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Determinants of Satisfaction and Continuance Intention to Use Cloud-Based E-Learning Among Undergraduate Students in Ningxia Universities

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Abstract

Purpose: This study examines what factors affect the satisfaction and continuance intention of college students majoring in English translation and interpreting on cloud-based e-learning. The conceptual framework consists of task-technology fit, learning-technology fit, interactivity, course content quality, course design quality, organizational support, perceived usefulness, satisfaction and continuance intention. **Research design, data, and methodology:** A quantitative research method was used to distribute questionnaires to three Ningxia universities and perform data analysis. Structural Equation Modeling (SEM) and Confirmatory Factor Analysis (CFA) were applied to analyze the collected results and examine the pre-designed hypotheses' model fit, reliability, and validity. **Results:** It was found that satisfaction was the strongest predictor of continuance intention, followed by perceived usefulness. In addition to learning-technology fit as an antecedent, task-technology fit, interactivity, course content quality, course design quality, and organizational support showed significant and positive effects on satisfaction and perceived usefulness. **Conclusion:** Achieving and improving the satisfaction of students to use cloud-based e-learning is the priority for developers, administrators, and teachers. For organizations, adequate support for users and cloud-based e-learning is beneficial to enhance users' perceived usefulness. For developers, updating and ensuring a high degree of technical alignment of the system with the user's mission is an effective approach.

Keywords: Cloud-Based E-Learning, Course Content Quality, Perceived Usefulness, Satisfaction, Continuance Intention

JEL Classification Code: E44, F31, F37, G15

1. Introduction

The modern society has developed to be technology-driven, and rapidly booming technology and its application have dramatically changed the global pattern of education. The COVID-19 pandemic has hit industries at home and abroad, including the education system (Alon et al., 2020). Since the beginning of the pandemic, electronic learning (e-learning), using electronic systems and applications (Ali et al., 2018), has been widely used. In detail, it mainly affected students' studies, examination arrangements, internal evaluation, and internship scenarios (Amita, 2020). To minimize the influence of the coronavirus pandemic on normal learning, educational institutions across the country

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had no choice but to move their teaching positions online. E-learning was an extremely convenient and effective way for students to learn with less contact. Alfraih and Alanezi (2016) stated that e-learning transforms the traditional learning method was so influential, which was reflected in the improvement of both teaching and learning. E-learning promoted distance interaction between students and experienced faculty/professors (Wang et al., 2009). Rapanta et al. (2020) stated that e-learning and e-assessment were representative mitigation efforts to abate the effect of COVID-19 on learning and teaching.

However, a study showed that learning processes of online and offline modes had different advantages and disadvantages, and the sudden shift of learning mode took work for students (Chadda & Kaur, 2021). Despite the convenience, online learning did not necessarily have good results, and students needed a better sense of experience. The pandemic has spurred the world to improve and innovate e-learning. At the same time, students and teachers were adapting to various technology platforms (Chadda & Kaur, 2021). Survey results recognized that most students were well prepared for the e-learning teaching model, though the degree of readiness varies (Adams et al., 2022). Cloud-based e-learning has gained wide focus from researchers and educators due to its ubiquitous accessibility, especially in developing countries (Liu et al., 2010). Hence, it is essential to check into the component that impacts students' satisfaction in the procedure of e-learning before understanding whether cloud-based e-learning is beneficial to students and furthering the effectiveness of e-learning. Figuring out the determinants was beneficial to improve students' sense of learning experience and helping them gain more knowledge (Samsudeen & Mohamed, 2019). As the importance of cloud-based e-learning becomes increasingly prominent during the epidemic, this study explores the factors affecting the satisfaction of cloud-based e-learning for college students, based on the investigation of college students majoring in English translation and interpreting in Ningxia, China. The results and suggestions of this study are aimed at providing a reference for educational institutions and relevant researchers to adopt effective strategies to improve student's learning efficiency through cloud-based online learning platforms.

2. Literature Review

2.1 Task-technology Fit

According to Hsiao and Chen (2015), task-technology fit (TTF) refers to how well your ability to use technology matches the demands of tasks you need to finish. Cheng (2019) stated that TTF was a cloud-based e-learning system that tested the possibility of helping students complete specific activities.

Hsiao and Chen (2015) noted that task-technology fit was instructive in perceived usefulness. His/Her perceived usefulness was enhanced if the technical ability matches the task the person was currently required to perform. That is, the person was likelier to believe that reading an e-book on an e-reader would improve his/her performance in completing learning activities. Furthermore, Cheng (2019) mentioned that task-technology fit, as a key antecedent, played a part in the perceived usefulness of the cloud-based e-learning system. Specifically, if the technology of the e-cloud learning system were sufficient to support users in completing tasks, it would improve perceived usefulness. In conclusion, this research proposed the hypothesis that:

H1: Task-technology fit has a significant impact on perceived usefulness.

