	0.0%
	40-49years old	0	0.0%
	More than 49 years old	0	0.0%
E-learning Experience	Pre-2015	56	11.2%
	2016-2017	68	13.6%
	2018-2019	278	55.6%
	2020-2021	98	19.6%
Type of Courses	Cloud-based e-learning	192	38.4%
	Traditional courses	139	27.8%
	Hybrid courses	169	33.8%

Source: Constructed by author

4.2 Confirmatory Factor Analysis (CFA)

CFA is a type of qualitative approach that aims to determine whether items in a conceptual model can be evaluated based on their effectiveness or acceptability, according to Alkhadim et al. (2019). For the factor loading to be considered significant, it must be greater than 0.5, and the p-value must be less than 0.05. In addition, the structural reliability of the model must be at least 0.7, and the variance extracted from the model must be at least 0.5 (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
Courses Attributes (CA)	(Daultani et al., 2020)	6	0.925	0.704-0.778	0.886	0.564
System Attributes (SA)	(Daultani et al., 2020)	4	0.898	0.776-0.828	0.878	0.642
Instructor Attributes (InsA)	(Daultani et al., 2020)	7	0.920	0.769-0.791	0.916	0.609
Interactive Attributes (IntA)	(Baber, 2022)	3	0.834	0.738-0.786	0.813	0.592
User Satisfaction (US)	(Venkatesh et al., 2003)	4	0.880	0.738-0.786	0.847	0.581
Social Influence (SI)	(Tsai et al., 2007)	4	0.969	0.751-0.777	0.852	0.591
Continuance Intention (CI)	(Chang, 2013)	3	0.924	0.747-0.816	0.816	0.597

In this study, chi-square (CMIN/df), goodness of fit index (GFI), adjusted goodness of fit index (AGFI), normalized fit index (NFI), Tucker Lewis index (TLI), comparative fit index (CFI), and root mean square approximation error (RMSEA) present good fit of measurement, as shown in Table 4.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	530.866/413 or 1.285
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.937
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.924
NFI	≥ 0.80 (Wu & Wang, 2006)	0.935
CFI	≥ 0.80 (Bentler, 1990)	0.985
TLI	≥ 0.80 (Sharma et al., 2005)	0.983
RMSEA	< 0.08 (Pedroso et al., 2016)	0.024
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, NFI = Normed fit index, CFI = Comparative fit index, TLI = Tucker-Lewis index, and RMSEA = Root mean square error of approximation.

Table 5 reports that if the root of the square of the average variance extracted from the model can be greater than the product of the coefficients derived from another structure that is a part of the same model, then discriminant validity is considered valid.

Table 5: Discriminant Validity

	CA	SA	InsA	IntA	SI	US	CI
CA	**0.751**						
SA	0.312	**0.801**					
InsA	0.342	0.338	**0.780**				
IntA	0.282	0.279	0.315	**0.769**			
SI	0.303	0.268	0.291	0.274	**0.769**		
US	0.319	0.336	0.378	0.259	0.217	**0.762**	
CI	0.298	0.288	0.254	0.359	0.146	0.323	**0.773**

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

4.3 Structural Equation Model (SEM)

For evaluating structural model fitness, the goodness-of-fit indices are the same as those for evaluating measurement model fitness. There are several indices evaluated, including Chi-square statistics (CMIN/df), Goodness-of-Fit-Index (GFI), Adjusted Goodness-of-Fit-Index (AGFI), Normed Fit Index (NFI), Comparative Fit Index (CFI), Tucker Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA).

The statistical results are shown in Table 6, with CMIN/DF = 2.120, GFI = 0.883, AGFI = 0.865, NFI = 0.890, CFI = 0.938, TLI = 0.933, and RMSEA = 0.047. Therefore, the structural model was adjusted to improve the goodness-of-fit indices until the fitness could be confirmed.

Table 6: Goodness of Fit for Structural Model

Index	Acceptable	Statistical Values
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	907.475/428 or 2.120
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.883
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.865
NFI	≥ 0.80 (Wu & Wang, 2006)	0.890
CFI	≥ 0.80 (Bentler, 1990)	0.938
TLI	≥ 0.80 (Sharma et al., 2005)	0.933
RMSEA	< 0.08 (Pedroso et al., 2016)	0.047
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, NFI = Normed fit index, CFI = Comparative fit index, TLI = Tucker-Lewis index, and RMSEA = Root mean square error of approximation.

4.4 Research Hypothesis Testing Result

To calculate the significance of every variable that appears within a model of a study, regression weights, and R2 variances are both used in conjunction with regression weights. This is so that we can calculate the importance of each variable in the analysis. Table 7 indicates that five of the six hypotheses were significantly supported by a p-value of 0.05, a significant significance level. Most hypotheses reported indicate that system attributes will likely increase satisfaction and continuance intentions to use e-learning. In this table, instructor attributes were 0.278, followed by course attributes (0.189), interactive attributes (0130), and user satisfaction (0.070). In contrast, social influence was found to be 0.384, which is unsupported. According to the model results, there is a variance associated with innovation at work, as shown in Table 7, based on the model results.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-Value	Result
H1: CA→US	0.189	3.841*	Supported
H2: SA→US	0.278	5.497*	Supported
H3: InsA→US	0.276	5.540*	Supported
H4: IntA→US	0.130	2.553*	Supported
H5: SI→CI	0.070	1.375	Not Supported
H6: US→CI	0.384	6.902*	Supported

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

The results in Table 7 can be further refined:

H1 indicated a positive relationship between course attributes and user satisfaction, as the standard coefficient is 0.189, and the t-value is 3.841. As Peltier et al. (2007) demonstrated, learners' and users' satisfaction with e-learning can be influenced by e-learning content, teaching effectiveness, and course structure.

