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Investigating Continuance Intention to Use E-Learning of Female Students Majoring in Music in Chengdu

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Abstract

Purpose: Remote learning is expected to become a normal tool after the epidemic's end and is an important means to promote the digital development of education. This study investigates the impact of system quality, subjective norms, interactivity, course content quality, perceived usefulness, and satisfaction on the continuance intention to use e-learning of music major college students in Chengdu, China. **Research design, data, and methodology:** The population is 500 female students at Sichuan University 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 and course content quality significantly impact satisfaction. Continuance intention is impacted by perceived usefulness and satisfaction. On the opposite, perceived usefulness has no significant impact on satisfaction. **Conclusions:** Educational institutions and the Chinese government can exploit the findings in this study to improve accessibility with the highest-performance online learning infrastructure for the country.

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

JEL Classification Code: E44, F31, F37, G15

1. Introduction

Online learning is a similar term to e-learning. E-learning refers to "the use of electronic devices for learning, including the delivery of content via electronic media such as internet/intranet/extranet, audio or videotape, satellite broadcast, interactive TV, or CD ROM" (Zhang et al., 2010). Online learning can be refined particularly to "the use of the internet to deliver education or training programs." Jönsson (2005) stated that "online or e-learning moves the traditional instruction paradigm to a learning paradigm." In Figure 1.1, the statistic in June 2022 shows that the number of online office users in China reached 461 million, down 8.18 million from December 2021, accounting for 43.8% of all Internet users.

The COVID-19 pandemic has tremendously affected to education systems in China. The outbreak fought to keep the continuance of learning in the education sector. Therefore,

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the Chinese government launched the emergency plan "Classes Suspended but Learning Continues," which urged schools to close and shift their teaching and learning activities entirely online (MOE China, 2020). China is the most populous nation worldwide. 270 million students were quickly encouraged to continue their studies online in the sudden outbreak, and the technological infrastructures and urgent preparation of distance learning were accounted for. However, inequality in digital accessibility has been a major issue in China (Gu & Li, 2022).

There are numerous studies assessing online learning adoption during the pandemic. Roy et al. (2020) urged that "the pressure and frustration due to the pandemic lead to low engagement and motivation." Huang et al. (2020) examined "the instructors on interactive teaching and learning that enhance students' participation and engagement." Brooks et al. (2020) supported that "COVID-19 relates to frustration, pressure, and anxiety of students during the period." Almanthari et al. (2020) investigated "the mechanisms that have been a challenge for teachers in the e-learning time." Huang et al. (2020) posited that "the time and assessment modes should be flexible and digital resources for learning should be chosen appropriately and aligned with online learning." Malkawi et al. (2020) suggested "technical support and provision of adequate training both for instructors and students for a better e-learning process."

Furthermore, limited studies have examined the factors affecting students' perceptions of online learning during COVID-19, especially music major college students. Moser et al. (2020) postulated that most studies on higher education only emphasize online learning applications in employment and raise competitiveness. Sari and Oktaviani (2021) focused on enhancing students' self-efficacy to acquire knowledge, develop skills, and build initiatives. The perceived usefulness, satisfaction, and continuance intention to use are varied in most studies. The measurement of online learning of college students in the post-COVID era is still not yet covered. The influencing factors in online learning are in a robust debate and can be further examined. Hence, this study investigates the impact of system quality, subjective norms, interactivity, course content quality, perceived usefulness, and satisfaction on the continuance intention to use e-learning of music major college students in Chengdu, China.

2. Literature Review

2.1 System Quality

System quality is "the desirable characteristics of an information system typically focus on usability aspects and performance characteristics of the system under examination" (Urbach & Müller, 2012). In the context of e-learning, the system quality is identified as "the platform selected by the university to utilize an online learning which can provide ease of use, convenience and reliability" (Cao & Jittawiriyanukoon, 2022). Pituch and Lee (2006) added that "e-learning system has been considered as a most useful platform due to their functions, such as complete controllability and flexibility, especially to users who are sensitive to the system quality." Cheng (2014) also pointed out that "if learners perceive that the e-learning system can provide them with fitting system functionality and timely response, and they can effectively get in contact with instructors and other learners via the system, they may feel that such a system is useful." Therefore, this study hypothesizes:

