pISSN: 1906 - 3296 © 2020 AU-GSB e-Journal.
eISSN: 2773 – 868x © 2021 AU-GSB e-Journal.
http://www.assumptionjournal.au.edu/index.php/AU-GSB/index

Factors Impacting on Satisfaction and Continuance Intention of English Literature Students on the Use of Cloud-based E-learning in Ningxia, China

Nan Chen*

Received: March 13, 2023. Revised: September 4, 2023. Accepted: August 20, 2023

Abstract

Purpose: This study examines factors impacting the satisfaction and continuance intention of college students majoring in English literature on the use of cloud-based e-learning in Ningxia, China. The key variables involve 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:** This study was quantitatively conducted by sampling and distributing questionnaires to English literature students from three universities in Ningxia for quantitative research. The data results were analyzed, and the conceptual model was validated using Confirmatory Factor Analysis (CFA) and Structural Equation Model (SEM). **Results:** It was found that satisfaction was the strongest predictor of continuance intention, followed by perceived usefulness. All antecedents showed significant and positive effects on satisfaction and perceived usefulness. However, there was no correlation between perceived usefulness and satisfaction. **Conclusion:** Achieving and improving the satisfaction of students by paying to be fully aware of the interactivity, course content quality, and course content quality to use of cloud-based e-learning is the priority for developers, administrators, and teachers. Apart from this, the cloud-based e-learning adopted by the college needs to be responsive, novel, have enough interaction, and be relevant to their studies.

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

JEL Classification Code: E44, F31, F37, G15

1. Introduction

Before the COVID-19 pandemic, the online learning industry continued developing in China. E-learning was widely adopted in high school education, having 68 professional online institutes and online platforms for university students (McConnell, 2018). Especially due to the epidemic of COVID-19, many schools have altered vis-a-vis education to online learning; online education will grow quickly. To decline the impact of the pandemic on school education, Chinese universities rapidly choose online education (e-learning) as a way of keeping students can allow and be able to connect with teachers overseas rather than cessation of teaching and learning (Yang, 2020).

1 *Nan Chen, Director of Student Office, The School of International Education, Ningxia University, China. Email: 343885288@qq.com

The situation of cloud-based e-learning will likely enhance in the long term. However, during the growth when online education transformed into a mainstream, many obstacles blocked the way. First, the available digital education system was improving slowly (Dai, 2017). By contrast with the rest of the world, online education mark share in China was restricted on the accountant of cost and problem of operation and maintenance. Some colleges were typically hesitant to embrace open-source platforms because they needed more technical expertise to administer and maintain them (Khan et al., 2015). Second, in the digital age, many students are not interested in taking the standard courses offered by universities but rather in courses relevant to their future careers. A multi-dimensional and fragmented learning process replaced a traditional classroom-based approach, which required full utilization of resources and tools for formal and informal learning. Online courses are proving to meet these needs perfectly. Research indicates that schools should develop and deliver shorter, more personalized courses to meet these needs. Universities that emphasize face-to-face education in general, these institutions were forced to adjust (Bijeesh, n.d.). Cloud-based e-learning has great advantages in implementation, whereas the disadvantages can partly be overcome by further study. Therefore, this research has significant research value in determining factors impacting cloud-based e-learning satisfaction for college students.

2. Literature Review

2.1 Task-technology Fit

Task-technology Fit was generated when the task needs of a user required a certain technology. It also explained the relationship between information utilization and efficiency in getting work done (Tu et al., 2021). Barhoumi (2016) defined task-technology fit (TTF) was utilized as a pattern to display characteristics of tasks through the utilization of massage services and the consequence of using the technique.

Tu et al. (2021) research, users using the Line@Library would have high reliability of this library if its technology could meet their needs well. In addition, Chang (2013) also signified that the higher the user's task-technology fit, the more likely users were to use the library application to find information. In turn, their usage intention was higher. Finally, the use intention of e-library can be predicted by users' perceived usefulness, and whether users have a good attitude towards this electronic service depends to some extent on TTF (Barhoumi, 2016). In conclusion, this research proposed the hypothesis that:

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

2.2 Learning-technology Fit

Stoel and Hye Lee (2003) put forward learning-technology fit as a conceptual instrument to assess user attainment on various conditions nationwide, which was altered by the experience of online learning technology. Meanwhile, learning-technology fit was considered a wise model to predict the probability of students using cloud-based technology persistently, with the approach of perceiving uselessness and ease of use (Alfadda & Mahdi, 2021).

In academic research, learning-technology fit was straight influenced by perceived usefulness to the extent users desire to apply (Alfadda & Mahdi, 2021). Rodríguez Lera et al. (2021) discussed perceived usefulness and ease of use. Perceived usefulness was considered a fundamental factor of three core factors contributing to learning-technology fit, including attitudes toward technology and perceived ease of use. Furthermore, a synchronous alteration existed regarding how perceived usefulness impacted learning-technology fit (Stoel & Hye Lee, 2003). By reviewing previous studies, the research made the following hypothesis:

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

2.3 Interactivity

According to Sarker et al. (2019), several interactions can lead to effective learning: teacher and student, among students and the learning environment, and the students themselves. Poondej and Lerdpornkulrat (2020) thought that interactivity was a main factor that may contribute to the achievement of courses in e-learning education.

Cheng (2012) found that if users realized the interaction between students and teachers and between users themselves through e-learning systems was two-way, they might find such systems used, so they pointed out that system interactivity would play a constructive role in the PU of the network learning system. Ho et al. (2021) also pointed out that the interactivity of the e-learning system helped learners have taken to learning, and students could feel the simple operation of the e-learning system. Hence, system interactivity would contribute to the perceived usefulness of the e-learning system. In Cheng’s (2013) study, a positive relationship was also proved between interactivity and perceived usefulness. Interactive factors indirectly affected students’ willingness to use the e-learning system through external motivators (perceived usefulness).