H2 found a positive correlation between system attributes and user satisfaction. This study's standard coefficient was 0.278, and the t-value was 5.497, indicating a strong link between the variables. Cidral et al. (2018) found that electronic learning systems facilitate collaborative learning and enhance interactive learning among learners, which leads to enhanced satisfaction with learning.

H3 postulated a positive relationship between instructor attributes and user satisfaction. According to the data, the standard coefficient value and the t-value are 0.276 and 5.540, respectively. Pham et al. (2019) found that students' satisfaction with e-learning is directly related to the quality of their instructors.

H4 found a positive correlation between interactive attributes and user satisfaction, with a standard coefficient of 0.130 and a t-value of 2.553. As stated by Zhang et al. (2006), a student's satisfaction with e-learning can also be influenced by interactive attributes, such as a learner's attitude and the platform's inherent capabilities, which can facilitate online classes.

H5 indicated that there is no positive correlation between social influence and continuance intention, as the standard coefficient value is 0.070, and the t-value is 1.375, indicating no positive relationship between them. Therefore, this study is different from previous studies that have been conducted. According to Tahiri et al. (2017), social influence can significantly affect behavioral intentions as people's opinions influence how they participate in specific actions.

H6 found that social influence had a positive relationship with continued intention. In this case, it shows a standard coefficient value of 0.3844 and a t-value of 6.902. Users will likely continue to use cloud computing services if they remain satisfied with the services and continue to rely on e-learning for their learning needs (Cheng, 2020; Tan & Kim, 2015; Xu et al., 2017).

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

The universities, education institutions, and lecturers can cope with the transition and adopt effective strategies for utilizing e-learning in a valuable manner by understanding the significant factors influencing university students' satisfaction and intention to continue learning. Universities, education institutions, and lecturers should ensure that their teaching and learning process is as effective as having traditional teaching methods. In order to conduct this research, questionnaires were developed for 500 students from five universities in Zhejiang. By referring to two fundamental research theories, TAM and UTAUT, along with previous empirical studies, a conceptual framework was developed for the study. To measure and test the conceptual model's validity and reliability, confirmatory factor analyses (CFA) were conducted. Therefore, the factors influencing innovative work behavior were analyzed using the Structural Equation Model (SEM).

As a result of the research, the following findings were described. A significant impact of User Satisfaction on Continuance Intention can be seen in the first paragraph. User satisfaction with technology has been shown to influence the intention to continue using the service (Bhattacherjee, 2001; Hoehle et al., 2011). It is also important to consider course attributes regarding user satisfaction. System Attributes strongly influence user satisfaction. Instructor attributes greatly influence satisfaction with instructors. Interactive Attributes significantly impact user satisfaction. There was support for five of the six hypotheses. Continuance intention is not significantly influenced by social influence.

5.2 Recommendation

The researcher discovered key factors impacting satisfaction and continuance intention to e-learning of university students, which are course attributes (CA), system attributes (SA), instructor attributes (InsA), interactive attributes (IntA), social influence (SI), user satisfaction (US) and continuance intention (CI). Therefore, the recommendation from the research findings for development is to encourage universities, education institutions, and lecturers to focus on these aspects to build a higher level of positive student experiences using e-learning, resulting in positive course attributes (CA) and instructor attributes. It has been found that e-learning is satisfying when it meets the specific demands of users at various levels, according to Lee (2010) and Liu et al. (2010). According to Pham et al. (2019), students' satisfaction with e-learning is directly correlated with the quality of their instructors. As a result, universities, educational institutions, and lecturers could be offered the possibility of raising their System attributes and instructor attributes.

Moreover, System Attributes (SA), Interactive Attributes (IntA), and User Satisfaction (US) are also important. Cidral et al. (2018) suggest that electronic learning systems enhance learners' ability to interact with each other and to collaborate, which in turn improves their overall satisfaction with the learning process. In Liaw's (2008) analysis, multimedia teaching appears to enhance the positive attitude of learners towards e-learning and produce an e-learning effect by promoting learners' enthusiasm and commitment toward e-learning. To promote the capability of an e-learning system and positive user experience, a functional e-learning platform is essential. In summary, this research is useful for universities, educational institutions, and lecturers to develop strategies for scaling and optimizing student satisfaction to facilitate student satisfaction and continued involvement in e-learning.

5.3 Limitation and Further Study

The study has some limitations regarding the aspect of the target group. Given the limited time and venue for the study, the sample size was relatively small due to space and time limitations. There is a reason for the narrow empirical base of the study, which can be attributed to the small sample size used in the study. While the partial least squares approach was well suited to the study despite its suitability, its limitations as to the number of participants limited the amount of explanation it could provide. Despite its suitability, they made it less adequate for representation of the student population as a whole. To rectify this situation, we are planning to conduct a lengthy, comprehensive case study on the topic over the next several years in order to introduce cloud services into more institutions, convince more teachers to use these services, and obtain additional metrics as a means of improving this situation that goes beyond teachers' self-reported perceptions.

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