2.2 Learning-technology Fit

According to Singh et al. (2020), learning-technology fit was an information system for evaluating the individuals' acceptance of computer technology used in education concerning the facts of users' convictions, attitudes, and preferences, figuring out endogenous causes in the meantime. Arteaga Sánchez-López (2013) conveyed that learning-technology fit was a tool that owns a great reputation for exploring and explaining user adoption of e-technologies by two main factors: perceived usefulness and attitude. Additionally, learning-technology fit, listed with virtual reality, artificial intelligence, and the Internet of Things, was a core form to produce user-made education as scheduled (Isaías, 2018).

In academic research, Singh et al. (2020) pointed out that perceived usefulness, which belonged to learning-technology fit, was fundamental. With interactivity and cost-effectiveness counterparts, learning-technology fit and perceived usefulness helped the usage of DCP in India. In addition, Arteaga Sánchez-López (2013) illustrated an analogical correlation between learning-technology fit and perceived usefulness. They showed that perceived usefulness and ease of use were the two main approaches influencing the adaptability of learning techniques. Based on this finding, promotion in learning-technology fit was not far to explore with the help of satisfied perceived usefulness. By reviewing previous studies, the research made the following hypothesis:

H2: Learning-technology fit has a significant impact on perceived usefulness.

2.3 Interactivity

Cheng (2020) proposed that interactivity was an entity's evaluation to do with the terrace's capacity to facilitate initiative charge and users' interaction, both of which are intersecting and isochronous. Learners' interactivity online refers to their active engagement in the learning process (Lee & An, 2018). Gunesekera et al. (2019) fundamentally defined interactivity in e-learning education as the following pivotal aspects: student-student, student-instructor, and student-content interaction.

Lee and An (2018) pointed out that learner interaction positively moderated the model's relationships. They concluded that their interactivity was stronger for learners with strongly perceived usefulness. This was consistent with the finding of Cheng (2020), which indicated that if cooperation between teachers and students through an e-learning platform were two-way and mutual, they would think reading was effective because of the interactive capabilities. Thus, they concluded that interactivity would positively affect cloud-based e-learning systems, especially PU.

Many previous researchers have also testified to the relativity of interactivity and satisfaction. Gunesekera et al. (2019) researched the application of Human-Computer Interaction in e-learning. They concluded that HCI interweaves the three relationships of e-learning, Student-Student Interaction, Student-Instructor Interaction, and Student-Content Interaction through interfaces that transform trio relationships, leading to higher or lower user satisfaction. This relationship can also be certified in Poondej and Lerdpornkulrat's (2020) research about gamification in e-learning, which proposed that gamification could effectively improve students' participation and learning motivation, overcome the challenge of motivation and participation in e-learning, and greatly improve students' favor and loyal of e-learning. Thus, in this research, the researcher made the following hypothesis:

H3: Interactivity has a significant impact on perceived usefulness.

H4: Interactivity has a significant impact on satisfaction.

2.4 Course Content Quality

Course content quality was defined as the quality of an independent and self-standing learning content element that tended to renew in various educational circumstances (Siqueira et al., 2007). According to Shea and Parayitam (2019), course content quality was the quality of what the professors illustrated in the syllabus on the initial day of the class.

According to Lee (2006), the impact of course content quality on perceived usefulness was marked. Research showed that once offered high-quality course content, students likely feel that e-learning courses are useful. Likely, notable learning outcomes could be seen. It was of more use and acceptance to users if using media methods such as audio tutorials and videos in online education. (Scholtz & Kapeso, 2014). Consequently, they concluded that the quality of content could effectively affect perceived usefulness. Teo (2010) pointed out that the learning environment concluding the provision of the course materials was one element that affected the perceived usefulness of online education. That was because a conducive learning environment contributed to positive results in the cognitive and affective fields.

A wide range of scholars has also proved another hypothesis. New structures that represented learning objects and learning activities could be materialized and represented to learners according to their circumstances, consequently satisfying their demands in personalized learning (Siqueira et al., 2007). In other research, course content quality proved student contentment to be strongly and emphatically connected (Shea & Parayitam, 2019). Generated from the previous studies, this research made the hypothesis that:

H5: Course content quality has a significant impact on perceived usefulness.

H8: Course content quality has a significant impact on satisfaction.

2.5 Course Design Quality

Course design quality was, for Gentile et al. (2020), the result of the own power of teachers, who was responsible for considering the construction of the course and teaching materials in the class. Meanwhile, a further definition of course, design quality, was given by Gentile et al. (2020), who described that course design quality was the result of numerous decisions and educational processes, which demanded suitable degrees of conversation and framework to make the route diminished. According to a definition provided by Combe (2005), course design quality could be illustrated from the perspective of Web pedagogy, which concentrates on the theoretical views and process of learning to benefit the construction of instructional design and content's harmonization and delivery system.