Many previous researchers have also testified to the relativity of interactivity and satisfaction. The usefulness of the e-learning system at higher educational institutions also confirmed that most students were enthusiastic about online courses and were eager for more interaction (Sarker et al., 2019). Additionally, the relative between interactivity and satisfaction was further testified by Hamdan et al. (2021) that Student-Content Interaction and Student-Student Interaction were significant predictors of the satisfaction degree of learners with the e-learning system. By investigating the case of e-learning adoption in India, Phutela and Dwivedi (2020) also concluded that the development of online education based on the Indian higher education system should not ignore student interaction, as this online interaction greatly affected student acceptance and satisfaction. 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

Cheng (2012) regarded course content quality as one of the most used information quality measures. It referred to an assurance that e-learning is efficient under appropriate management (Scholtz & Kapeso, 2014). In some other research, the standard of the e-learning course content was defined as the quality of electronic instrumental content delivered via the internet (Lee, 2006).

Rui-Hsin and Lin's (2017) study found that course content quality played a constructive role in users' perception of the usefulness of e-learning. They summarized that pluralistic and effective courses led to the general view that information and knowledge were accurate and, therefore, useful. In another research, providing rich and updated regular course content compared to traditional ones was useful for learning. Hence, high-quality content was a key reference in judging the learners' perceived usefulness (Cheng, 2020).

According to Cheng (2012), in all probability, high levels of content quality provide students with enjoyment. Aristovnik et al. (2016) suggested that course material was one of the aspects while students estimated their satisfaction. If offered rich or up-to-date course content, learners' level of satisfaction would be enhanced remarkably (Lee, 2006). 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 the quality of four perspective-education, social, psychological, and technological, to help students construct knowledge (Liu, 2009). Moon et al. (2005) regraded that course design quality was the quality of offering an asynchronous communication facility to stimulate exchanging opinions and reconsideration and include activities. According to Gentile et al. (2020), course design quality in entrepreneurship can be explained from the perspective of some activities, including some parts of the educational system-education, research, and entrepreneurship. Successfully course design quality of online teaching depends on the advanced knowledge of instructional design and technologies (Murillo & Jones, 2020).

Teo (2010) expressed in the study that course design quality, which could also be referred to as the course delivery of the whole course design, was one of the important factors of perceived usefulness. He pointed out that if the participants were exposed to the accurate knowledge delivered by the course, they would perceive e-learning to be useful. Sánchez-López (2013) found that course design quality, including technical support, could enhance the user's acceptance, increase perceived usefulness, and achieve success.

Besides, Rodríguez Lera et al. (2021) mentioned that course design quality which can ensure social integration and prompt interaction with others, could increase students' satisfaction. Hamdan et al. (2021) also expressed a similar opinion that user satisfaction with online classes could increase course design quality and learning contents, which were the major factors. Based on the previous studies, the researcher hypothesized as follows:

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

Organizational support came from the discipline of social psychology and was "the extent to which a person's basic needs are met through interaction with others" (Hajli et al., 2013). Kapo et al. (2020) thought that organizational support factors were important to employees and served as a method of ensuring the sustainability of e-learning. According to Zainab et al. (2015), organizational support can be regarded as recognition, encouragement, and an optimistic attitude when providing training information, system development, and operations.

In previous research, in Kapo et al.'s (2020) study, a positive relationship was proved between perceived usefulness and organizational support. They regarded the perceived usefulness of acceptance model construction from technical and organizational support as relevant. This was consistent with Cheng (2012) study, which found that

organizational support influenced the perceived usefulness of the blended e-learning system. They point out that better organizational assistance was more likely to immerse people entirely in their activities. Besides, Zainab et al. (2015) also pointed out a close relationship between organizational support and perceived usefulness regarding e-learning uptake. 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

Rui-Hsin and Lin (2017) defined perceived usefulness as the results of utilizing an online studying system on user learning. Moreover, by Teo (2010), perceived usefulness was considered the extent to which a learner insisted that depending on a particular technology was to improve his or her performance on the job. Shao (2017) regarded perceived usefulness as the degree to which an individual believed e-learning was a promotion to make goals come true.

Teo (2010) found that through pre-class and after-class surveys, perceived usefulness was the strongest predictor of students' satisfaction with e-learning management education courses. Kashive et al.'s (2020) study also proved a direct correlation between perceived usefulness and satisfaction. They found that learners' perceived usefulness to e-learning affected their learning satisfaction. Meanwhile, according to Hussein et al. (2021), perceived usefulness positively influenced teachers' satisfaction with a search engine in the classroom. 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

E-satisfaction was the student's perception of their online experience during a specific time (Salimon et al., 2021). Students who were engaged in effective peer interaction tended to improve their study and achieve expected learning outcomes, hence feeling a high level of satisfaction (Gunesekera et al., 2019). Shehzadi et al. (2020) defined student satisfaction as the positive conception that the knowledge and information or their quality agree with students' expectations.

Chang (2013) pointed out that a pleased user would utilize a service more frequently in the future, consistent with expectation confirmation and adaptive expectations theories. Other studies also expressed a similar opinion. Sawang et al. (2012) stated that individual satisfaction was a major element in deciding whether or not they would use e-learning again. Users with higher self-efficacy and who were open to change would be more satisfied and adopt e-learning in years to come. Furthermore, satisfaction would positively impact the intention to continue (Choi et al., 2015). In this study, satisfaction, a user's positive feelings toward using online library resources, was a major component in the desire to use it regularly. Similar results have been obtained from Mouakket and Bettayeb (2015); satisfaction positively influenced the intention to continue using the Blackboard system. According to their findings, instructors who were satisfied with the Blackboard system were likelier to continue using it. In conclusion, this research proposed the hypothesis that:
H11: Satisfaction has a significant impact on continuance intention.

2.9 Continuance Intention

Continuance intention was considered as the result of the reputation of the university and the cause's openness, which were the significant factors (Chen et al., 2017). Chang (2013) pointed out that continuance intention was a complete result, such as perceived value and satisfaction. Cheng (2021) defined that continuance intention to e-learning was the decisive factor in making the e-learning system successful.

