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Exploring What Drives E-Learning Satisfaction and Continued Use Among Undergraduate Students in Jiangxi, China

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Abstract

Purpose: This paper generally explores the key factors influencing undergraduate students' satisfaction and continued use intentions at a university in Jiangxi, China, when engaging in e-learning. **Research design, data, and methodology:** The study's student population was 500 undergraduate students. Questionnaires were used to survey university students at a Jiangxi, China university with experience with e-learning to get statistical data. The gathered data was analyzed using Systematic Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) to determine the correlations between the variables. **Results:** The research indicates high-quality course content will likely meet students' expectations and needs. Students generally have certain expectations for online courses, including the content's relevance, depth, and practicality. Students feel their choice has been validated when course content meets or exceeds these expectations. Therefore, the quality of course content helps students gain recognition for online learning. **Conclusions:** With the progression of the times and continuous advancements in information technology, e-learning has become the preferred choice for most learners, especially during the widespread adoption of online learning during the COVID-19 pandemic. E-learning has greatly complemented traditional teaching methods.

Keywords: Course Content Quality, Confirmation, Perceived Value, Perceived Usefulness, Satisfaction

JEL Classification Code: E44, F31, F37, G15

1. Introduction

From the ancient past to today's rapidly evolving technological era, the world has undergone profound changes. Naturally, as learning has become increasingly remote—from traditional in-person classrooms to e-learning—students' learning patterns have also been growing

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(Khan, 1997; Taylor, 2014). Computers have become ubiquitous in every household and profession, and teaching methods have shifted from traditional lectures to multimedia presentations. Thanks to the ongoing advancements in network technology, the world has transformed into a worldwide knowledge repository with a central network that resembles a global library. Distance and physical location are no longer barriers to learning, and e-learning has made it possible to take advantage of more learning options.

In the past, accessing educational resources from globally renowned universities has always been a challenge. E-learning allows people to experience information flow without changing their living environment and habits or sacrificing academic or career pursuits with long journeys. It enables learning to take place anywhere without barriers. There is no bias or discrimination based on status; everyone can enjoy equal learning resources. Successful learning is possible regardless of where you are, creating an endless treasure trove of resources (Sharpe & Benfield, 2005).

Today, e-learning platforms such as Mushrooms After Rain, Chinese University MOOC, Superstar Learning, and Learning Power provide students with rich learning resources and methods. These platforms make learning more convenient, breaking through geographical and time limitations and allowing knowledge to be disseminated globally. At the same time, E-learning provides a fair, competitive environment, enabling everyone to enjoy equal educational opportunities and creating more possibilities for our society.

As technology advances, the author can foresee that online learning will become more deeply ingrained in society and become the mainstream mode of education. It will promote educational fairness, enhance educational quality, and allow more people to access knowledge. In this globalized learning environment, individuals will continually broaden their horizons, elevate themselves, and contribute to society's progress. E-learning not only changes our learning methods but also creates a learning new world full of infinite possibilities.

E-learning can also promote students' learning and communication and will not be affected by stressful environments. Communication without face-to-face communication can encourage students to be more logical and think when expressing themselves, so there is no need to worry about racial or gender discrimination, etc. In ordinary classrooms, students from Asia are often considered shy and introverted. Through online learning, Asian students can answer questions and express their opinions easily and freely. Such a learning model allows everyone to express their learning experiences (Sharpe & Benfield, 2005).

2. Literature Review

2.1 Course Content Quality

The course content quality refers to the standards of the learning content generated within the e-learning system, and the diverse and regularly updated course content provided by the e-learning system may lead learners to perceive it as a valuable learning resource (Cheng, 2020). The course content quality is defined as the quality of the presentation of learning content within an e-learning system. Suppose learners perceive that the design of the course content provided by the e-learning system can be customized to meet their individual needs and adapt to different levels of requirements. In that case, they will recognize that the system could be a beneficial learning tool (Lee, 2006). The course content quality refers to the effectiveness of the content in helping learners achieve their learning objectives. It is also an important reference indicator for students using e-learning (Adeyinka & Mutula, 2010).

H1: Couse content quality has a significant impact on confirmation.

H2: Couse content quality has a significant impact on satisfaction.

