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

The Impacting Factors of Continuance Intention to Use E-Learning After Covid-19 Of Male Students Majoring in Music in Chengdu

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Received: February 8, 2023. Revised: July 29, 2023. Accepted: August 16, 2023

Abstract

Purpose: Affected by the COVID-19 epidemic, telecommuting and learning has become important Internet application for the continuous prevention and control of the epidemic and the normal operation of the social economy. Online learning platforms would enhance the continuance intention of students after COVID-19. This study investigates the continuance intention to use e-learning of music major college students in Chengdu, China. **Research design, data, and methodology:** The population is 500 male students at Sichuan University who have been using three selected e-learning platforms: DingDing, Tencent meeting, and WeLink. The sample techniques are judgmental, stratified random, and convenience sampling. The Item Objective Congruence (IOC) Index and the pilot test (n=50) by Cronbach's Alpha were approved before the data collection. The data was analyzed through Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM). **Results:** The findings reveal that system quality and subjective norms significantly impact perceived usefulness. Interactivity, course content quality, and perceived usefulness significantly impact satisfaction. Continuance intention is impacted by perceived usefulness but not by satisfaction. **Conclusions:** The findings can contribute to the educators, and e-learning platform providers collaborating for more effective use of e-learning and promote the strong continuance intention to use among students in higher education in China.

Keywords: Perceived Usefulness, Satisfaction, Continuance Intention to Use, E-learning, College Students

JEL Classification Code: E44, F31, F37, G15

1. Introduction

Due to China has advanced developing economy, online education has accelerated (Ding et al., 2010). The country has become the second-largest economic country in the world. Chinese universities have provided education through postal communication and printing technology since the 1950s. Distance education has been promoted through broadcast radio and TV countrywide for decades. E-learning or online education was introduced in higher education in 1998, responding to the rise of computer network technology, satellite TV technology, and telecommunications technology (Ting et al., 2018).

According to Ding et al. (2010), the digital divide posed challenges in China: most rural areas still need to improve distance learning due to inadequate technology resources and support. The advancements in education are major barriers, especially the accessibility to online education. Most areas still use traditional broadcasting for learning in most public schools. In addition, most rural areas need more resources, including insufficient teachers, inadequate teaching and learning tools, and limited technical support.

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Therefore, the development of online education in China is uneven.

According to China Internet Network Information Center (2022), only 1.6% of a 700-million-strong rural population registered in e-learning programs in 2009, reflecting that the adoption rate could be much higher. The major issues are Chinese cultural influence and national security governed by the government. On the contrary, major cities like Beijing, Shanghai, and Chengdu have been well-equipped with online and internet technologies. Recently, the Chinese government focused on innovation and technology as the top priority to enhance stability and world competitiveness (Ting et al., 2018).

China is a country where it has a massive population and wide territory. Inequality and uneven education are major challenges (Wang, 2007). Only some schools have well-developed tools and technology for online learning. E-learning is viewed as "a promising approach since it offers students ways to interact with experienced teachers or professors." In post-COVID-19, The Chinese government has upgraded the technology infrastructure for online and distance education with various e-learning programs and domestic online learning platforms.

The issues are whether the owned country-developed online learning platforms would enhance the continuance intention of students after COVID-19. Thus, this study aims to fill the research gap to investigate the continuance intention to use e-learning of music major college students in Chengdu, China. The main constructs are system quality, subjective norms, interactivity, course content quality, perceived usefulness, satisfaction, and continuance intention.

2. Literature Review

2.1 System Quality

System quality refers to "the accuracy, convenience, efficiency, flexibility, reliability, and responsiveness in the function of an information system. It is explained when an e-learning system can provide learners with more high-quality and relevant functions to achieve their learning goals" (Roca et al., 2006). System quality is also the key construct of the information system success model by DeLone and McLean (2003). DeLone and McLean (2003) identified that system quality is "the quality of the functionality of an IS itself. It signifies the accuracy, convenience, efficiency, flexibility, reliability, and responsiveness in the function of an IS." The relationship between service quality and perceived usefulness can be explained "when an e-learning system can provide learners with more high-quality and relevant functions to achieve their learning goals, they will consider that the system can provide useful functions for their learning needs. Further, this will enhance their satisfaction with the system, and they will be more interested in using it" (Roca et al., 2006). Therefore, this study hypothesizes:

H1: System quality has a significant impact on perceived usefulness.