According to Cheng (2012), informal quality, including course design and content quality, could be the antecedent of e-learning acceptance to lay the foundation for perceived usefulness. Besides, the relationship was further explained in the research that if the course design quality could satisfy the user's needs, learners would perceive the course as easier and more useful to acknowledge. Furthermore, this study found a remarkable effect of course design quality on perceived usefulness was found in the research that course design quality would help learners to adapt to the online system and class more easily, which positively affects the perceived usefulness and subsequently improve the enthusiasm of using e-learning system (Al-Omairi et al., 2021). This was in line with the study of Rui-Hsin and Lin (2017), which stated that course design quality would act positively on perceived usefulness. They pointed out that if an e-learning system could function well and provide effective lessons, learners would perceive it as a useful tool for obtaining accurate knowledge.

Besides, Lee (2006) pointed out in his research that users' satisfaction would increase significantly if course design quality could help them obtain accurate information. Other studies also expressed similar ideas. Course design quality can positively influence satisfaction (Cheng, 2020). He pointed out that if the course design quality could meet different levels of users, they would be satisfied with the system. Similarly, Daultani et al. (2020) concluded in their research that course design quality was a critical factor of user s satisfaction and one of the predictors of results and satisfaction in acquiring knowledge. Based on the previous studies, the researcher hypothesized as follow:

H6: Course design quality has a significant impact on perceived usefulness.

H9: Course design quality has a significant impact on satisfaction.

2.6 Organizational Support

Sawang et al. (2012) thought that organizational support could be recognized as the extent to which an individual believes the organizational infrastructure favors e-learning. Cheng et al. (2019) defined organizational support as the provision of personal computers and printers, online library services, and to offer instruments of e-learning and assistance in high technology for those studying in schools.

Previous research proved that there was a close relationship between organizational support and the effectiveness of better e-learning perceived usefulness by Sawang et al. (2012). They found that if perceptions of organizational support were low, employees who were less open to transformation and thought the former e-learning was more complicated would have less initiative to use e-learning further. If perceptions of organizational support were high, employees who were highly open to transformation and thought the former e-learning was less complicated would have more initiative to use e-learning further. In Cheng et al. (2019) study, they proposed that organizational support may affect perceived ease of use and perceived usefulness. The teacher intended to examine curriculum components to combine web-enhanced instruction with traditional classroom lessons. The findings revealed a strong link between organizational support, employee satisfaction, and perceived usefulness. Generated from the previous studies, this research made the hypothesis that:

H7: Organizational support has a significant impact on perceived usefulness.

2.7 Perceived Usefulness

Kashive et al. (2020) thought that perceived usefulness was when someone believed they could improve their performance by using special systems. Considering Salimon et al. (2021), perceived usefulness was one of the prime variations of the technology adoption pattern, and it was also regarded as the degree to which online learners believed that their performance in some courses chosen by themselves could be improved by using an online learning platform.

Salimon et al. (2021) pointed out that PU provided some benefits, such as job uploading, while other connected benefits could improve performance and bring the necessary satisfaction. Thus, they concluded that the relationship between perceived usefulness and satisfaction was positively significant. This follows the study of Cheng (2013), which illustrated that nurses' perceived usefulness to the hybrid e-learning system significantly impacted their satisfaction and willingness to continue. In summary, this research proposed the hypothesis that:

H10: Perceived usefulness has a significant impact on satisfaction.

H12: Perceived usefulness has a significant impact on continuance intention.

2.8 Satisfaction

In Shea and Parayitam (2019) research, students who think their education is worthy of the invested money and time felt satisfied. Satisfaction was thought of as the perception of the cheerful fulfillment of demands and desires, which was generally accepted as an ideal result of any product or service experience in marketing. In the e-learning context, it took on a different meaning that includes many sides of the message systems (Siritongthaworn & Krairit, 2006).

Satisfaction had a substantial direct influence on intention, with a significant positive association between satisfaction and sustained intention to use (Chen et al., 2017; Min et al., 2022). For example, students who felt that these online courses helped improve their learning quality and competitiveness would like to use the platforms. This was in line with the study of Chang (2013); quality awareness influences value and satisfaction, which was a crucial mediator in understanding the direct relationship between quality and intention to continue; therefore, contentment

would affect continued satisfaction. In conclusion, this research proposed the hypothesis that:
H11: Satisfaction has a significant impact on continuance intention.

2.9 Continuance Intention

Continuance intention is defined as the degree to which a person intends to continue using it in the future and persuade others to use it (Mouakket & Bettayeb, 2015). Cheng (2014) regarded continuance intention as the key to achieving the eventual success of blended e-learning. According to Mouakket and Bettayeb (2015), perceived usefulness significantly impacted continuation intention. He concluded that if an individual believed that e-learning could be useful for his/her personal development, it would be positive to continuance intention. Cheng (2014) found that perceived usefulness, confirmation, and flow explained user satisfaction, affecting continuance intention. Therefore, this research put forward the hypothesis that:

3. Research Methods and Materials

3.1 Research Framework

This study aims to determine the variables that influence cloud-based e-learning satisfaction for college students majoring in English translation and interpreting in Ningxia, China. The researcher applied three major previous research frameworks to support and, as illustrated in Figure 1, developed the research's conceptual framework. The previous study's framework, the first one is conducted by Cheng (2020), and it provides the study of Satisfaction (Satisfy), Course Design Quality (CDQ), Interactivity (Int), Continuance intention (CI), Course Content Quality (CCQ) and Perceived Usefulness (PU). The second research, carried out by Cheng (2020), is concerned with the investigation of Organizational Support (OS) and Perceived Usefulness (PU). The third one is conducted by Cheng (2021), and it provides the study of Perceived Usefulness (PU), Task-Technology Fit (TTF), Continuance intention (CI), and Learning-Technology Fit (LTF).