2.2 Confirmation

Confirmation refers to students' expectation level for e-learning to achieve anticipated outcomes. Research shows that this sense of confirmation positively enhances user satisfaction, which in turn strengthens their intention to continue using the e-learning system (Lee, 2010). Confirmation signifies the positive outcomes produced by users when engaging with e-learning, which align with their expectations of the e-learning experience (Chow & Shi, 2014). Confirmation refers to the expected understanding of the actual functions and effectiveness of the e-learning information content (Joo & Choi, 2016). When a consumer uses e-learning, confirmation results from their assessment of the service impacts and expected returns (Oh & Ma, 2018).

H3: Confirmation has a significant impact on satisfaction.

2.3 Perceived Value

According to Isik (2008), perceived value refers to consumers' overall assessment of a product's utility based on their perceptions of what they receive and give in exchange for the product or service. Customer satisfaction is closely related to perceived value; when perceived value increases, customer satisfaction also increases accordingly. In designing e-learning systems, using perceived value as a measurement standard helps designers gain a deeper understanding of customer needs, strive to achieve customer

goals, and enhance customer satisfaction with e-learning applications. Perceived value is the overall customer evaluation of a product or service's usefulness after a cost-benefit analysis, according to Prebensen et al. (2013) and Kumar and Reinartz (2016).
H4: Perceived value has a significant impact on satisfaction**.**

2.4 Perceived Easiness

According to Davis (1989), perceived easiness is the extent to which a person feels that utilizing a specific technology would require little physical or mental effort. According to Aggelidis and Chatzoglou (2012), perceived easiness refers to how simple users believe a system to be to use. People will be more satisfied and likely to use a system again if they believe it to be simple, boosting their positive attitude (De Smet et al., 2012). Perceived easiness refers to an individual's belief that utilizing information technology systems will not be inconvenient or require significant effort (Wijana, 2010). Perwitasari (2022) states that perceived easiness refers to the extent to which an individual believes that a particular system will take little effort or less work than necessary. Perceived ease is the extent to which an individual believes that accessing information is easy and does not require additional effort (Wibisono & Ang, 2019).
H5: Perceived easiness has a significant impact on satisfaction.

2.5 Perceived Usefulness

According to Cheok and Wong (2015), perceived usefulness is defined as the perceived level at which improvements occur after implementing the system. Users are more inclined to use the system when they believe e-learning may help them acquire the necessary knowledge and skills. Perceived usefulness refers to the enhancement in outcomes after using the system. The more scholars believe that e-learning can aid in acquiring skills, experience, and knowledge, the more likely they are to use the system (Khasawneh & Yaseen, 2017). Perceived usefulness of an e-learning among learners is mainly based on how much learning outcomes improve after utilizing the system. (Sun et al., 2008). Burke (1997) asserts that the perceived utility of e-learning platforms encourages users to continue using them. Perceived usefulness is a crucial factor influencing user satisfaction and the possibility that a user would continue using a service, claim Humbani and Wiese (2019). The study defines perceived utility as the user's belief that utilizing the IB website will enhance their ability to do the activity at hand.
H6: Perceived usefulness has a significant impact on satisfaction.

2.6 Satisfaction

Satisfaction refers to the degree to which the e-learning system meets users' information needs at a high level (Gay, 2016). According to Larsen et al. (2009), users' level of satisfaction with e-learning can influence their propensity to utilize it going forward. Ambalov (2018) thinks satisfaction is a psychological state users generate when using e-learning, producing a positive subjective consciousness, and positively impacting users' perceptions of e-learning. Satisfaction is a metric that compares the experience of using an e-learning system with consumers' expectations after use. Moreover, when users are satisfied, they may adjust their expectations and intentions (Mazuri et al., 2017). Satisfaction is interpreted as fulfilling a need, desire, or expectation. Management studies consider it to fulfill customer needs (Oliver, 1999).
H7: Satisfaction has a significant impact on continuance intention.

2.7 Continuance Intention

Continuance intention is the likelihood of users persisting in adopting the e-learning system. This concept is often used as a key indicator to measure e-learning usage's sustainability and predict users' ongoing behaviors (Chiu et al., 2007). Continued intention refers to the deep-seated desire of users to continue using the e-learning system, meaning that users are inclined to persist in utilizing the e-learning system to achieve specific goals (Liaw, 2008). Continuance intention describes the variables that affect an information system's (IS) extended use. It entails being aware of the long-term elements that are essential to achievement (Bhattacherjee, 2001; Lin et al., 2017; Wang, 2015).