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

2.2 Subjective Norms

Subjective norms are described as "the external pressure exerted on an individual carrying out a certain activity. In other words, students' attitude depends on who is important to them to engage in e-learning after COVID-19" (Bag et al., 2022). O'Neal (2007) classified that "subjective norms relate to the perceived social influences/pressures to indulge or not to indulge in a given behavior" Supported by Ajzen (1991), subjective norms are "beliefs of individuals about how their reference groups would view them if they perform a certain behavior." Subjective norms can greatly predict perceived usefulness and behavioral intention (Huang, 2011). Subjective norms or social influence is viewed to affect users' perceived utility of e-learning significantly. 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

According to Sallaku and Vigolo (2022), interactivity incurs "brand's technical facilitation of the interaction (e.g., the brand's presence on social media) and the demonstration of a genuine desire for connectedness (e.g., the brand's interactions with customers on the brand's social profile)." In the context of e-learning, interactivity focuses on the interaction of students towards the e-learning system or platforms. Cheng (2020) clarified that "a high degree of interactivity develops more connection between a system and learners." Hassanzadeh et al. (2012) additionally cascaded that if an e-learning system can provide learners with the functions of interactive features, it will enhance

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their satisfaction with the system. Cidral et al. (2018) and Mohammadi (2015) supported that an e-learning system allows communication and interactivity between lecturers and learners, thereby affecting their satisfaction. Thus, the effect of interactivity on satisfaction can be hypothesized:
H3: Interactivity has a significant impact on satisfaction.

2.4 Course Content Quality

Shattuck et al. (2014) determined that "the online course quality includes course overview, introduction, learning objectives, assessment and measurement, instructional materials, course activities and learner interaction, course technology, learner support, accessibility, and usability." Parasuraman et al. (1988) introduced the SERVQUAL model, which can be adapted to academic services. It is believed that course-quality content is an essential service provided to students, and they evaluate service based on course content quality. In addition, course design quality refers to "the quality of the form for learning contents that the e-learning system generates" (Cheng, 2020). Moreover, Roca et al. (2006) noted that the high quality of course contents and information provided by the e-learning system might enhance their satisfaction with the system. Accordingly, a hypothesis of this study is developed:
H4: Course content quality has a significant impact on satisfaction.

2.5 Perceived Usefulness

Perceived usefulness is "the degree to which an individual believes adapting and using a particular technology would improve the individual's job performance. Hence, this study has addressed the use of e-learning for investigating the students' continuance intention toward the online education system after COVID-19" (Bag et al., 2022). Shiau and Chau (2016) identified the usability of e-learning in that most education institutions have provided e-learning systems for students to engage in their studies from anywhere and at any time. Perceived usefulness refers to "the degree to which a person believes that using a particular system would enhance his/her job performance and is users' perception of the expected benefits of the IS/IT use" (Bhattacherjee, 2001). Xu et al. (2017) acclaimed that using e-learning systems such as accessibility, convenience, and reliability can impact learners' satisfaction with using the system. Yang and Lin (2015) further explained that "users who believe that cloud computing services are useful and effective will tend to have a more favorable continuance intention. According to the evidence from previous studies, this research confirms the causal relationships below:
H5: Perceived usefulness has a significant impact on satisfaction.
H6: Perceived usefulness has a significant impact on continuance intention.

2.6 Satisfaction

Elliott and Shin (2002) explicated that student satisfaction can be implied as "the degree of satisfied students and school's services or performance meets or exceeds their expectations." Bay and Daniel (2001) pointed out that satisfaction can be derived from the learning process, which impacts students' perceived value and service quality in their schools. Kunanusorn and Puttawong (2015) define satisfaction as "a customer's assessment of the service being provided or a feeling that customers expect what they will get will be as what they expect." Elliott and Healy (2001) argued that students' satisfaction is "a short-term attitude that resulted from their experiences with educational services." Cheng (2019) mentioned that satisfaction is developed from the experience with e-learning systems that meet or exceed learners' expectations. Thus, they have the willingness to continue using it. Xu et al. (2017) also agreed that "students' satisfaction with e-learning system can greatly impact their continuance intention of the system." Thereby, a proposed hypothesis is indicated:
H7: Satisfaction has a significant impact on continuance intention.