Perceived usefulness (PU) was critical to long-term system utilization intentions. It would continue to affect users' willingness to use e-learning systems (Li & Kitcharoen, 2022). Perceived value was a determining factor in the user's continuance intention of the e-learning system. Indeed, perceived usefulness plays a mediating role between quality and continuance intention (Chang, 2013). The perception of usefulness would contribute to the cloud-based e-learning system's long-term goals. It is worth noting that reasonable users may change their intention to continue using this system depending on their perceived usefulness (Cheng, 2021). 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 literature in Ningxia, China. The framework for the current research was formed through the three types of research, as illustrated in Figure 1. The first study, presented by Cheng in 2020, verified whether three factors, including interactivity, course content quality, and course design quality identified from students' attitudes and viewpoints, could be used as a prerequisite for influencing the willingness of educational institutions to continue to utilize cloud-based e-learning. In the second study, Cheng aimed to create an integrated model incorporating ECM, flow theory, and human-organization-technology fit framework to verify if humanity, organization, and technology are antecedent variables that influence medical staff's willingness to continue. The third study in 2021 introduced task-technology and learning-technology fit to explain and quantify the coordination between task and learning technology, the fitness between learning activity and learning technology, and integrated the third variable, cognitive absorption, to research how they influence continuation intentions.

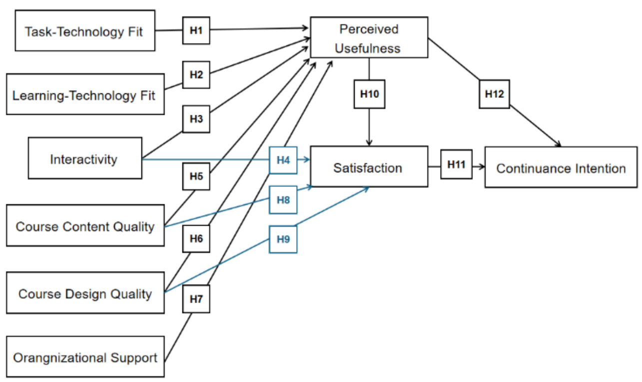

Figure 1: Conceptual Framework

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. The data collection had been made during March to June 2023. Three parts are implemented to the questionnaire survey in this study. The questionnaire had three parts: screening questions, measuring nine variables, and respondent's demographic profile. Part two used a five-point Likert scale (1=strongly disagree, 5=strongly agree) to evaluate nine factors influencing cloud-based e-learning satisfaction.

To ensure the dependability and mobility of each measurement item, before a larger group distributed the questionnaire, we conducted an Item Objective Congruence (IOC) test on three specialists and a pilot test on 45 respondents. 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

Clark-Carter (2009) stated that a crowd of people who share common behaviors for elements compose the target population. To ensure a certain degree of homogeneity among the research objects, the target population was selected from three universities: Ningxia University, North Minzu University, and Ningxia Normal University. Among them, the students at Ningxia Normal University were first-rank, North Minzu University students were second-rank, and Ningxia University was third-rank. Concurrently, the researcher focused on the target population of undergraduate students majoring in English literature.

According to Kotler (2000), the sample size was the number of respondents of all interest to the researcher. Wolf et al. (2013) pointed out that determining the appropriate sample size required for a structural equation model was 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

Babbie (1990) stated that by using judgment sampling techniques, investigators can empirically narrow down the most representative factors in the study. 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. Per the judgmental sampling, the target group must be undergraduate students in the academic year 2023, aged 18 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. For multiple sampling techniques, convenience sampling was the most popular method among researchers (Gray, 2017). There were three basic requirements considered by researchers when they decided to use it, namely accessibility, willingness to participate, and time availability (Dörnyei, 2007). This study sampled Ningxia University, Northern Minzu University, and Ningxia Normal University, as the three universities had similar educational levels. Meanwhile, the cloud-based e-learning platform was used to realize the sharing of course resources among the three universities so that students can freely choose online courses and improve learning efficiency. 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	200	100
North Minzu University	277	150
Ningxia University	430	250
Total	**907**	**500**

Source: Created by the author.

4. Results and Discussion

4.1 Demographic Information

Table 2 demonstrates the demographical data from 500 respondents. Most respondents are females at 54.2 percent, and males are 45.8 percent. Juniors are 33.2 percent, followed by sophomores at 29 percent, first-year students at 24.6 percent, and seniors at 13.2 percent.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	229	45.8%
	Female	271	54.2%
Year of Study	Freshmen	123	24.6%
	Sophomore	145	29.0%
	Junior	166	33.2%
	Senior	66	13.2%

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, four measures, such as average variance extraction (AVE), composite reliability (CR), Cronbach's alpha reliability (CA), and factor loadings, were used to measure convergent validity in this present study. 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. All values of the Cronbach coefficients were greater than the benchmark value, 0.7, and all figures of factors loading were also accepted within the range of 0.820 to 0.911. In parallel to the above two instruments, composite Reliability (CR) and Average Variance Extracted (AVE) were applied to evaluate the reliability or consistency of the multi-scaled questionnaire. The CR exhibited a peak value of 0.941 and a bottom value of 0.894, which signifies that all values are below the tolerance interval and that the structural consistency of the scale can be pledged. The values of the AVEs tested on this scale all exceeded 0.4.

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	0.940	0.888-0.907	0.941	0.799
Learning-technology Fit (LTF)	Stoel and Hye Lee (2003)	4	0.910	0.827-0.911	0.919	0.740
Interactivity (INT)	Sarker et al. (2019)	3	0.900	0.826-0.889	0.900	0.751
Course Content Quality (CCQ)	Cheng (2012)	3	0.893	0.837-0.873	0.894	0.737
Course Design Quality (CDQ)	Liu (2009)	4	0.937	0.878-0.894	0.937	0.789
Organizational Support (OS)	Hajli et al. (2013)	3	0.895	0.836-0.878	0.896	0.741
Perceived Usefulness (PU)	Teo (2010)	5	0.929	0.820-0.870	0.929	0.724
Satisfaction (SAT)	Cheng (2012)	4	0.934	0.864-0.892	0.934	0.779
Continuance Intention (CI)	Chang (2013)	4	0.927	0.822-0.894	0.927	0.760

The measurement model fit is shown in Table 4 whose content is the acceptable value of the goodness-of-fit index. The statistical value of indices could be compared to the acceptance criteria, where CMIN/DF=3.339, GFI=0.802, AGFI=0.801, NFI=0.901, CFI=0.928, TLI=0.918, and RMSEA=0.068.