3. Research Methods and Materials

3.1 Research Framework

This study is based on a conceptual framework that integrates existing theoretical foundations with research evidence confirmed in previous studies. The conceptual framework clearly illustrates the causal relationships among these variables. The primary objective is to examine and research the factors that affect college students' happiness with and desire to continue utilizing e-learning in Jiangxi, China.

"Course content quality," "confirmation," "satisfaction," and "continuance intention" are the variables used in the first framework, "Student Satisfaction and Continued Intention in Cloud-Based E-Learning: The Role of Interactivity and

Course Quality Factors." The variables included in the second framework, which examines the factors influencing students' intention to continue using academic library electronic learning systems, are "perceived value" and "satisfaction." In the model known as "E-Learning Satisfaction and Retention: Parallel Perspectives of Cognitive Absorption, Perceived Social Presence, and Technology Acceptance Model," the variables considered include "perceived usefulness," "perceived ease of use," and "e-satisfaction."

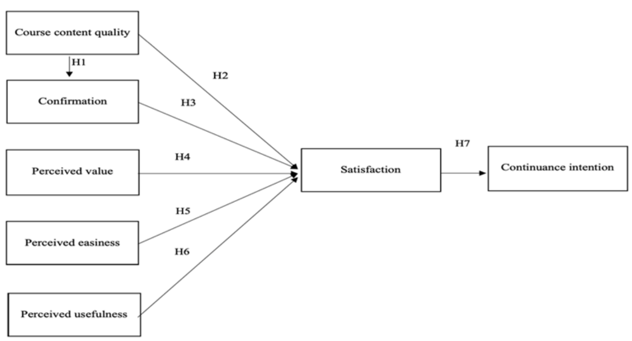

Figure 1: Conceptual Framework

H1: Course content quality has a significant impact on the confirmation.
H2: Course content quality has a significant impact on satisfaction.
H3: Confirmation has a significant impact on satisfaction.
H4: Perceived value has a significant impact on satisfaction.
H5: Perceived easiness has a significant impact on the satisfaction.
H6: Perceived usefulness has a significant impact on the satisfaction.
H7: Satisfaction has a significant impact on continuance intention.

3.2 Research Methodology

Quantitative research includes methods designed to analyze social phenomena systematically using numerical or statistical data. Measuring is, therefore, a part of quantitative research, which likewise operates under the presumption that study subjects are measurable. Quantitative research aims to measure things to gather data, analyze them to find patterns and connections and verify the measurements (Watson, 2015). Quantitative methods and the scientific method are the cornerstones of modern science. Research begins with specific theories, whether known or newly proposed, forming concrete hypotheses. Subsequently, following established research procedures, these hypotheses undergo quantitative measurement, rigorous analysis, and evaluation (Bloomfield & Fisher, 2019).

3.3 Population and Sample Size

According to the information compiled by the Student Affairs Management Office of Nanchang Institute of Technology, there are 13,873 undergraduate students at Nanchang Institute of Science and Technology.

Researchers can secure the statistical reliability and representativeness of the study outcomes by determining the right sample size and assessing the responses. To accomplish this paper's research tasks, the minimum required sample size is 425. For this study, the author has chosen a sample size of 500 undergraduate students to gain a more comprehensive understanding of the research.

3.4 Sampling Technique

Using stratified random sampling, a probabilistic sampling technique, each stratum is sampled randomly once the population is divided into non-overlapping subgroups (Aoyama, 1954). By ensuring that each subgroup has an equal representation in the sample, this procedure seeks to provide a more realistic picture of the variety within the population.

Therefore, the researchers opted for stratified random sampling to ensure representativeness at each stratum, enabling the sample to reflect the overall diversity better and gain a deeper understanding of the distinct feedback from students with different educational backgrounds. To obtain precise statistical data, the authors selected 500 undergraduate students.

Table 1: Sample Units and Sample Size

Three Main Grades	Undergraduate user count	Propositional Sample Size
Fresh Year	5,626	203
Sophomore Year	4,460	161
Junior Year	3,787	136
Total	**13,873**	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