2.7 Continuance Intention

Originally, the technology acceptance model offered behavioral intentions as a crucial element to measure successful adoption (Fan et al., 2021). Continuing intentions have been widely studied and identified as motivations to continue using system technology for some period. The extended model of ECT and task-technology fit in online learning indicate the association between satisfaction and continuance intention (Wang et al., 2021). Mailizar et al. (2021) posited that the acceptance of technologies incorporated attitude and behavioral intention in the Technology Acceptance Model (TAM). During COVID-19, the e-learning system was intensely promoted as an effective way to continue teaching and learning (Rizana et al., 2020). Therefore, performance expectancy, effort expectancy, social influence, facilitating conditions, and satisfaction are key factors affecting students' behavioral intentions (Robinson et al., 2020).

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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).

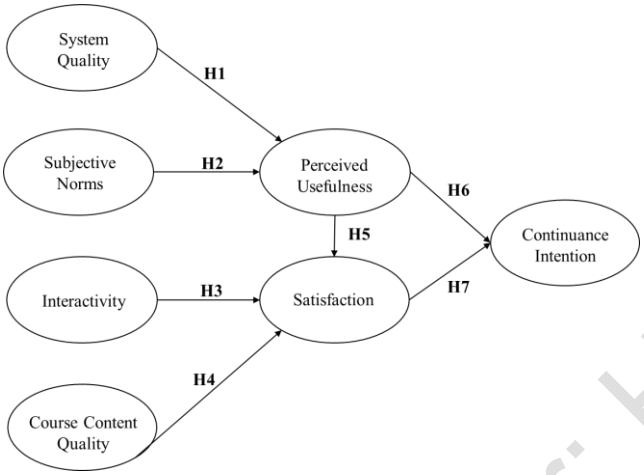

Figure 1: Conceptual Framework

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 impact of system quality, subjective norms, interactivity, course content quality, perceived usefulness, and satisfaction on continuance intention to use e-learning of music major college students in Chengdu, China. The population is 500 female 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

Prior to the data collection, the Index of Item–Objective Congruence (IOC) was used to verify the content validity by three experts who titled Ph.D. or in the c-level. The IOC results showed that all items passed at a score of 0.6 or over. According to In (2017), pilot study is "the data collection on a smaller scale than the main or full-scale study, which is crucial for improvement of the quality and efficiency of the main study. In this study, 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 (0.741), subjective norms (0.850), interactivity (0.881), course content quality (0.609), perceived usefulness (0.745), satisfaction (0.869), and continuance intention (0.725).

3.4 Population and Sample Size

Sichuan University is a well-known higher education institution, where it can be a representative target population for this study. The total number of students is 37,000 people, whereas music major college students has about 6,400 people. The population is 500 female students majoring in music at Sichuan University who have been using three selected e-learning platforms: DingDing, Tencent meeting, and WeLink. According to Soper (2022), the result recommended minimum sample size about 425 participants. The research considered collecting 500 participants for efficient data analysis for the study.

3.5 Sampling Technique

This study employed probability and nonprobability sampling to determine a proper research procedure, including judgmental, stratified random, and convenience sampling. Judgmental sampling is to select female 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 target group of students.

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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 60.6 percent (303), and the least group is 23 years old or over at 7.6 percent (38). Seniors account for 31.8 percent, followed by juniors (27 percent), sophomores (24.2 percent), and freshmen (17 percent). Most respondents have used e-learning for 4-6 days per week (64.8 percent), whereas only 13.8 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	303	60.6%
	21-22 years old	159	31.8%
	23 years old or over	38	7.6%
Year of Study	Freshmen	85	17.0%
	Sophomore	121	24.2%
	Junior	135	27.0%
	Senior	159	31.8%
Frequency Of E-Learning Use	1-3 days/week	107	21.4%
	4-6 days/week	324	64.8%
	7 days/week	69	13.8%