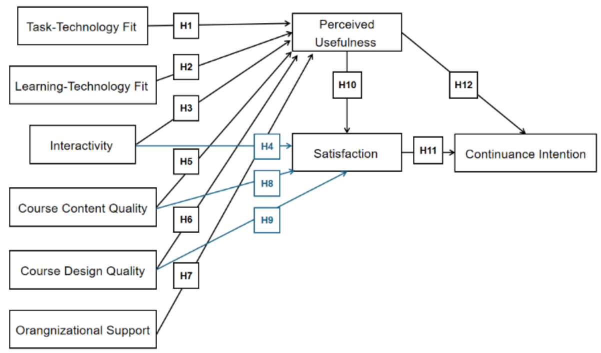

Figure 1: Conceptual Framework

H1: Task-technology fit has a significant impact on perceived usefulness.
H2: Learning-technology fit has a significant impact on perceived usefulness.
H3: Interactivity has a significant impact on perceived usefulness.
H4: Interactivity has a significant impact on satisfaction.
H5: Course content quality has a significant impact on perceived usefulness.
H6: Course design quality has a significant impact on perceived usefulness.
H7: Organizational support has a significant impact on perceived usefulness.
H8: Course content quality has a significant impact on satisfaction.
H9: Course design quality has a significant impact on satisfaction
H10: Perceived usefulness has a significant impact on satisfaction.
H11: Satisfaction has a significant impact on continuance intention.
H12: Perceived usefulness has a significant impact on continuance intention.

3.2 Research Methodology

The researcher designed a quantitative study to collect data by questionnaire. Three parts are implemented to the questionnaire survey in this study. The first part was screening questions. Second, they measured nine variables: task-technology fit, learning-technology fit, interactivity, course content quality, course design quality, organizational support, perceived usefulness, satisfaction, and continuance intention. Specifically, a five-point Likert scale (1=strongly disagree, 5=strongly agree) was chosen to evaluate nine factors influencing cloud-based e-learning satisfaction. The third part is to identify the demographics of the respondents.

Before distributing the questionnaire to the target population, the researcher conducted Item-Objective Congruence (IOC) to test content validity. Then, pilot testing was done to validate the constructs' reliability, which meant that 45 participants matched the character of the sample units that filled out the questionnaire. IOC results were passed by three expert rating at 0.6. and the Cronbach coefficients were greater than the acceptable value at 0.7 (Hair et al., 2007). After gathering quantitative data, the data was analyzed by testing the convergent and discriminant validity and applying SEM as the statistical treatment.

3.3 Population and Sample Size

According to Hair et al. (2007), the target population related to the research project and was a complete set of components. This study concentrated on undergraduate students majoring in English with detailed majors in English translation and interpreting at three universities in Ningxia Province, where all sample data were collected. Initially, to guarantee the conclusion's reliability and rigor, the target population was selected from Ningxia University, North Minzu University, and Ningxia Normal University.

Taherdoost (2016) pointed out that the sample capacity was vital to any empirical research to reach conclusions about the sample population. Therefore, minimum sample size should be around 200-500.Based on the points of leading scholars and a sample size calculator for modeling structural equations, the final decision of this study was to set the sample size at 500.

3.4 Sampling Technique

Judgment sampling is that the research judged and selected a sample and evaluated it under the standard of the attributes required by the sample participants (Hair et al., 2007). In this context, student respondents were expected to have a good command of English to understand the questionnaire and have e-learning experiences with a high probability. The target group must be undergraduate students aged 16 to 24 studying at Ningxia University, Northern Minzu University, and Ningxia Normal University.

According to the quota sampling, the total population majoring in English literature and the proportional sample size are displayed in Table 1. Convenience Sampling was defined by Dörnyei (2007) as a non-probabilistic or non-random sampling of respondents in a sampling survey who meet specific functional requirements. Therefore, convenience sampling is to distribute online questionnaire due to respondents can be quickly responded.

Table 1: Population and Sample Size by University

Three Universities in Ningxia	Proportion	Proportional Sample Size
Ningxia Normal University	466	100
North Minzu University	679	150
Ningxia University	898	250
Total	**2043**	**500**

Source: Created by the author.