In this study, researchers surveyed 500 bachelor's degree students and collected their basic information. Among the participants, first-year students accounted for 40.6%, second-year students 32.2%, and third-year students 37.2%. Regarding professional distribution, 23.6% of the students were majoring in E-commerce, 20.4% in Big Data and Accounting, 9.8% in Marketing management, 33.2% in Business Administration, and 13% in Big Data Management and Application. Regarding the frequency of E-learning, the data showed that 53.4% of the students engaged in E-learning five times a week, while 46.6% used E-learning resources only once a week.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Level	Undergraduate college	500	100%
Grade	Year 1	203	40.6%
	Year 2	161	32.2%
	Year 3	136	27.2%
Major	E-commerce	118	23.6%
	Big Data and Accounti	102	20.4%
	Marketing management	49	9.8%
	Business Administration	166	33.2%
	Big Data Management	65	13%
Frequency of using mobile learning	Regular (5 times a week)	267	53.4%
	Rare (Once a week)	233	46.6%

4.2 Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis (CFA) is a structural equation modeling technique that focuses on exploring and confirming the mapping relationships between observed variables, such as test items, scores, behavioral observations, and latent factors (Brown & Moore, 2012). This technique is used to test the validity of measurement models. The application of CFA in scale reliability estimation allows researchers to validate the structure of the scale, ensuring that each item is related to the latent factors as expected. The scale can be considered highly reliable if the CFA results indicate a good model fit (Raykov, 2001). Simply put, CFA is a technique that aims to determine the number of latent factors and test whether the loadings of the observed variables on these latent factors align with theoretical predictions (Malhotra et al., 2007).

Convergent validity refers to the correlation between the scores of a measurement tool and the scores of other tools used to measure the same or related concepts (Tudor-Locke et al., 2002). The Fornell and Larcker (1981) criterion is widely used to assess the shared variance between latent variables in a model, evaluating the convergent validity of the measurement model through Average Variance Extracted (AVE) and Composite Reliability (CR). AVE measures the variance captured by the construct versus the variance due to measurement error; an AVE value above 0.7 is considered good, while a value of 0.5 is acceptable. CR provides a less biased reliability estimate than Cronbach's Alpha, with an acceptable CR value above 0.7.

As shown in Table 3, the factor loadings range from 0.731 to 0.819, exceeding the required threshold of 0.5. The CR (Composite Reliability) values range from 0.774 to 0.887, greater than the required 0.7. The AVE (Average Variance Extracted) values range from 0.533 to 0.651, all exceeding the threshold of 0.5. Based on these values, the convergent validity for perceived enjoyment, attitude, and usage intention is favorable.

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
Course content quality (CCQ)	Cheng (2020)	5	0.886	0.731-0.811	0.887	0.611
Confirmation (C)	Oh and Ma (2018)	3	0.848	0.788-0.819	0.848	0.651
Perceived value (PV)	Isik (2008)	3	0.774	0.739-0.742	0.774	0.533
Perceived easiness (PE)	Davis (1989)	3	0.814	0.755-0.780	0.814	0.593
Perceived usefulness (PU)	Cheok and Wong (2015)	3	0.825	0.780-0.785	0.825	0.611
Satisfaction (S)	Larsen et al. (2009)	5	0.983	0.735-0.819	0.884	0.603
Continuance intention (CI)	Chiu et al. (2007)	4	0.871	0.746-0.906	0.877	0.642

As listed in Table 4, the final fit indices are as follows: the ratio of chi-square to degrees of freedom (CMIN/df) is 1.879, the Goodness of Fit Index (GFI) is 0.926, the Adjusted Goodness of Fit Index (AGFI) is 0.907, the Normed Fit Index (NFI) is 0.928, the Comparative Fit Index (CFI) is 0.965, the Tucker-Lewis Index (TLI) is 0.959, and the Root Mean Square Error of Approximation (RMSEA) is 0.042. These indices fall within acceptable ranges, indicating a good fit for the model.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	522.321/303 or 1.879
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.926
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.907
NFI	≥ 0.80 (Wu & Wang, 2006)	0.928
CFI	≥ 0.80 (Bentler, 1990)	0.965
TLI	≥ 0.80 (Sharma et al., 2005)	0.959
RMSEA	< 0.08 (Pedroso et al., 2016)	0.042
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, CFI = comparative fit index, TLI = Tucker Lewis index, and RMSEA = root mean square error of approximation

According to Fornell and Larcker (1981), testing for discriminant validity was evaluated by computing the square root of each AVE. Based on this study, the value of discriminant validity is larger than all inter-construct/factor correlations; therefore, discriminant validity is supportive. The convergent and discriminant validity were proved; therefore, the evidence is sufficient for establishing construct validity.