4.2 Confirmatory Factor Analysis (CFA)

In CFA, the measurement model can be examined to approve convergent and discriminant validity. According to Table 3, CFA was assessed 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	0.805	0.687-0.740	0.806	0.510
2. Subjective Norms (SN)	Bag et al. (2022)	3	0.727	0.579-0.809	0.730	0.479
3. Interactivity (IN)	Cheng (2020)	3	0.890	0.833-0.879	0.890	0.730
4. Course Content Quality (CCQ)	Cheng (2020)	3	0.760	0.624-0.779	0.772	0.533
5. Perceived Usefulness (PU)	Cheng (2020)	4	0.774	0.634-0.715	0.781	0.471
6. Satisfaction (SAT)	Cheng (2014)	4	0.793	0.634-0.780	0.796	0.496
7. Continuance Intention (CI)	Cheng (2020)	4	0.770	0.561-0.741	0.779	0.471

The measurement model in CFA can be also assessed by the goodness of fit indices. Hair et al. (2006) suggested that the acceptable values in defining the goodness of fit is mandatory for CFA. Per Table 4, this study approved the measurement model fit without any adjustment, including CMIN/DF = 1.593, GFI = 0.939, AGFI = 0.921, NFI = 0.923, CFI = 0.970, TLI = 0.964, and RMSEA = 0.034.

Table 4: Goodness of Fit for Measurement Model

Index	Acceptable Values	Statistical Values
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015)	404.591/254 = 1.593
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.939
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.921
NFI	≥ 0.80 (Wu & Wang, 2006)	0.923
CFI	≥ 0.80 (Bentler, 1990)	0.970
TLI	≥ 0.80 (Sharma et al., 2005)	0.964
RMSEA	< 0.08 (Pedroso et al., 2016)	0.034
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.

In Table 5, testing for discriminant validity was evaluated by computing the square root of each AVE (Fornell & Larcker, 1981). The results show that the value of discriminant validity is larger than all inter-construct/factor correlations, therefore, the discriminant validity is supportive. The convergent and discriminant validity were proved; Consequently, the evidence is sufficient for establishing construct validity.

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Table 5: Discriminant Validity

	SAT	SQ	PU	CI	SN	IN	CCQ
SAT	**0.704**						
SQ	0.287	**0.714**					
PU	0.367	0.682	**0.686**				
CI	0.599	0.537	0.677	**0.686**			
SN	0.149	0.266	0.265	0.263	**0.692**		
IN	0.412	0.550	0.678	0.679	0.284	**0.855**	
CCQ	0.439	0.566	0.670	0.642	0.209	0.586	**0.730**

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 can be measured by the goodness of fit indices. Per Table 6, this study approved the structural model fit without any adjustment, including CMIN/DF = 3.469, GFI = 0.867, AGFI = 0.838, NFI = 0.824, CFI = 0.867, TLI = 0.851, and RMSEA = 0.070.

Table 6: Goodness of Fit for Structural Model

Index	Acceptable Values	Statistical Values
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015)	929.730/268 = 3.469
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.867
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.838
NFI	≥ 0.80 (Wu & Wang, 2006)	0.824
CFI	≥ 0.80 (Bentler, 1990)	0.867
TLI	≥ 0.80 (Sharma et al., 2005)	0.851
RMSEA	< 0.08 (Pedroso et al., 2016)	0.070
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.

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. In Table 7, the results demonstrate that most hypotheses are supported except H5.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: SQ→PU	0.677	10.444*	Supported
H2: SN→PU	0.135	2.724*	Supported
H3: IN→SAT	0.330	6.322*	Supported
H4: CCQ→SAT	0.294	5.076*	Supported
H5: PU→SAT	0.008	0.149	Not Supported
H6: PU→CI	0.562	9.101*	Supported
H7: SAT→CI	0.501	8.591*	Supported

Note: * p<0.05

Based on the SEM findings, this study can further be discussed:

H1 shows that system quality strongly impacts perceived usefulness, resulting in the standardized path coefficient value of 0.677 (t-value = 10.444). Aligned with Pituch and Lee (2006), e-learning system quality can be perceived by learners to be the most useful platform due to their functions, such as complete controllability and flexibility.