Table 4: Goodness of Fit for Measurement Model

Index	Acceptable Values	Statistical Values
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	1629.589/488 or 3.339
GFI	≥ 0.80 (Doll et al., 1994)	0.802
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.801
NFI	≥ 0.80 (Wu & Wang, 2006)	0.901
CFI	≥ 0.80 (Bentler, 1990)	0.928
TLI	≥ 0.80 (Sharma et al., 2005)	0.918
RMSEA	< 0.08 (Pedroso et al., 2016)	0.068
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

Strauss and Smith (2009) stated that discriminant validity demonstrates the likelihood of no association between different constructs on a test given the same conditions. Table 5 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	**0.894**								
LTF	0.394	**0.860**							
INT	0.386	0.315	**0.867**						
CCQ	0.361	0.301	0.485	**0.859**					
CDQ	0.251	0.261	0.417	0.419	**0.888**				
OS	0.488	0.428	0.565	0.587	0.512	**0.861**			
PU	0.436	0.423	0.540	0.570	0.479	0.602	**0.851**		
SAT	0.420	0.383	0.494	0.635	0.466	0.626	0.509	**0.883**	
CI	0.388	0.378	0.496	0.458	0.356	0.531	0.526	0.562	**0.872**

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

4.3 Structural Equation Model (SEM)

The hypothesized relationships between observed and potential variables, either directed or undirected, can be estimated by SEM (MacCallum & Austin, 2000). 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 fit indices after the adjustment are acceptable, including CMIN/DF=2.871, GFI=0.840, AGFI=0.805, NFI=0.915, CFI=0.943, 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)	2723.191/515 or 5.288	1398.040/487 or 2.871
GFI	≥ 0.80 (Doll et al., 1994)	0.690	0.840
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.642	0.805
NFI	≥ 0.80 (Wu & Wang, 2006)	0.835	0.915
CFI	≥ 0.80 (Bentler, 1990)	0.861	0.943
TLI	≥ 0.80 (Sharma et al., 2005)	0.849	0.910
RMSEA	< 0.08 (Pedroso et al., 2016)	0.093	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	0.086	2.117*	Supported
H2: LTF→PU	0.177	4.031**	Supported
H3: INT→PU	0.191	4.077**	Supported
H4: INT→SAT	0.186	3.842**	Supported
H5: CCQ→PU	0.258	5.110**	Supported
H6: CDQ→PU	0.132	3.619**	Supported
H7: OS→PU	0.129	2.187*	Supported
H8: CCQ→SAT	0.507	9.212**	Supported
H9: CDQ→SAT	0.169	4.360**	Supported
H10: PU→SAT	0.045	0.824	Not Supported
H11: SAT→CI	0.385	7.987**	Supported
H12: PU→CI	0.359	7.304**	Supported

Note: ** p<0.01, * p<0.05

English literature's hypotheses were supported by all but not H10. The test results showed that satisfaction was the strongest forecast indicator to use cloud-based e-learning continuously compared with the perceived usefulness. On the other hand, the antecedents which have a significant contribution to satisfaction were ranked from course content quality, interactivity, and course design quality in the respondents. Meanwhile, there were significant and positive relationships among perceived usefulness and task-technology fit, learning-technology fit, interactivity, course content quality, course design quality, and organizational support. However, perceived usefulness does not correlate with satisfaction.

All six hypotheses that contributed to perceived usefulness hold. Course content quality (CCQ) with standardized coefficients of 0.258 and t-value of 5.110** demonstrated the most significant effect on perceived usefulness. Therefore, H5 was valid and strongly supported by previous researchers, Lee (2006), Scholtz and Kapeso (2014), Teo (2010), Rui-Hsin and Lin (2017), and Cheng (2020), respectively. The quality of course content is one of the key factors influencing strong user confidence in cloud-based e-learning. The main measures are the richness of content, regularity of updates, and quality of information.

The second variable that played a significant role in perceived usefulness was interactivity (Int) in H3, including a normalized way factor of 0.191 as well as a t-value of 4.077**, validating several experiments from Gunesekera et al. (2019), Poondej and Lerdpornkulrat (2020), Sarker et al. (2019), Hamdan et al. (2021), Phutela and Dwivedi (2020). The results prove that interactivity, consisting of three components of steerability, receptiveness, and bidirectional correspondence, would greatly encourage students to embrace cloud-based e-learning in a technology-enhanced learning environment.

Learning-technology fit (LTF) was also one of the highly significant factors influencing perceived usefulness, evidenced by a standardized coefficient of 0.177 and a t-value of 4.031**. The same assumption (H2) was proved by Singh et al. (2020), Arteaga Sánchez-López (2013), Alfadda and Mahdi (2021), Rodríguez Lera et al. (2021), Stoel and Hye Lee (2003). Specifically, LTF is used as an essential element to promote perceived usefulness.

Course design quality as a highly significant factor influencing perceived usefulness in H6 can be seen in the t-value of 3.619**. The experiment of Cheng (2012) shows that similar consequences can be discovered. Al-Omairi et al. (2021), Rui-Hsin and Lin (2017), Teo (2010) 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, has optimistic impacts on how they are concerned about the cloud-based e-learning by learners to improve performance.

In H7 and H1, the other variables, organizational support (OS) and task-technology fit (TTF), with t-values of 2.187* and 2.117*, also impacted perceived usefulness. The former, H7 confirmed the previous Sawang et al. (2012), Cheng (2020), Kapo et al. (2020), Cheng (2012), and Zainab et al. (2015) 's points, which implied that learners would embrace e-platforms and recognize them when the organization provides the specific supports. Similarly, the view of Chen et al. (2017), Cheng (2013), Tu et al. (2021), Chang (2013), and Barhoumi (2016) were argued once again by the latter, H1. When users perceive that utilizing cloud-based e-learning in technology can add substantial value, they will be more confident that the e-platform will facilitate their learning.