4. Results and Discussion

4.1 Demographic Information

Based on Table 2, the results demonstrate the demographical data from 500 respondents. Most respondents are males at 53.8 percent, and females are 46.2 percent. The major group of students is juniors at 31.6 percent, seniors at 25 percent, first-year students at 23 percent, and sophomores at 20.4 percent.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	269	53.8%
	Female	231	46.2%
Year of Study	Freshmen	115	23.0%
	Sophomore	102	20.4%
	Junior	158	31.6%
	Senior	125	25.0%

4.2 Confirmatory Factor Analysis (CFA)

Jöreskog (1969) mentioned that the confirmatory factory analysis could be employed to verify the measurement model's convergent and discriminant validity. In this study, effective methods of convergent validity included average variance extraction (AVE), composite reliability (CR), Cronbach's alpha reliability (CA), and factor loadings. As demonstrated in Table 3, there was a very high degree of consistency within the structure established in this study, and the data reflected in the questionnaire are reliable. Specifically, the Cronbach coefficients were greater than 0.7, and factors loading were greater than 0.5, within the range of 0.768 to 0.889. Similarly, For the Composite Reliability, this was evidenced where CR ranged between 0.872 and 0.919. The values of the AVEs tested on this scale all exceeded 0.4, specifically around the range of 0.674 to 0.739.

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
Task-technology Fit (TTF)	Barhoumi, 2016	4	0.918	0.820-0.886	0.919	0.739
Learning-technology Fit (LTF)	Stoel & Hye Lee, 2003	4	0.909	0.826-0.889	0.910	0.716
Interactivity (INT)	Sarker et al., 2019	3	0.874	0.800-0.888	0.876	0.702
Course Content Quality (CCQ)	Cheng, 2012	3	0.876	0.813-0.860	0.877	0.704
Course Design Quality (CDQ)	Liu, 2009	4	0.894	0.768-0.847	0.895	0.680
Organizational Support (OS)	Hajli et al., 2013	3	0.870	0.810-0.869	0.872	0.694
Perceived Usefulness (PU)	Teo, 2010	5	0.911	0.802-0.836	0.912	0.674
Satisfaction (SAT)	Cheng, 2012	4	0.915	0.846-0.875	0.916	0.731
Continuance Intention (CI)	Chang, 2013	4	0.911	0.805-0.871	0.913	0.723

The acceptable value of goodness-of-fit indices presented the measurement model fit. The statistical value of indices could be compared to the acceptance criteria, which are CMIN/DF=2.940, GFI=0.925, AGFI=0.800, NFI=0.891, CFI=0.925, TLI=0.913, and RMSEA=0.062.

Table 4: Goodness of Fit for Measurement Model

Index	Acceptable Values	Statistical Values
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	1428.828/486 or 2.940
GFI	≥ 0.80 (Doll et al., 1994)	0.925
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.800
NFI	≥ 0.80 (Wu & Wang, 2006)	0.891
CFI	≥ 0.80 (Bentler, 1990)	0.925
TLI	≥ 0.80 (Sharma et al., 2005)	0.913
RMSEA	< 0.08 (Pedroso et al., 2016)	0.062
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 = Normed fit index, CFI = Comparative fit index, TLI = Tucker-Lewis index, and RMSEA = Root mean square error of approximation

Zait and Bertea (2011) recommend that discriminant validity can be appraised with the assistance of three instruments: q-sort, chi-squared difference test, and average variance extraction (AVE). Table 4 demonstrated that the square root values of AVE in all variables were larger than the correlation between that variable and the other variables. Consequently, this study was good discriminant validity.

Table 5: Discriminant Validity

	TTF	LTF	INT	CCQ	CDQ	OS	PU	SAT	CI
TTF	**0.859**								
LTF	0.202	**0.846**							
INT	0.216	0.255	**0.838**						
CCQ	0.312	0.226	0.279	**0.839**					
CDQ	0.296	0.167	0.302	0.297	**0.825**				
OS	0.230	0.229	0.182	0.182	0.247	**0.833**			
PU	0.360	0.248	0.313	0.324	0.378	0.386	**0.821**		
SAT	0.396	0.365	0.311	0.346	0.333	0.338	0.331	**0.855**	
CI	0.328	0.226	0.350	0.251	0.283	0.251	0.358	0.413	**0.851**

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

4.3 Structural Equation Model (SEM)

Rigdon (1998) defines Structural Equation Modeling (SEM) as a multivariant statistical analysis technique that demonstrates, evaluates, and then rests linear relationships within variables on the background of study through a theoretical network. In the current study, the researcher utilized SEM to measure the adjustability of the previously constructed model, validate the correlation within the variables, and further search the influencing elements that impacted university students' favorability using cloud-based e-learning. The statistical values of indices the structural model are within the acceptance criteria after the adjustment, which are CMIN/DF=3.004, GFI=0.837, AGFI=0.803, NFI=0.887, CFI=0.921, TLI=0.910, and RMSEA=0.063.