In **H2**, the relationship between subjective norms and perceived usefulness is supported by a standardized path coefficient value of 0.135 (t-value = 2.724). Huang (2011) approved that subjective norms can greatly predict perceived usefulness and behavioral intention as such social influence is viewed to affect users' perceived utility of e-learning among students.

H3 reveals that interactivity significantly impacts satisfaction, reflecting the standardized path coefficient value of 0.330 (t-value = 6.322). The results are supported by numerous scholars that additionally cascaded that if an e-learning system can provide learners with the functions of interactive features, it will enhance their satisfaction with the system (Cidral et al., 2018; Hassanzadeh et al., 2012; Mohammadi, 2015).

H4 verifies the significant impact course content quality on student satisfaction, representing a standardized path coefficient value of 0.294 (t-value = 5.076). It was confirmed that course design quality as the quality of the form for learning contents can enhance student satisfaction (Cheng, 2020; Roca et al., 2006).

H5 signifies that the significant relationship between perceived usefulness and student satisfaction is not significant. A standardized path coefficient is 0.008 and t-value is 0.149. The results are opposite to previous claims that perceived usefulness is addressed to have significant relation with satisfaction of students to use e-learning (Bhattacherjee, 2001; Xu et al., 2017).

H6 approves that perceived usefulness significantly impacts continuance intention with a standardized path coefficient of 0.562 (t-value = 9.101). Yang and Lin (2015) supported that perceived usefulness of learners positively enhance continuance intention to use e-learning.

Last, **H7** confirms that satisfaction significantly impacts continuance intention with a standardized path coefficient value of 0.501 (t-value = 8.591). Many researchers had a consensus that students' satisfaction with e-learning system can greatly impact their continuance intention of the system (Cheng, 2019; Elliott & Healy, 2001; Xu et al., 2017).

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5. Conclusions and Recommendation

5.1 Conclusion and Discussion

This study aims to determine the factors of continuance intention to use e-learning of female students majoring in music in Chengdu. The data was analyzed by Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM). The findings reveal that system quality and subjective norms significantly impact perceived usefulness. Interactivity and course content quality significantly impact satisfaction. Continuance intention is impacted by perceived usefulness and satisfaction. On the opposite, perceived usefulness has no significant impact on satisfaction. In summary, most hypotheses are supported except the relationship between perceived usefulness and satisfaction.

This study can relate the findings with the theories. First, system quality presents the strongest effect on perceived usefulness. Even though students expect the system's good quality, they feel it is useful to use such a learning mode. Cao and Jittawiriyanukoon (2022) studied e-learning's behavioral intention during the pandemic. Students expect the e-learning platform selected by the university can provide ease of use, convenience, and reliability. Furthermore, subjective norms such as social pressure significantly impact perceived usefulness, demonstrating that teachers and peers convince students about the usefulness of e-learning (Bag et al., 2022; O'Neal, 2007).

Second, interactivity and course content quality significantly impact student satisfaction with e-learning. The interactivity of e-learning is expected and impacts students' evaluation. Cheng (2020) explained that a high degree of interactivity could greatly impact students' satisfaction levels. Furthermore, Roca et al. (2006) noted that the high quality, of course, contents as information provided by the e-learning system might enhance student satisfaction with the system.

Next, continuance intention is impacted by perceived usefulness and satisfaction. Bhattacherjee (2001) indicated that perceived usefulness is the degree to which a person believes using a particular system would enhance his/her job performance and can determine users' behavioral intention. Students' satisfaction with e-learning can level their confidence and encourage them to continue using it (Xu et al., 2017). Therefore, students' satisfaction with the e-learning system can greatly impact their continuance intention.

Last, this study found that perceived usefulness has no significant impact on satisfaction. The results disapproved earlier study mentioned that e-learning can drive students' continuance intention (Bag et al., 2022). It can be assumed that students do not see the convenience and accessibility of e-learning as a major point but more on other factors.

5.2 Recommendation

According to Chang (2020), the online education market had about 200 million users in 2018, reflecting year-on-year growth of 25.7% to reach revenues of RMB 251.7 billion ($35.9 billion). The forecast showed that China's online education was expected to reach RMB 500 billion ($70.6 billion) by 2022. These statistical results demonstrated that the use of e-learning would be continued and increase in the future. Accordingly, this study provides recommendations based on the findings that educational institutions and the Chinese government should exploit the factors impacting the continuance intention of students in higher education to improve accessibility with the highest-performance online learning infrastructure for the country.