2.2 Subjective Norms

Subjective norms are "the perception of social pressure from significant others to perform or not to perform the behavior that would influence behavioral intention" (Ajzen, 1991). Kitcharoen and Vongurai (2021) explicated that subjective norms directly affect behavioral intention, as explained in the theory of planned behavior (TPB). White et al. (2009) indicated that subjective norms are also known as social influence in the technology acceptance model. Cialdini et al. (1991) pointed out that "subjective norms in the TPB share a similar meaning with the injunctive norm." Bag et al. (2022) indicated the relationship between subjective norms and perceived usefulness in examining the "behavioral intention of digital natives toward adapting the online education system in higher education." Maher and Mady (2010) attested that subjective norms as social factors play a key influential factor in the users' perception of using new technologies. Based on the discussion of the relationship between subjective norms and perceived usefulness, this research proposes a hypothesis:

H2: Subjective norms have a significant impact on perceived usefulness.

2.3 Interactivity

Interactivity refers to "an e-learning system that should provide technological features to enable a collaboration environment, and it can further allow the articulation of communication and collaboration between learners and instructors" (Cidral et al., 2018). Interactivity is identified as "an essential feature of the online environment, particularly in the marketing literature" (Song & Zinkhan, 2008). Labrecque (2014) extended that Interactivity relies on "the user's perception of taking part in a two-way communication with a mediated persona." In terms of branding, Interactivity is "the customer's perception of the brand's desire for integration with the customer" (France et al., 2016). Cheng (2020) clarified Interactivity as "the degree to which participants in a communication process have control over and can exchange roles in their mutual discourse." In the e-learning context, Cho et al. (2009) refined that students may feel satisfied with e-learning systems because they perceive interactive functionality. Thus, the effect of Interactivity on satisfaction can be hypothesized:

H3: Interactivity has a significant impact on satisfaction.

2.4 Course Content Quality

Course content quality is "the quality of online courses is especially critical for learners to consider whether they intend to continue using the online platform for learning activities after they finish the current courses" (Liu et al., 2010). Drago et al. (2002) developed the evaluation of the course, content quality, incorporating with the course is effective and challenging, course materials can motivate the student to learn, the course is easy to understand, and the course is relevant to the learning objectives. Loafman and Altman (2014) suggested that quality management and service quality are fundamental theories for assessing course content quality. Course content quality or information quality is a component of the e-learning system that is expected to be updated, comprehensive, and easy to understand. Therefore, users express satisfaction with the use (Lee, 2006). The quality of course contents and information that meets learners' expectations, they would feel positive and comfortable engaging with the e-learning system (Liu et al., 2010). Based on the above discussions, this research hypothesizes that:

H4: Course content quality has a significant impact on satisfaction.

2.5 Perceived Usefulness

Davis et al. (1989) defined perceived usefulness as "the extent to which a person feels his/her task performance would be enhanced by using a certain system technology. Perceived usefulness indicates that "customers have confidence in their ability to access information and service and improve their information transfer performance in virtual communities" (Lin, 2007). Perceived usefulness is a user's motivation to adopt a particular information system (Huang & Duangekanong, 2022). Bhattacherjee and Sanford (2006) emphasized that using technology can endorse behavioral intention. The relationship between perceived usefulness and satisfaction has been widely examined in e-learning (Cheng, 2014). Lin and Wang (2012) assumed that "users' PU of the e-learning system is a positive predictor of their satisfaction with the system.". In the e-learning context, Cheng (2019) noted that "users who think that e-learning systems are useful and effective will tend to have a more favorable satisfaction with the services, that is, users' PU of such system can lead to their satisfaction." Based on technology acceptance model, perceived usefulness has been proven to have a direct impact on intention to use technology (Davis et al., 1989). Referring to the study by Cheng (2020), the users' behavior in using an e-learning system showed that they perceived the usefulness of such a system and were more likely to continue using it. Thus, two hypotheses are set:

H5: Perceived usefulness has a significant impact on satisfaction.