Table 6: Goodness of Fit for Structural Model

Index	Acceptable Values	Statistical Values Before Adjustment	Statistical Values After Adjustment
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	2062.541/515 or 4.005	1481.177/493 or 3.004
GFI	≥ 0.80 (Doll et al., 1994)	0.761	0.837
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.724	0.803
NFI	≥ 0.80 (Wu & Wang, 2006)	0.842	0.887
CFI	≥ 0.80 (Bentler, 1990)	0.876	0.921
TLI	≥ 0.80 (Sharma et al., 2005)	0.865	0.910
RMSEA	< 0.08 (Pedroso et al., 2016)	0.078	0.063
Model Summary		**Not in harmony with empirical data**	**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

Standardized and regression coefficients are instruments commonly used to verify that all hypotheses formulated in the study are supported. Table 7 evidenced the correlation between the independent and dependent variables in the hypotheses.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: TTF→PU	0.192	3.871**	Supported
H2: LTF→PU	0.063	1.448	Not Supported
H3: INT→PU	0.134	2.916*	Supported
H4: INT→SAT	0.176	3.558**	Supported
H5: CCQ→PU	0.119	2.534*	Supported
H6: CDQ→PU	0.200	3.828**	Supported
H7: OS→PU	0.274	5.478**	Supported
H8: CCQ→SAT	0.221	4.444**	Supported
H9: CDQ→SAT	0.192	3.397**	Supported
H10: PU→SAT	0.161	3.059**	Supported
H11: SAT→CI	0.336	6.893**	Supported
H12: PU→CI	0.297	5.964**	Supported

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

The hypotheses of English translation and interpreting were held except for H2. The test results showed the masses of important factors influencing the continuance intentions satisfaction, with perceived usefulness (PU) being the second. Equally, satisfaction (Sat) has a strong significance with interactivity (Int), course content quality (CCQ), and course design quality (CDQ). However, learning-technology fit (LTF) out of the seven independent variables does not correlate with perceived usefulness (PU).

Of the five established hypotheses, organizational support (OS) with standardized coefficients of 0.274 and t-value of 5.478** demonstrated the most significant effect on perceived usefulness. Therefore, H7 was valid and strongly supported by previous researchers, Sawang et al. (2012), Cheng et al. (2019), Cheng (2014), and Zainab et al. (2015), respectively. According to the research, learners accept and recognize e-platforms when the organization provides specific support.

The second variable in H1 that has a significant impact on perceived usefulness is task-technology fit (TTF), whose normalized path coefficient is 0.192 and T-value is 3.871**, validating the study of Hsiao and Chen (2015), Cheng (2019) and Barhoumi (2016). When users realize that cloud-based e-learning technology can add substantial value to them, they will be more confident that the e-platform will facilitate their learning.

Course design quality (CDQ), one of the highly significant factors influencing perceived usefulness, had a standardized coefficient of 0.200 and a t-value of 3.828**. The same assumption (H6) was proved by Cheng (2012), Al-Omairi et al. (2021), Rui-Hsin and Lin (2017), Teo et al. (2015), and Sánchez-López (2013). Specifically, course design quality, including the suitability of course content to technology, effective online learning design, type of tasks, appropriate learning materials, and correctly identified student needs, actively affects learners' perceptions of cloud-based e-learning and improves learning outcomes.

In H3 and H5, the other variables, interactivity (Int) and course content quality (CCQ), with t-values of 2.916* and 2.534*, also impacted perceived usefulness. The former, H3, confirmed the previous Lee and An (2018), Cheng (2020), Cheng (2012), Ho et al. (2021), and Cheng (2013)'s point, which implied that interactivity, composed of three factors: steerability, reaction, and interactive linkup, would greatly encourage students to embrace cloud-based e-learning in a technology-enhanced learning environment. Similarly, the views of Lee (2010), Scholtz and Kapeso (2014), Teo (2010), Rui-Hsin and Lin (2017), and Cheng (2020) were argued once again by the latter, H4. Course content quality, with content richness, regularity of updates, and quality of information as the main measures, is one of the key elements influencing users to have strong confidence in cloud-based e-learning.

However, H2 was not supported in this study because the t-value of 1.448 showed no causal relationship between the English translation and interpreting students' learning-technology fit (LTF) and perceived usefulness. It was contradictory to the validation of Singh et al. (2020), McGill and Klobas (2009), Alfadda and Mahdi (2021), Rodríguez Lera et al. (2021), and Stoel and Hye Lee (2003).

After being significantly and positively influenced by the five variables, perceived usefulness influenced Continuity Intention (CI) and Satisfaction (Sat) in that order. A standardized path coefficient of 0.297 and t-value of 5.964** confirmed the causality of H12, and a standardized path coefficient of 0.161 and t-value of 3.059** confirmed H10. The former results had a relation to the discoveries of Mouakket and Bettayeb (2015), Cheng (2014), Chang (2013), and Cheng (2021). This means that if users are highly aware of the enhanced effect of cloud-based e-learning on their performance, they will automatically change their behavior and stick to it over time. Continuance intention relies on the correct identification of perceived usefulness. The conclusions of Salimon et al. (2021), Cheng (2013), Teo (2010), Kashive et al. (2020), and Hussein et al. (2021) were similarly tested by the current study. Specifically, as students' perceptions of expected benefits increase, their satisfaction with cloud-based e-learning increases.