After the six independent variables positively impacted perceived usefulness, perceived usefulness only affected continuance intention (CI). However, not on, a normalized way factor remains 0.359 while the t-value continues at 7.304**, confirming the causality of H12. In contrast, a normalized way factor remains at 0.045 while the t-value continues at 0.824, which did not confirm H10. The former results were equivalent to the consequences of Mouakket and Bettayeb (2015), Cheng (2013), Chang (2013), and Cheng (2021). It implies that if users highly recognize that reveals their performance with an enhancing impact, they will automatically modify their behavior and thus stick with them over time. Continuance intention relies on the correct identification of perceived usefulness. The conclusions of Salimon et al. (2021), Cheng (2013), Teo (2010), Hussein et al. (2021), and Kashive et al. (2020) were not tested by the current study.

Besides, three independent variables relate to satisfaction significantly and positively causally, which concludes course content quality, course design quality, and interactivity. Course content quality (CCQ) most significantly influenced satisfaction with a t-value of 9.212**, 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 makes it possible to satisfy the individual learning requirement of different learners in a virtual circumstance, which makes students more satisfied with the features and content provided by the platform of e-learning.

According to the course design quality, they set the t-value as 4.360** and the t-value of 3.842** for interactivity; they also played a positive role in satisfaction as other factors in H9 and H4. The views of the former scholars, namely Lee (2006), Cheng (2020), Daultani et al. (2020), Rodríguez Lera et al. (2021), and Hamdan et al. (2021) were supported by H9, while Gunesekera et al. (2019), Poondej and Lerdpornkulrat (2020), Sarker et al. (2019), Hamdan et al. (2021) and Phutela and Dwivedi (2020) 's perspectives were equally supported by H4. In detail, if the cloud-based is designed to satisfy the requirements of different levels of users and help them acquire more knowledge and accurate information, user satisfaction will be greatly enhanced. Moreover, the high level of interactivity demonstrated through the activity among learners, the communication between learners and teachers, and the content within learners' formats can effectively strengthen the connection between students and cloud-based e-learning, thus increasing student enjoyment and 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 7.987**. In the study of Chen et al. (2017), Cheng (2012), Chang (2013), Sawang et al. (2012), Choi et al. (2015), and Mouakket and Bettayeb (2015), the same results were identified by them. Satisfaction is the determining aspect of successful long-period and sustained use of cloud-based e-learning among students.

5. Conclusions and Recommendation

5.1 Conclusion and Discussion

The investigation was conducted to analyze the factors influencing the satisfaction of cloud-based e-learning among university students at Ningxia, namely Ningxia University, North Minzu University, and Ningxia Normal University. Students who majored in English literature at three Ningxia universities and who have used cloud-based e-learning for a period were the target of the sample selection. Twelve hypotheses have been proposed to correspond with the defined study questions, which are to examine whether six anecdotes have a significant impact on perceived usefulness, whether interactivity, course content quality, course design quality, and perceived usefulness have an important impact on satisfaction, and whether satisfaction and perceived availability have a significant impact on ongoing intent to use cloud-based e-learning. The study also adopted CFA and SEM to validate and analyze the data and hypotheses. The analysis of the data in this study is discussed as follows:

First, satisfaction is the strongest forecast indicator for using cloud-based e-learning continuously. In the meantime, continued willingness to use cloud-based e-learning is primarily influenced by satisfaction. Therefore, improving students' satisfaction is the key to promoting students' willingness to continue learning. Additionally, users' satisfaction can be maintained by providing high-quality courses and setting interaction. The developers, universities, and teachers need to guarantee that the interactivity of courses, course content quality, and course design quality are available when using cloud-based e-learning. Only in this way can students use the cloud-based e-learning system more conveniently, ultimately making them satisfied and willing to continue to use it.

Secondly, perceived usefulness is generated by six independent variables. However, the connection between satisfaction and perceived usefulness does not exist. Hence, further research into the reasons for this is a key way to help practices improve their satisfaction with the help of perceived usefulness.

5.2 Recommendation

Regarding implications for theory, flow theory is the main basis for determining the antecedents of users' beliefs in this study. Firstly, Csikszentmihalyi (1975) found that endogenous motivational factors, including personal interest and commitment, affected perceptions of experience. In order to compensate for the fact that ECM limits the expectation of endogenous motivation for users to use the e-learning, which may be a key factor influencing users' continuance intention, flow theory helps the researcher to explore what internal factors contribute to the post-acceptance experiences of users. Secondly, experience design, particularly in terms of human-human interaction and human-computer interaction, is widely used to help improve the user experience through flow theory. Recently, researchers often use this theory in terms of human, organizational, and technological aspects to stimulate positive flow experiences to motivate continuance intention ultimately.

Regarding implications for practice, researchers continue to give priority and paramount consideration to promoting continuance intention by increasing user satisfaction. Specifically, course content quality demonstrates its significant and positive influence on satisfaction by a significant margin relative to the other two antecedents. Therefore, how to design course content that meets students' multiple needs is a primary task for the instructor when completing his course schedule with the help of a cloud-based e-learning platform.

Second, getting students to perceive the e-learning system as useful is also the key to success. Course content quality and interactivity are two of the most significant factors that positively and significantly contributed to perceived usefulness, which provides favorable implications for teachers and developers associated with e-learning systems. On the one hand, there is a need for both developers and teachers to pay extra attention to the availability of course content so that users can confirm whether these courses meet the needs of their professional learning and are useful to them. Providing access to a wide range of courses involving applied linguistics, cultural literacy, and cultural knowledge of the humanities and social sciences, coupled with updating regular, personalized, and student-centered course content is an effective way to improve students' perceived usefulness. On the other hand, it is advisable for cloud-based e-learning developers to deeply develop and establish mechanisms for interactivity based on the three distinguishing features of controllability, two-way communication, and responsiveness. Users will experience more useful if the system's functionality is easily controlled, well-matched to the learner's needs, and serve as a bridge between the teacher and the student intuitively and fluidly.