Table 5: Discriminant Validity

	CCQ	C	PV	PE	PU	S	CI
CCQ	**0.782**						
C	0.472	**0.807**					
PV	0.520	0.412	**0.730**				
PE	0.570	0.544	0.658	**0.770**			
PU	0.443	0.367	0.482	0.453	**0.782**		
S	0.619	0.503	0.522	0.627	0.508	**0.777**	
CI	0.493	0.426	0.433	0.490	0.547	0.558	**0.802**

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 Structural Equation Modeling (SEM), the acceptable range for the fit indices is the same as that used in the previous Confirmatory Factor Analysis (CFA). The analysis of the data included in the study aims to construct a satisfactory model. The indicators shown in Table 5 illustrate the changes before and after the adjustments, with CMIN/DF = 3.158, GFI = 0.860, AGFI = 0.828, NFI = 0.876, CFI = 0.911, TLI = 0.899, and RMSEA = 0.066. All these indicators meet the fit criteria requirements.

Table 6: Goodness of Fit for Structural Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	903.326/286 or 3.158
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.860
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.828
NFI	≥ 0.80 (Wu & Wang, 2006)	0.876
CFI	≥ 0.80 (Bentler, 1990)	0.911
TLI	≥ 0.80 (Sharma et al., 2005)	0.899
RMSEA	< 0.08 (Pedroso et al., 2016)	0.066
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, CFI = comparative fit index, TLI = Tucker Lewis index, and RMSEA = root mean square error of approximation

4.4 Research Hypothesis Testing Result

Using p-values, the results are assessed to determine whether the regression analysis results align with the hypotheses proposed by the researcher. Standardized path coefficients are used to measure the strength of the effect of independent variables on dependent variables. These seven hypotheses have been tested based on Table 7. Specifically, when students choose e-learning, their perceived usefulness and ease of use positively influence their attitude toward online learning. In contrast, the compatibility of mobile learning affects their perception of enjoyment from the mobile learning experience. Additionally, compatibility, perceived enjoyment of mobile learning, attitude, cognitive needs, and social influence all directly impact students' intention to use mobile learning.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: CCQ→C	0.477	8.817*	Supported
H2: CCQ→S	0.387	6.897*	Supported
H3: C→S	0.176	3.326*	Supported
H4: PV→S	0.110	2.367*	Supported
H5: PE→S	0.325	6.589*	Supported
H6: PU→S	0.253	5.406*	Supported
H7: S→CI	0.528	10.198*	Supported

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

In the study targeting undergraduate students, it was found that course content quality significantly impacts confirmation. The regression analysis results of the first sample data support this finding. The standardized path coefficient for hypothesis H1 is 0.477, with a corresponding t-value of 8.817, indicating that course content quality is crucial in shaping students' confirmation of e-learning. Additionally, Mtebe and Raisamo (2014) suggest that high-quality course content can motivate users to focus more on their studies, achieve expected learning outcomes, and gain confirmation.

In this study, course content quality significantly impacted undergraduate students' satisfaction, as validated by the regression analysis of the sample data. The standardized path coefficient for hypothesis H2 is 0.387, with a corresponding t-value of 6.897, indicating that course content quality is crucial in shaping students' satisfaction with e-learning. Therefore, if undergraduates perceive that course content quality can enhance their academic performance, their satisfaction will significantly change the study. Lee (2006) also confirmed this in his research, stating that regularly updated and content-rich courses that meet students' expectations enable them to learn effortlessly, increasing their satisfaction with e-learning.

Confirmation significantly impacts perceived enjoyment, with a standardized path coefficient for H3 of 0.176 and a t-value of 3.326. The study indicates that confirmation affects undergraduate students' satisfaction with e-learning, supporting Bhattacherjee (2001) findings. The research suggests that if undergraduates believe e-learning meets their expected expectations, they are likely to feel satisfied using it and will continue to use it.

The impact of perceived value on satisfaction with e-learning is also very positive. The standardized path coefficient for H4 is 0.110, with a t-value of 2.367. According to McDougall and Levesque (2000), this hypothesis is confirmed, indicating that perceived value can significantly influence satisfaction. When undergraduates feel that the outcomes they achieve through e-learning are valuable, their satisfaction with e-learning will increase, and they will likely continue using it. Perceived easiness also significantly impacts satisfaction; the standardized path coefficient for H5 is 0.325, with a t-value of 6.589. Phuong et al. (2020) also confirmed this theoretical perspective, stating that perceived ease of use can bring satisfaction to users in the context of e-learning. This implies that when undergraduates find e-learning easy to operate and use, it enhances their satisfaction with the platform, leading to a continued intention to use it.