In addition, the three independent variables of course content quality, interactivity, and course design quality also showed a prominent positive causal relationship with satisfaction. Course content quality (CCQ) most significantly influenced satisfaction with a t-value of 4.444**, which proved that H8 was consistent with the study of Siqueira et al. (2007), Shea and Parayitam (2019), Cheng (2012), Aristovnik et al. (2016) and Lee (2006). Up-to-date course content can be used to satisfy the individual learning demands of different students through a virtual environment, resulting in greater student satisfaction with the features and content of the e-learning platform.

According to the t-value of 3.558** for interactivity and the t-value of 3.397** for course design quality, they also played a positive role in satisfaction as other factors in H4 and H9. The views of the former scholars, namely Gunesekera et al. (2019), Sarker et al. (2019), Poondej and Lerdpornkulrat (2020), Hamdan et al. (2021), and Phutela and Dwivedi (2020) were supported by H4, while Lee (2006), Cheng (2020), Daultani et al. (2020), Rodríguez Lera et al. (2021) and Hamdan et al. (2021)'s perspectives were equally supported by H9. At great length, the high level of interactivity displayed in student-to-student, student-to-teacher, and student-to-content can effectively strengthen the connection between students and cloud e-learning, thus increasing student enjoyment and satisfaction. Furthermore, suppose the cloud-based design caters to consumers at different levels, thus helping them gain more knowledge and accurate information. In that case, this will undoubtedly greatly increase user satisfaction.

The significant factors affecting satisfaction are described above. Student satisfaction reaches a certain level, and it continues to impact the continuance intention. Such a causality is demonstrated by H11 at the high t-value of 6.893**. In the study of Chen et al. (2017), Cheng (2012), Sawang et al. (2012), Choi et al. (2015), and Mouakket and Bettayeb (2015), the same results were identified by them. A decisive element in the prosperity, no end in sight, and sustained use of cloud-based e-learning by students is satisfaction.

5. Conclusions and Recommendation

5.1 Conclusion and Discussion

The investigation was carried out to explore the factors which impact students' continuance intention to use cloud-based e-learning in universities located in Ningxia, namely Ningxia University, North Minzu University, and Ningxia Normal University. Students who majored in English translation and interpreting in three Ningxia universities and who have used cloud-based e-learning for a period were the target of the sample selection. This study established nine variables and twelve hypotheses. It decided to apply Structural Equation Modelling and Confirmatory Factor Analysis to data collected from English translation and interpreting students in three universities in Ningxia. The analysis of the data in this study is discussed as follows:

First, satisfaction as a key antecedent works with perceived usefulness to shape continuance intention. It acts as a mediating variable to assist in the formation of users' continuance intention. Such results suggest that satisfaction is a central factor when finding ways to facilitate learners' eventual successful acceptance of cloud-based e-learning. Besides, perceived usefulness, which comes second to satisfaction, is another factor that can predict continuance intention.

Secondly, perceived usefulness and satisfaction are generated by different independent variables. In detail, it is worth noting that one of the six variables, namely the relevance between learning-technology fit and perceived usefulness, is unimportant, meaning that the existence of high fitness between studying activity and learning techniques by the user could not influence the confirmation of user's perceived usefulness of the cloud-based e-learning. Simultaneously, an improvement in three variables (interactivity, course content quality, and course design quality) promotes the emotion of users' satisfaction with the antecedents. Thirdly, the connection between satisfaction and perceived usefulness exists. After using cloud-based e-learning, it is possible to forecast the satisfaction of students working as English translators regarding their perceived usefulness.

5.2 Recommendation

Regarding implications for theory, ECM, a fundamental theory, created a framework for understanding the variables affecting college students' intentions to use cloud-based e-learning systems in Ningxia universities regularly. ECM contributed to these three variables in the study, comprising perceived usefulness, satisfaction, and continuance intention. ECM is an extension of ECT proposed by Oliver (1980), which focuses on testing the perceptual performance of users in response to the use of information systems/information technology (IS/IT). Simultaneously, the continuance intention, frequently referred to as the study's central research question is a behavioral manifestation of adoption. This is why ECM is one of the core theories of this present study. The three variables, including perceived usefulness, satisfaction, and continuance intention, are designed from an external perspective to explore the logical chain that influences continuance intention. To precisely represent the user's subjective view of the tool's capacity to enhance performance, perceived usefulness is employed as an expectation that may be implemented later (Davis, 1989).