Finally, the invalid assumption of the English literature group deserves considerable attention regarding why there is no significant correlation between perceived usefulness and satisfaction in this group. The researcher suggests that due to the nature of the profession under study, there may be mediators, such as flow, or moderators, such as major, between the two variables. Perceived usefulness refers to the tangible benefits brought to the users of the English literature group through cloud-based e-learning, and satisfaction refers to a high state of pleasurable experience. Since this specialization focuses not only on the accumulation of literary works but on academic literacy and general qualities that are developed over a long period and are determined by individual abilities, consequently, when they learn useful knowledge on cloud-based e-learning, they must perform certain actions to transform it into a sense of psychological satisfaction and accomplishment. Based on the above analysis, some insights can be adopted by researchers or developers, and teachers. For researchers, exploring the connection path between perceived usefulness and satisfaction is still a different thesis that can be investigated later. Developers or teachers need to play a role in stimulating the flow of students to keep them focused or to improve the consistency of their expectations before using the cloud-based e-learning and their confirmation after using it.

5.3 Limitation and Further Study

This study has several boundedness that should be noticed, followed by recommendations for further research. Firstly, the respondents are limited. According to our initial design, the respondents are college students only. Nevertheless, the users of cloud-based e-learning systems are students, teachers, and managers. It can also be related to the parents of students and the developers. In a further study, we can include more subjects into the scope of respondents, for example, high school and even elementary school students, teachers, parents, and managers, to obtain more views from a different point of view.

Besides the suggestions above, researchers can add qualitative research to understand further college students' behavioral intentions using cloud-based e-learning. Moreover, experiments can be used to control for additional factors that may confound cause and effect. For instance, the researcher can define a specific influence factor to observe the influence of a single variable on the intention of relying on cloud-based e-learning.

References

Alfadda, A., & Mahdi, H. S. (2021). Measuring Students' Use of Zoom Application in Language Course Based on the Technology Acceptance Model (TAM). *Journal of Psycholinguistic Research*, *50*(3), 883-900. https://doi.org/10.1007/s10936-020-09752-1

Al-Mamary, Y. H., & Shamsuddin, A. (2015). Testing of the technology acceptance model in context of yemen. *Mediterranean Journal of Social Sciences, 6*(4), 268-273. https://doi.org/10.5901/mjss.2015.v6n4s1p268

Al-Omairi, L., Al-Samarraie, H., Alzahrani, A. I., & Alalwan, N. (2021). Students' intention to adopt e-government learning services: a developing country perspective. *Library Hi Tech*, *39*(1), 308-334. https://doi.org/10.1108/lht-02-2020-0034

Aristovnik, A., Keržič, D., Tomaževič, N., & Lan, U. (2016). Demographic determinants of usefulness of e-learning tools among students of public administration. *Interactive Technology and Smart*, *13*(4), 289-304. https://doi.org/10.1108/itse-09-2016-0033

Awang, Z. (2012). *Structural equation modeling using AMOS graphic* (1st ed.). Penerbit University Teknologi MARA.

Babbie, E. R. (1990). *Survey research methods* (1st ed). Cengage Learning Press.

Barhoumi, C. (2016). User acceptance of the e-information service as information resource: A new extension of the technology acceptance model. *New Library World*, *117*(9/10), 626-643. https://doi.org/10.1108/nlw-06-2016-0045

Bentler, P. M. (1990). Comparative fit indexes in structural models. *Psychological Bulletin, 107*(2), 238-246. https://doi.org/10.1037/0033-2909.107.2.238

Bijeesh, N. A. (n.d.). *Advantages and Disadvantages of Distance Learning.* https://www.indiaeducation.net/online-education/articles/advantages-and-disadvantages-of-distance-learning.html

Chang, C.-C. (2013). Exploring the determinants of e-learning systems continuance intention in academic libraries. *Library Management, 34*(1/2), 40-55. https://doi.org/10.1108/01435121311298261

Chen, C. C., Lee, C. H., & Hsiao, K. L. (2017). Comparing the determinants of non-MOOC and MOOC continuance intention in Taiwan Effects of interactivity and openness. *Library Hi Tech*, *36*(4), 705-719. https://doi.org/10.1108/lht-11-2016-0129

Cheng, Y. M. (2013). Extending the expectation confirmation model with quality and flow to explore nurses continued blended e-learning intention. *Information Technology & People*, *27*(3), 230-258. https://doi.org/10.1108/itp-01-2013-0024

Cheng, Y. M. (2021). Can tasks and learning be balanced? A dual-pathway model of cloud-based e-learning continuance intention and performance outcomes. *Kybernetes*, *51*(1), 210-240. https://doi.org/10.1108/k-07-2020-0440

Cheng, Y.-M. (2012). The Effects of Information Systems Quality on Nurses' Acceptance of the Electronic Learning System. *Journal of Nursing Research, 20*(1), 19-31. https://doi.org/10.1097/jnr.0b013e31824777aa

Cheng, Y.-M. (2020). Students' satisfaction and continuance intention of the cloud-based e-learning system: roles of interactivity and course quality factors. *Education + Training, 62*(9), 1037-1059. https://doi.org/10.1108/et-10-2019-0245

Choi, J. H., Kim, N. H., & An, D. (2015). Practical options for selecting data-driven or physics-based prognostics algorithms with reviews. *Reliability Engineering and System Safety, 133,* 223- 226. https://doi.org/10.1016/j.ress.2014.09.014

Clark-Carter, D. (2009). *Quantitative psychological research: the complete student's companion* (3rd ed.). Psychology Press. https://doi.org/10.4324/9781315398143

Csikszentmihalyi, M. (1975). *Beyond Boredom and Anxiety: Experiencing Flow in Work and Play* (1st ed.). Jossey-Bass Publishers.

Dai, Y. (2017). Teaching Analysis for 3D Animation Course Based on The Flipped Classroom. *Science & Technology Industry Parks*, *22*(1), 69-70.