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

2.6 Satisfaction

DeLone and McLean (1992) have identified user satisfaction as one of the primary variables in the model of information system (IS) success. IS success model is conceptualized in three aspects: technical, semantic, and effectiveness. The most used terms for IS success model are information quality, system quality, and service quality (Kitcharoen, 2018). Satisfaction is "the evaluation by customers of a favorable response, related to emotional states that stimulate consideration of particular objects and probably influence continuous behavior" (Shahsavar & Sudzina, 2017). In this study, satisfaction is termed as "the evaluation of students on how they are satisfied with their decision to use e-learning and how well it meets their expectations, and they express the intention to use e-learning mode after the COVID-19" (Feng et al., 2022). Cheng (2020) examined the satisfaction to have a significant impact on continuance intention. Larsen et al. (2009) reported that "users' satisfaction with the e-learning system can lead to their continuance intention of the system." In this study, satisfaction was investigated to contribute to the continuance intention to use an e-learning by students. Therefore, a hypothesis is developed:

H7: Satisfaction has a significant impact on continuance intention.

2.7 Continuance Intention

Continuance intention is determined as "students' willingness to continue using the e-learning system after the pandemic because of the perception that it can increase their learning effectiveness and performance" (Chang, 2020). Bhattacherjee (2001) posited that continuance intention is the individuals' decision to continue using a technology after its first use. According to Marandu et al. (2022), the conceptual model incorporates the online continuance intention, which is significantly affected by performance expectancy, effort expectancy, social influence, facilitating conditions, and satisfaction. Many scholars have examined the continuance intention to use technologies derived from the expectation confirmation theory (ECT) (Cheng, 2014, 2020; Marandu et al., 2022). Lu et al. (2020) also noted that user confirmation and expectations predict satisfaction toward the continuance intention.

3. Research Methods and Materials

3.1 Research Framework

From the literature review, this study points out the main variables used, which include system quality, subjective norms, interactivity, course content quality, perceived usefulness, satisfaction, and continuance intention. The conceptual framework was constructed from the previous research model of Bag et al. (2022), Cheng (2014), and Cheng (2020).

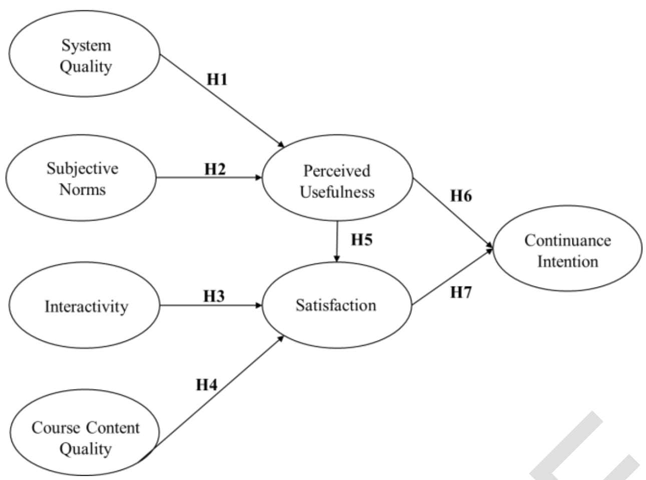

Figure 1: Conceptual Framework

H1: System quality has a significant impact on perceived usefulness.
H2: Subjective norms have a significant impact on perceived usefulness.
H3: Interactivity has a significant impact on satisfaction.
H4: Course content quality has a significant impact on satisfaction.
H5: Perceived usefulness has a significant impact on satisfaction.
H6: Perceived usefulness has a significant impact on continuance intention.
H7: Satisfaction has a significant impact on continuance intention.

3.2 Research Methodology

This study investigates the continuance intention to use e-learning of music major college students in Chengdu, China. This study points out the main constructs: system quality, subjective norms, interactivity, course content quality, perceived usefulness, satisfaction, and continuance intention. The population is 500 male students majoring in music at Sichuan University who have been using three selected e-learning platforms: DingDing, Tencent meeting, and WeLink. The sample techniques are judgmental, stratified random, and convenience sampling. The Item Objective Congruence (IOC) Index and the pilot test (n=50) by Cronbach's Alpha were approved before the data collection. The data was analyzed through Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM). The survey has three parts: screening questions, measuring items (25) with a five-point Likert scale, and demographic questions.

3.3 Validity and Reliability

Before the data collection, the Index of Item–Objective Congruence (IOC) was used in this research to validate the content by three experts who titled Ph.D. or in the high-level of management. The IOC results showed that all items passed at a score of 0.6 or over. Additionally, a pilot test was conducted with 50 participants. The Cronbach Alpha coefficient's rule of thumb is shown that internal consistency in this study is recommended at 0.6 or above (Griethuijsen et al., 2014), including system quality (0.670), subjective norms (0.806), interactivity (0.740), course content quality (0.807), perceived usefulness (0.888), satisfaction (0.804), and continuance intention (0.656).