Perceived usefulness particularly impacts satisfaction; the standardized path coefficient for H6 is 0.253, with a t-value of 5.406. This result indicates that the perceived usefulness of e-learning can enhance satisfaction. Seddon and Kiew (1996) explored the hypothesis between perceived usefulness and satisfaction, which is also significantly demonstrated in this study. Undergraduates' satisfaction with e-learning is largely due to the system's ability to provide useful knowledge, enabling them to gain more knowledge.

Simultaneously, satisfaction significantly impacts the intention to continue using e-learning, with the standardized path coefficient for H7 being 0.528 and a t-value of 10.198. This result proves that satisfaction is a crucial factor influencing the intention to continue using e-learning. Zhang et al. (2015) and Chen (2010) provided evidence in their previous studies to support this hypothesis. Undergraduates' satisfaction with e-learning can foster their intention to continue using it.

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

This study explores the main factors impacting students from a higher education institution in Jiangxi Province, China, regarding satisfaction and continuance intention towards e-learning platforms. The student population for the study was divided into undergraduates students. The conceptual model created in the research integrates the best elements of achievements from related academic disciplines and thoroughly examines related theories in order to offer important insights for the study.

The theoretical frameworks for this research are the Expectation Confirmation Model (ECM) and the Technology Acceptance Model (TAM). The Expectation Confirmation Model (ECM) is often used in research to thoroughly examine the several aspects affecting users' intention to continue. Translation: The Expectation Confirmation Model proposed by Bhattacherjee (2001) measures the consistency between users' expected outcomes and actual experiences, influencing users' satisfaction with the product and their intention to continue using it. Oliver (1980) stated that the Expectation Confirmation Model can affect users' decision-making. The Technology Acceptance Model (TAM) constructed by Davis (1989) significantly impacts users' continued usage behavior. According to Seçkin et al. (2016), based on TAM, users' evaluations of a product's ease of use and usefulness are key factors influencing their intention to continue using it. In this dissertation, the factors associated with TAM and ECM have finally been thoroughly investigated.

It is advised to use questionnaires to conduct a survey among undergraduate students at a Jiangxi, China university who have experience with e-learning in order to get statistical data. The gathered data was analyzed using Systematic Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) to determine the correlations between the variables.

5.2 Recommendation

The results of this study confirm that course content quality, confirmation, perceived value, perceived ease of use, and perceived usefulness can enhance student satisfaction with online learning and their intention to continue using it. Additionally, these findings offer several recommendations for online learning providers, researchers, educators, and institutions to optimize their platforms and course content, thereby improving student satisfaction and continued usage. Firstly, ensure high-quality content by developing and offering well-structured, comprehensive, and easy-to-understand courses that include the latest research findings and practical case studies, ensuring students gain cutting-edge knowledge and skills. Regularly update and improve the content based on student feedback and the latest academic developments to maintain its high quality and relevance. Provide diverse teaching materials such as videos, audio, text, and interactive exercises to cater to various learning styles. Clearly define learning objectives and benefits at the start of the course, outlining the goals, expected outcomes, and specific benefits to academic and career development. Offer valuable certificates or credentials recognized in the academic and professional markets to enhance the perceived value of the course and establish a reasonable pricing strategy to ensure students feel they receive value for their investment.

5.3 Limitation and Further Study

This study examines various factors affecting college students' satisfaction with e-learning and their intention to continue using it. It provides actionable insights for e-learning providers, researchers, educators, and institutions. However, it is important to acknowledge some limitations of this study.

Firstly, the study may be constrained by sample selection. If the sample is concentrated in specific regions or disciplines, it may only partially represent the e-learning experiences of some college students. Therefore, future research could expand the sample to include more regions and disciplines to obtain more representative results.

Secondly, while the study covers multiple aspects of the e-learning experience, other variables may be unexplored, such as individual learning motivation, social support, and learning environment. These factors could also significantly impact students' satisfaction and their intention to continue using online learning. Subsequent research could explore these potential factors further to provide a more comprehensive understanding.

Finally, although this study's conclusions and recommendations offer valuable guidance for improving current e-learning platforms, the effectiveness of these recommendations may vary across different technological environments and educational contexts. Therefore, e-learning providers should tailor and optimize these recommendations according to local conditions.

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