Daultani, Y., Goswami, P. M., Kumar, A., & Pratap, S. (2020). Perceived outcomes of e-learning: identifying key attributes affecting user satisfaction in higher education institutes. *Measuring Business Excellence*, *25*(2), 216-229. https://doi.org/10.1108/mbe-07-2020-0110

Doll, W. J., Xia, W., & Torkzadeh, G. (1994). A confirmatory factor analysis of the end-user computing satisfaction instrument. *MIS Quarterly, 18*(4), 357-369. https://doi.org/10.2307/249524

Dörnyei, Z. (2007). *Research methods in applied linguistics* (2nd ed.). Oxford University Press. https://doi.org/10.5054/tj.2010.215611

Gentile, T. A. R., Reina, R., De Nito, E., Bizjak, D., & Canonico, P. (2020). E-learning design and entrepreneurship in three European universities. *International journal of Entrepreneurial Behavior & Research*, *26*(7), 1547-1566. https://doi.org/10.1108/ijebr-06-2019-0407

Gray, D. E. (2017). *Doing Research in the Business World.* SAGE Publications Ltd.

Gunesekera, A., Bao, Y. K., & Kibelloh, M. (2019). The role of usability on e-learning user interactions and satisfaction: a literature review. *Journal of Systems and Information Technology*, *21*(3), 368-394. https://doi.org/10.1108/jsit-02-2019-0024

Hair, J. F., Money, A. H., Samouel, P., & Page, M. (2007). Research methods for business. *Education + Training*, *49*(4), 336-337. https://doi.org/10.1108/et.2007.49.4.336.2

Hajli, M., Bugshan, H., Lin, X., & Featherman, M. (2013). From e-learning to social learning – a health care study. *European Journal of Training and Development*, *37*(9), 851-863. https://doi.org/10.1108/ejtd-10-2012-0062

Hamdan, K. M., Al-Bashaireh, A. M., Zahran, Z., Al-Daghestani, A., AL-Habashneh, S., & Shaheen, A. M. (2021). University students' interaction, Internet self-efficacy, self-regulation, and satisfaction with online education during pandemic crises of COVID-19 (SARS-CoV-2). *International Journal of Educational Management*, *35*(3), 713-725. https://doi.org/10.1108/ijem-11-2020-0513

Ho, N. T. T., Sivapalan, S., Pham, H. H., Nguyen, L. T. M., Pham, A. T. V., & Dinh, H. V. (2021). Students' adoption of e-learning in emergency: the case of a Vietnamese university during COVID-19. *Interactive Technology and Smart Education*, *18*(2), 246-269. https://doi.org/10.1108/itse-08-2020-0164

Hussein, M. H., Ow, S. H., Ibrahim, I., & Mahmoud, M. A. (2021). Measuring instructors continued intention to reuse Google Classroom in Iraq: a mixed method study during COVID-19. *Interactive Technology and Smart*, *18*(3), 380-402. https://doi.org/10.1108/itse-06-2020-0095

Jöreskog, K. G. (1969). A general approach to confirmatory maximum likelihood factor analysis. *Psychometrika*, *34*(2), 183-202. https://doi.org/10.1007/BF02289343.

Kapo, A., Mujkic, A., Turulja, L., & Kovačević, J. (2020). Continuous e-learning at the workplace: the passport for the future of knowledge. *Information Technology & People*, *34*(5), 1462-1489. https://doi.org/10.1108/itp-04-2020-0223

Kashive, N., Powale, L., & Kashive, K. (2020). Understanding user perception toward artificial intelligence (AI) enabled e-learning. *The International Journal of Information and Learning Technology*, *38*(1), 1-19. https://doi.org/10.1108/ijilt-05-2020-0090

Khan, H., Talib, F., & Faisal, M. N. (2015). An analysis of the barriers to the proliferation of m-commerce in Qatar: A relationship modeling approach. *Journal of Systems and Information Technology*, *17*(1), 54-81. https://doi.org/10.1108/jsit-12-2014-0073

Kotler, P. (2000). *Marketing in the twenty-first century: marketing management* (10th ed.). Millenium.

Lee, Y. (2006). An empirical investigation into factors influencing the adoption of an e-learning system. *Online Information Review*, *30*(5), 517-541. https://doi.org/10.1108/14684520610706406

Li, Y., & Kitcharoen, S. (2022). Determinants of Undergraduates' Continuance Intention and Actual Behavior to Play Mobile Games in Chongqing, China. *AU-GSB E-JOURNAL*, *15*(2), 206-214. https://doi.org/10.14456/augsbejr.2022.86

Liu, M. (2009). The design of a web-based course for self-directed learning. *Campus-Wide Information Systems*, *26*(2), 122-131. https://doi.org/10.1108/10650740910946846

MacCallum, R. C., & Austin, J. T. (2000). Applications of structural equation modeling in psychological research. *Annual Review of Psychology*, *51*, 201-226. https://doi.org/10.1146/annurev.psych.51.1.201

McConnell, D. (2018). E-learning in Chinese higher education: the view from inside. *Higher Education*, *75*(6), 1031-1045. https://doi.org/10.1007/s10734-017-0183-4

Moon, S., Birchall, D., Williams, S., & Vrasidas, C. (2005). Developing design principles for an e-learning program for SME managers to support accelerated learning at the workplace. *The Journal of Workplace Learning*, *17*(5/6), 370-384. https://doi.org/10.1108/13665620510606788

Mouakket, S., & Bettayeb, A. M. (2015). Investigating the factors influencing continuance usage intention of Learning management systems by university instructors. *International Journal of Web Information Systems*, *11*(4), 491-509. https://doi.org/10.1108/ijwis-03-2015-0008

Murillo, A. P., & Jones, K. M. L. (2020). A "just-in-time" pragmatic approach to creating Quality Matters-informed online courses. *Information and Learning Sciences*, *121*(5/6), 365-380. https://doi.org/10.1108/ils-04-2020-0087

Pedroso, R., Zanetello, L., Guimarães, L., Pettenon, M., Gonçalves, V., Scherer, J., Kessler, F., & Pechansky, F. (2016). Confirmatory factor analysis (CFA) of the Crack Use Relapse Scale (CURS). *Archives of Clinical Psychiatry (São Paulo), 43*(3), 37-40. https://doi.org/10.1590/0101-60830000000081

Phutela, N., & Dwivedi, S. (2020). A qualitative study of students' perspective on e-learning adoption in India. *Journal of Applied Research in Higher Education*, *12*(4), 545-559. https://doi.org/10.1108/jarhe-02-2019-0041