The system quality demonstrates the highest effect on perceived usefulness towards the continuance intention. Educational institutions could investigate the functionality and system quality of numerous e-learning platforms available in the market. The Chinese government should elevate the technological infrastructure to cope with future demand. The usefulness of e-learning can also be promoted through the system's high quality. The major influence on continuance intention can be promoted through educators and e-learning developers. Social norms can be that e-learning is a mega deployment during the Covid-19 pandemic due to social distance and other measures.

Additionally, interactivity and course content quality can elevate student satisfaction. Thus, universities should consistently measure and evaluate the satisfaction level of students for better improvement of interactivity and course content. This study focuses on the continuance intention of students to use e-learning. Perceived usefulness and satisfaction directly affect continuance intention. Consequently, educators and academic practitioners can investigate further the acceleration of these motivations and achieve the successful adoption of e-learning.

5.3 Limitation and Further Study

The limitations of this research are sample size and methodology that can be further conducted in the future. First, the data was collected from a specific group of respondents who were female students majoring in music in Chengdu. There would be a different perspective on another respondent's characteristics. Second, the selected e-learning systems are DingDing, Tencent meeting, and WeLink., which limit learners' experience. Any other platforms or upgraded systems in the future can provide different findings. Last, the data was analyzed by quantitative statistics. The findings cannot cover the clear view of participants. Thus, the qualitative method should be useful to extend or compare the results.

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References

Ajzen, I. (1991). Theory of planned behavior. *Organization Behavior and Human Decision Process, 50*(2), 179-211.

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.

Almanthari, A., Maulina, S., & Bruce, S. (2020). Secondary School Mathematics Teachers' Views on E-learning Implementation Barriers during the COVID-19 Pandemic: The Case of Indonesia. *Eurasia Journal of Mathematics, Science and Technology Education, 16*(7), 18-60.

Bag, S., Aich, P., & Islam, M. A. (2022). Behavioral intention of "digital natives" toward adapting the online education system in higher education. *Journal of Applied Research in Higher Education, 14*(1), 16-40. https://doi.org/10.1108/JARHE-08-2020-0278

Bay, D., & Daniel, H. (2001). The student is not the customer-An alternative perspective. *Journal of Marketing for Higher Education, 11(*1), 1-19.

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

Bhattacherjee, A. (2001). Understanding information systems continuance: an expectation-confirmation model. *MIS Quarterly, 25*(3), 351-370.

Brooks, S. K., Webster, R. K., Smith, L. E., Woodland, L., Wessely, S., Greenberg, N., & Rubin, G. J. (2020). The psychological impact of quarantine and how to reduce it: rapid review of the evidence. *The Lancet, 395*(10227), 912-920. https://doi.org/10.1016/S0140-6736(20)30460-8

Cao, Y., & Jittawiriyanukoon, C. (2022). Factors Impacting Online Learning Usage during Covid-19 Pandemic Among Sophomores in Sichuan Private Universities. *AU-GSB E-JOURNAL*, *15*(1), 152-163. https://doi.org/10.14456/augsbejr.2022.52

Chang, M. A. (2020, July 8). *Virtual Education.* https://english.ckgsb.edu.cn/knowledges/virtual-education-in-china/

Cheng, Y.-M. (2014). 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. (2019). How does task-technology fit influence cloud-based e-learning continuance and impact?. *Education + Training, 61*(4), 480-499.

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.

Cidral, W. A., Oliveira, T., Felice, M. D., & Aparicio, M. (2018). E-learning success determinants: Brazilian empirical study. *Computers and Education, 122*(7), 273-290.

Elliott, K. M., & Shin, D. (2002). Student Satisfaction: An alternative approach to assessing this important concept. *Journal of Higher Education Policy and Management, 24*(2), 197-209.

Elliott, K. M., & Healy, M. A. (2001). Key factors influencing student satisfaction related to recruitment and retention. *Journal of marketing for higher education, 10*(4), 1-11.