3.4 Population and Sample Size

The renowned university in Chengdu, Sichuan University, is an appropriate target sample for this study as it has over 37,000 students. The number of music major college students at Sichuan University has about 6,400 people. Due to the research aim to investigate the continuance intention to use e-learning of music major college students in Sichuan University, Chengdu, China, this study points out the population of 500 male students majoring in music at Sichuan University who have been using three selected e-learning platforms which are DingDing, Tencent meeting, and WeLink. According to the online statistical calculator to estimate the minimum sample size by Soper (2022), the result recommended about 425 participants. The research considered collecting 500 participants for efficient data analysis for the study.

3.5 Sampling Technique

According to Taherdoost (2016), the sampling procedure is the heart of the research and is applied to conduct accurate data analysis and results per its objectives. Therefore, this study applied probability and nonprobability sampling to determine a proper research procedure, including judgmental, stratified random, and convenience sampling. Judgmental sampling is to select male students majoring in music at Sichuan University who have been using three selected e-learning platforms: DingDing, Tencent meeting, and WeLink. Stratified random sampling is demonstrated in Table 1. Convenience sampling is to distribute the online questionnaire to students majoring in music at Sichuan University.

Table 1: Stratified Random Sampling

Three Most Used Platforms	Total Number of Music Major College Students in Sichuan University	Proportionate Sample Size
1. DingDing	2,300	180
2. Tencent Meeting	2,600	203
3. WeLink	1,500	117
Total	**6400**	**500**

4. Results and Discussion

4.1 Demographic Information

The demographic results were collected in the survey to specify participants' characteristics. Most respondents are aged between 18-20 years old at 64.2 percent (321). Juniors account for 33.4 percent, followed by sophomores (24.6 percent), freshmen (21.6 percent), and seniors (20.4 percent). Most respondents have used e-learning for 4-6 days per week (71.8 percent), whereas only 9.2 percent have used e-learning seven days a week.

Table 2: Demographic Profile

Demographic and General Data (n=500)		Frequency	Percentage
Age	18-20 years old	321	64.2
	21-22 years old	115	23.0
	23 years old or over	64	12.8
Year of Study	Freshmen	108	21.6
	Sophomore	123	24.6
	Junior	167	33.4
	Senior	102	20.4
Frequency Of E-Learning Use	1-3 days/week	95	19.0
	4-6 days/week	359	71.8
	7 days/week	46	9.2

4.2 Confirmatory Factor Analysis (CFA)

According to Dragan and Topolšek (2014), the CFA is "the confirmation of the factor structures based on the investigation and in the compliance with some theoretical knowledge is verified." CFA's result depends on "the measurement model, which describes the loadings of the indicator variables on corresponding latent factors." The measurement and structural models estimate the causal relationship between key constructs in the conceptual framework. In Table 3, CFA can be verified by factor loading at 0.5 or above, The Cronbach Alpha coefficient value at 0.6 or above (Griethuijsen et al., 2014), and the Composite Reliability (CR) at 0.7 or above. According to Fornell and Larcker (1981), the Composite Reliability (CR) is greater than the cut-off points of 0.6, and Average Variance Extracted (AVE) is higher than the cut-off point of 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
1. System Quality (SQ)	Cheng (2014)	4	0.774	0.644-0.715	0.775	0.463
2. Subjective Norms (SN)	Bag et al. (2022)	3	0.885	0.819-0.893	0.884	0.718
3. Interactivity (IN)	Cheng (2020)	3	0.884	0.823-0.877	0.884	0.718
4. Course Content Quality (CCQ)	Cheng (2020)	3	0.732	0.658-0.721	0.734	0.480
5. Perceived Usefulness (PU)	Cheng (2020)	4	0.880	0.753-0.853	0.883	0.653
6. Satisfaction (SAT)	Cheng (2014)	4	0.814	0.643-0.797	0.815	0.526
7. Continuance Intention (CI)	Cheng (2020)	4	0.776	0.631-0.706	0.778	0.467

The goodness of fit indices has been commonly used to check the fit degree of the measurement and structural model and determine whether it requires an adjustment to confirm CFA and SEM (Dragan & Topolšek, 2014).

This study approved the measurement model fit, including CMIN/DF = 1.486, GFI = 0.945, AGFI = 0.929, NFI = 0.940, CFI = 0.979, TLI = 0.976, and RMSEA = 0.031, as shown in Table 4.