Poondej, C., & Lerdpornkulrat, T. (2020). Gamification in e-learning: A Moodle implementation and its effect on student engagement and performance. *Interactivity Technology and Smart Education*, *17*(1), 56-66. https://doi.org/10.1108/itse-06-2019-0030

Rodríguez Lera, F. J., Fernández González, D., Martín Rico, F., Guerrero-Higueras, Á. M., & Conde, M. Á. (2021). Measuring Students Acceptance and Usability of a Cloud Virtual Desktop Solution for a Programming Course. *Applied Sciences*, *11*(15), 7157. https://doi.org/10.3390/app11157157

Rui-Hsin, K., & Lin, C. T. (2017). The usage intention of e-learning for police education and training. *Policing: An International Journal*, *41*(1), 98-112. https://doi.org/10.1108/pijpsm-10-2016-0157

Salimon, M. G., Sanuri, S. M. M., Aliyu, O. A., Perumal, S., & Yusr, M. M. (2021). E-learning satisfaction and retention: a concurrent perspective of cognitive absorption, perceived social presence and technology acceptance model. *Journal of Systems and Information Technology*, *23*(1), 109-129. https://doi.org/10.1108/jsit-02-2020-0029

Sánchez-López, L. (2013). Service-Learning Course Design for Languages for Specific Purposes Programs. American *Association of Teachers of Spanish and Portuguese,* 96(2), 383-396. https://doi.org/10.1353/hpn.2013.0059

Sarker, M. F. H., Mahmud, R. A., Islam, M. S., & Islam, M. K. (2019). Use of e-learning at higher educational institutions in Bangladesh: opportunities and challenges. *Journal of Applied Research in Higher Education*, *11*(2), 210-223. https://doi.org/10.1108/jarhe-06-2018-0099

Sawang, S., Newton, C., & Jamieson, K. (2012). Increasing learners' satisfaction/ intention to adopt more e-learning. *Education + Training*, *55*(1), 83-105. https://doi.org/10.1108/00400911311295031

Scholtz, B., & Kapeso, M. (2014). An m-learning framework for ERP systems in higher education, *Interactive Technology and Smart Education*, *11*(4), 287-301. https://doi.org/10.1108/itse-09-2014-0030

Shao, Z. (2017). Examining the impact mechanism of social psychological motivations on individuals' continuance intention of MOOCs the moderating effect of gender. *Internet Research*, *28*(1), 232-250. https://doi.org/10.1108/intr-11-2016-0335

Sharma, G. P., Verma, R. C., & Pathare, P. (2005). Mathematical modeling of infrared radiation thin layer drying of onion slices. *Journal of Food Engineering, 71*(3), 282-286. https://doi.org/10.1016/j.jfoodeng.2005.02.010

Shea, T., & Parayitam, S. (2019). Antecedents of graduate student satisfaction through e-portfolio: content analysis. *Education + Training*, *61*(9), 1045-1063. https://doi.org/10.1108/et-04-2019-0064

Shehzadi, S., Nisar, A. Q., Hussain, M. S., Hameed, W. S., & Chaudhry, N. I. (2020). The role of digital learning toward students' satisfaction and university brand image at educational institutes of Pakistan: a post-effect of COVID-19. *Digital learning and university brand image, 1*(9), 1-10. https://doi.org/10.1108/aeds-04-2020-0063

Sica, C., & Ghisi, M. (2007). The Italian versions of the Beck Anxiety Inventory and the Beck Depression Inventory-II: Psychometric properties and discriminant power. In M. A. Lange (Ed.), *Leading-Edge Psychological Tests and Testing Research* (pp. 27-50). Nova.

Singh, A., Sharma, S., & Paliwal, M. (2020). Adoption intention and effectiveness of digital collaboration platforms for online learning: the Indian students' perspective, *Interactive Technology and Smart Education*, *18*(4), 493-514. https://doi.org/10.1108/itse-05-2020-0070

Siqueira, F. V., Reichert, F. F., & Araujo, C. L. P. (2007). Gender differences in leisure-time physical activity. *International Journal of Public Health, 53*(8), 1-10. https://doi.org/10.1007/s00038-006-5062-1

Stoel, L., & Hye Lee, K. (2003). Modeling the effect of experience on student acceptance of Web-based courseware. *Internet Research*, *13*(5), 364-374. https://doi.org/10.1108/10662240310501649

Strauss, M., & Smith, G. (2009). Construct validity: Advances in theory and methodology. *Annual review of clinical psychology*, *5*, 1-25. https://doi.org/10.1146/annurev.clinpsy.032408.153639

Teo, T. (2010). Modeling the determinants of pre-service teachers' perceived usefulness of e-learning. *Campus-Wide Information Systems*, *28*(2), 124-140. https://doi.org/10.1108/10650741111117824

Tu, Y. F., Hwang, G. J., Chen, J. C. C., & Lai, C. (2021). University students' attitudes towards ubiquitous library-supported learning: an empirical investigation in the context of the Line@Library. *The Electronic Library*, *39*(1), 186-207. https://doi.org/10.1108/el-03-2020-0076

Wolf, E. J., Harrington, K. M., Clark, S. L., & Miller, M. W. (2013). Sample size requirements for structural equation models: An evaluation of power, bias, and solution propriety. *Educational and Psychological Measurement*, *76*(6), 913-934. https://doi.org/10.1177/0013164413495237

Wu, J.-H., & Wang, Y.-M. (2006). Measuring KMS success: A respecification of the DeLone and McLean's model. *Information & Management, 43*(6), 728-739. https://doi.org/10.1016/j.im.2006.05.002

Yang, R. (2020). China's higher education during the COVID-19 pandemic: some preliminary observations. *Higher Education Research and Development*, *39*(7), 1317-1321. https://doi.org/10.1080/07294360.2020.1824212

Zainab, B., Bhatti, M. A., Pangil, F. B., & Battour, M. M. (2015). E-training adoption in the Nigerian civil service. *European Journal of Training and Development*, *39*(6), 538-564. https://doi.org/10.1108/ejtd-11-2014-0077