Satisfaction is defined in the context of workplace conditions as the degree to which a pleasant or positive emotion is used to demonstrate an evaluation of the work (Locke, 1976). The degree to which someone decides to use something consistently over time and tries to convince others to use it is their "continuance intention" (Mouakket & Bettayeb, 2015). The degree to which someone decides to use something consistently over time and tries to convince others to use it is their "continuance intention" (Mouakket & Bettayeb, 2015). On the other hand, perceived usefulness can be mediated by satisfaction to reveal the difference between users' expectations before using the e-earning system and their actual performance after using it. The subsequent affective changes induced can be vitally important in influencing continuance intention. Other than that, the conclusion supports the study of Lee (2010), McKeown and Anderson (2016), Lwoga and Komba (2015), and Larsen et al. (2009). However, it is found that contradictions with ECM, as the data from the second group, the English Literature group, indicates that perceived usefulness does not serve as a concept to measure student satisfaction. Such a result also raises new thoughts about the fact that students' attitudes and behaviors in their experience are not well represented due to their different needs or the constraints of their environment.

Regarding implications for practice, maximizing the incentive for user loyalty to cloud-based e-learning is a priority for university system developers, administrators, and practitioners. According to the study's results on the antecedents of satisfaction, the significant effects on satisfaction are, in descending order, course content quality, course design quality, and interactivity. Hence, developers and teachers must make sure that learning materials' information on English translation and interpreting is current and rich in real-time, keeping up with the latest requirements of the subject and the different aspects of students' needs. Meanwhile, teachers need to design class sessions to be more interactive, which means encouraging students to practice English translation materials and receive frequent teacher feedback.

Second, getting students to perceive the e-learning system as useful is also the key to success. Organizational support and task-technology fit are two of the most significant factors that positively and significantly contributed to perceived usefulness, which provides favorable implications for both organizations and developers associated with e-learning systems. On the one hand, the organization must mobilize resources to guarantee the smooth process of the system. Specifically, training sessions, such as presentations on the beginner and advanced features of cloud-based e-learning systems, can be introduced by school organizations to support students in completing their learning tasks and gaining recognition. In addition, the organization requires a full-fledged technical department to support users, facilitating the user's experience and thus eventually achieving the purpose of perceived usefulness. The department members should concentrate on the post-use services of the system, such as securing sufficient storage space in the cloud and giving timely help for problems. On the other hand, the significant effect of task technology fit on perceived usefulness indicates that implementing the e-system made the task more explicit and identifiable for students majoring in English translation and interpreting. Hence, to achieve a high match between technology and task, university administrators and developers can survey students before designing the system to grasp their task needs, such as emphasizing translation skills, knowledge building, or hands-on practice.

Finally, the invalid assumption of the English translation and interpreting group deserves considerable attention regarding why there is no significant correlation between learning-technology fit and perceived usefulness in this group. The researcher concludes that particularly pronounced individual student differences lead to a mismatch between the technology given by the cloud-based e-learning system and the learning objectives, thus preventing users from perceiving the system's usefulness. The characteristics of the English translation and interpreting group determine that the accumulation of students' knowledge and skills in the subject depends on the level of individual application ability. More important than acquiring rigid theories and knowledge is using available resources to improve one's translation ability in the long term. For those students who have solid basic knowledge and are willing to work hard, the learning goal is not limited to the basic requirements of the translated materials but pursues how to translate the materials to meet the advanced standards of credibility and elegance. Therefore, when using the cloud-based e-learning platform, such students take the initiative to explore the platform's various features and focus on different aspects of the curriculum to meet their learning needs and plans. However, for students with low standards in their subject, their learning planning may be short-term, and then naturally, they will not care about the benefits, such as resources that the platform brings to them, and neglect to use them.

Based on the above analysis, some suggestions can be considered. The most important is to increase the motivation of students at different levels to use the cloud-based e-learning system in the teaching process. How can teachers use the e-platform to weigh a teaching model that enables students at different levels to get what they need in lesson planning and classroom teaching? This is a question that deserves to be explored in depth. It is not only a consideration of teachers' ability to respond to stratification in e-platform teaching but also of the comprehensiveness and specificity of teachers' preparation before class and of how teachers can effectively connect lesson preparation and teaching to reflect maximum teaching effectiveness and usefulness. In this process, teachers must pay more attention to the actual situation, analyze the needs of students and teaching objectives at different levels, set teaching objectives at different levels, and give guidance to ensure that students at all levels can acquire knowledge in a targeted manner.

5.3 Limitation and Further Study

This study has several boundedness that should be This study has several boundedness that should be noticed, followed by recommendations for further research. Firstly, the scope and sample size of the survey was modest. This research was mainly focused on undergraduates who majored in English translation and interpreting. At the same time, the sampling scope was limited to the three universities in Ningxia region (Ningxia University, North Minzu University, and Ningxia Normal University). Secondly, the study subjects have limitations. This study mainly focuses on the cloud-based e-learning system. Further study will expand the subject to other systems of different types and objectives, such as online e-learning like Massive Open Online Courses. The more diverse the research objects are, the more different findings are likely to be produced, and the more generalized results can be obtained.

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