Table 4: Goodness of Fit for Measurement Model

Index	Acceptable Values	Statistical Values
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015)	377.362/254 = 1.486
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.945
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.929
NFI	≥ 0.80 (Wu & Wang, 2006)	0.940
CFI	≥ 0.80 (Bentler, 1990)	0.979
TLI	≥ 0.80 (Sharma et al., 2005)	0.976
RMSEA	< 0.08 (Pedroso et al., 2016)	0.031
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
Source: Created by the author.

Discriminant validity is "the extent that measures of different constructs diverge or minimally correlate with one another." (Taherdoost, 2016). In Table 5, the convergent and discriminant validity are approved due to the square root of the average variance extracted, determining that all the correlations are larger than the corresponding correlation values.

Table 5: Discriminant Validity

	SAT	SQ	PU	CI	SN	IN	CCQ
SAT	**0.725**						
SQ	0.538	**0.681**					
PU	0.231	0.227	**0.808**				
CI	0.654	0.602	0.203	**0.684**			
SN	0.512	0.676	0.278	0.631	**0.847**		
IN	0.451	0.628	0.229	0.552	0.657	**0.847**	
CCQ	0.547	0.541	0.188	0.622	0.531	0.521	**0.692**

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 structural model refers to "the relationships among latent variables, and allows the researcher to determine their degree of correlation (calculated as path coefficients), which shows the causal and correlational links among latent variables in a theoretical model." (Wong et al., 2014). The results after the adjustment in Table 6 were acceptable fit with CMIN/DF = 3.712, GFI = 0.858, AGFI = 0.811, NFI = 0.857, CFI = 0.890, TLI = 0.865, and RMSEA = 0.074.

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)	1266.628/268 = 4.726	905.737/244 = 3.712
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.823	0.858
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.785	0.811
NFI	≥ 0.80 (Wu & Wang, 2006)	0.799	0.857
CFI	≥ 0.80 (Bentler, 1990)	0.834	0.890
TLI	≥ 0.80 (Sharma et al., 2005)	0.814	0.865
RMSEA	< 0.08 (Pedroso et al., 2016)	0.086	0.074
Model summary		**Unacceptable Model Fit**	**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
Source: Created by the author.

4.4 Research Hypothesis Testing Result

The statistical results for the hypotheses testing of this study can be measured by the standardized path coefficient value (β) and t-value. The significant effect is determined at p-value<0.05. Therefore, SEM was applied to examine the causal relationship between system quality, subjective norms, interactivity, course content quality, perceived usefulness, satisfaction, and continuance intention.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: SQ→PU	0.198	3.452*	Supported
H2: SN→PU	0.191	4.130*	Supported
H3: IN→SAT	0.263	6.131*	Supported
H4: CCQ→SAT	0.395	7.145*	Supported
H5: PU→SAT	0.112	2.257*	Supported
H6: PU→CI	-0.040	-0.626	Not Supported
H7: SAT→CI	0.389	7.361*	Supported

Note: * p<0.05

According to Table 7, most hypotheses are supported except H6, which can be further interpreted below:

H1 reveals that system quality significantly impacts perceived usefulness, resulting in the standardized path coefficient value of 0.198 (t-value = 3.452). The results suggest a relationship between service quality and perceived usefulness. Roca et al. (2006) stated that when an e-learning system can provide learners with more high-quality and relevant functions to achieve their learning goals, they will consider the system useful.

For **H2**, the relationship between subjective norms and perceived usefulness is supported by a standardized path coefficient value of 0.191 (t-value = 4.130). Many scholars provided evidence that subjective norms have a direct effect on behavioral intention (Bag et al., 2022; Cialdini et al., 1991; Kitcharoen & Vongurai, 2021; White et al., 2009)

H3 shows that interactivity significantly impacts satisfaction, reflecting the standardized path coefficient value of 0.263 (t-value = 6.131). The results can be implied that an e-learning system as an interactive learning tool can enhance the satisfaction of both learners and instructors (Cidral et al., 2018; Song & Zinkhan, 2008).

H4 verifies the impact of course content quality on student satisfaction, representing a standardized path coefficient value of 0.395 (t-value = 7.145). It was suggested that course content quality is a crucial component of the e-learning system that students are expected. Therefore, they tend to express satisfaction with the use (Lee, 2006; Liu et al., 2010; Loafman & Altman, 2014).

H5 approves the significant relationship between perceived usefulness and student satisfaction, resulting in a standardized path coefficient of 0.112 (t-value = 2.257). Cheng (2019) demonstrated that students expect e-learning systems to be useful and effective. Thus, they tend to express satisfaction with the use.

H6 disapproves that perceived usefulness significantly impacts continuance intention with a standardized path coefficient of -0.040 (t-value = -0.626). Even though Cheng (2020) explained that the users' perceived usefulness of such a system could drive continuance intention, the results show that the motivation to use is not significantly relevant.

H7 results show that satisfaction significantly impacts continuance intention with a standardized path coefficient value of 0.389 (t-value = 7.361). It confirms that satisfaction as the evaluation of students on how they are satisfied with the use of e-learning can determine their intention to use e-learning after COVID-19" (Cheng, 2020; Feng et al., 2022; Larsen et al., 2009).

5. Conclusions and Recommendation

5.1 Conclusion and Discussion

The research objectives have been met to determine the factors of continuance intention to use e-learning of male students majoring in music in Chengdu. This quantitative study is verified from the data collection in a group of 500 male students at Sichuan University who have been using three selected e-learning platforms: DingDing, Tencent meeting, and WeLink. The findings reveal that system quality and subjective norms significantly impact perceived usefulness. Interactivity, course content quality, and perceived usefulness significantly impact satisfaction. Continuance intention is impacted by perceived usefulness but not by satisfaction.

Based on the findings, most hypotheses are verified. First, system quality and subjective norms significantly impact perceived usefulness. System quality is developed by DeLone and McLean's (2003)' s IS success model, which has been widely investigated to enhance the users' perception of the use of the technology. Maher and Mady (2010) tested that subjective norms as social influence can drive learners' perception of the user benefits of e-learning.

Next, interactivity, course content quality, and perceived usefulness significantly impact satisfaction. Interactivity is an essential feature of the online environment and can be a satisfaction indicator for users (Song & Zinkhan, 2008). Due to e-learning being perceived to have a low engagement compared with physical classrooms, Drago et al. (2002) pointed out that course content quality is very important to enhance student satisfaction with e-learning. Lin and Wang (2012) also supported that the perceived usefulness of the e-learning system is a positive predictor of student satisfaction with the system's use.

Finally, continuance intention is impacted by perceived usefulness rather than satisfaction. Although continuance intention is the individuals' decision to continue using a technology after its first use, users' experience of its usefulness is demonstrated (Bhattacherjee & Sanford, 2006). Nevertheless, satisfaction has no significant impact on continuance intention, and it can be assumed that both variables are phycological factors that are difficult to measure. Moreover, during the pandemic, satisfaction level cannot determine the continuance intention because e-learning follows the schools' conduct and policy.

5.2 Recommendation

According to Yan (2022), over 10.76 million graduates in China face the challenges of finishing school during and after the COVID-19 pandemic. However, students are increasingly familiar with online education and have increased their digital competence. Many online learning platforms have emerged during the pandemic and are expected to continue blooming in the post-COVID-19 era. China is entering a fast-growing high-tech development, which offers opportunities for the growth of online learning because of the advancement of technology. Swanson and Valdois (2022) added that online education in China, previously considered ineffective, has undergone significant infrastructural improvements due to the COVID-19 pandemic requiring students to attend classes at home. Therefore, this study addressed impacting factors of continuance intention to use an e-learning by students in China.

The findings can contribute to the educators and e-learning platform providers collaborating for more effective use of e-learning and promote the strong continuance intention to use among students in higher education in China. Student satisfaction and continuance intention of e-learning are to measure the successful adoption and how the student can continue using such learning mode to ensure their learning effectiveness. In the current situation, the COVID-19 situation is still prolonged, but the policy of health control is more relaxed. Educators and government could join forces to develop more advanced and engaging course content quality and closely measure students' satisfaction and continuance intention. Additionally, e-learning developers should consistently maintain and upgrade the e-learning system or platform to enhance system quality, usefulness, and interactivity.

5.3 Limitation and Further Study

The limitations of this study can be further explored. First, this study only employed respondents who were male students majoring in music in Chengdu. There would be a different perspective in the female or another student major group. Second, the researcher scopes only three e-learning systems; DingDing, Tencent meeting, and WeLink. Thus, learners' experience on the selected platform on the psychological level is limited. Last, quantitative data can be interpreted in statistical analysis, but it cannot determine the clear view of participants in this study. Hence, the qualitative method can fill this research gap in the future research.

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