Fan, X., Duangekanong, S., & Xu, M. (2021). Factors Affecting College Students' Intention to Use English U-learning in Sichuan, China. *AU-GSB E-JOURNAL, 14*(2), 118-129. https://doi.org/10.14456/augsbejr.2021.20

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39-50. https://doi.org/10.2307/3151312

Griethuijsen, R. A. L. F., Eijck, M. W., Haste, H., Brok, P. J., Skinner, N. C., Mansour, N., Gencer, A. S., & BouJaoude, S. (2014). Global patterns in students' views of science and interest in science. *Research in Science Education, 45*(4), 581-603. https://doi.org/10.1007/s11165-014-9438-6

Gu, X., & Li, L. (2022). China's Experience of Online Education during the COVID-19 Pandemic: Policies, Lessons and Challenges. In V. Dennen, C. Dickson-Deane, X. Ge, D. Ifenthaler, S. Murthy & J. C. Richardson (Eds.), *Global Perspectives on Educational Innovations for Emergency Situations. Educational Communications and Technology: Issues and Innovations.* Springer. https://doi.org/10.1007/978-3-030-99634-5_28

Hair, J., Black, W., Babin, B., Anderson, R., & Tatham, R. (2006). *Multivariate Data Analysis* (6th ed.). Pearson Education.

Hassanzadeh, A., Kanaani, F., & Elahi, S. (2012). A model for measuring e-learning systems success in universities. *Expert Systems with Applications, 39*(12), 10959-10966.

Huang, J. T. (2011). Application of planned behavior theory to account for college students occupational intentions in contingent employment. *Career Development Quarterly, 59*(5), 455-466.

Huang, R. H., Liu, D. J., Tlili, A., Yang, J. F., & Wang, H. H. (2020). *Handbook on facilitating flexible learning during educational disruption: The Chinese experience in maintaining undisrupted learning in COVID-19 Outbreak* (1st ed.). Beijing: Smart Learning Institute of Beijing Normal University.

In, J. (2017). Introduction of a pilot study. *Korean journal of anesthesiology*, *70*(6), 601-605. https://doi.org/10.4097/kjae.2017.70.6.601

Jönsson, B. A. (2005). A case study of successful e-learning: A web-based distance course in medical physics held for school teachers of the upper secondary level. *Medical Engineering & Physics, 27*(7), 571-581. https://doi.org/10.1016/j.medengphy.2004.11.009

Kunanusorn, A., & Puttawong, D. (2015). The Mediating effect of satisfaction on student loyalty to higher education institution. *European Scientific Journal, 1*(special), 1857-7881.

Mailizar, M., Burg, D., & Maulina, S. (2021). Examining university students' behavioural intention to use e-learning during the COVID-19 pandemic: An extended TAM model. *Contemporary Educational Technology, 13*(2), 7057-7077. https://doi.org/10.1007/s10639-021-10557-5

Malkawi, E., Bawaneh, A. K., & Bawa'aneh, M. S. (2020). Campus Off, Education On: UAEU Students' Satisfaction and Attitudes Towards E-Learning and Virtual Classes During COVID-19 Pandemic. *Contemporary Educational Technology, 13*(1), 283.

The Scholar: Human Sciences

MOE China. (2020, June 17). *Guidance on the organization and management of online teaching and learning in regular higher education institutions during the epidemic prevention and control period.* http://www.moe.gov.cn/srcsite/A08/s7056/202002/t20200205_418138.html

Mohammadi, H. (2015). Investigating users' perspectives on e-learning: an integration of TAM and is success model. *Computers in Human Behavior, 45,* 359-374. https://doi.org/10.1016/j.chb.2014.07.044

Moser, K. M., Wei, T. E., & Brenner, D. (2020). Remote teaching During COVID-19: Implications from a National Survey of language educators. *System, 97*, 102431.

O'Neal, P. W. (2007). *Motivation of Health Behavior* (1st ed.). Nova Publishers.

Parasuraman, A., Zeithaml, V. A., & Berry, L. L. (1988). SERVQUAL: a multiple-item scale for measuring consumer perceptions of service quality. *Journal of Retailing and Consumer Services, 61*(1), 12-40.

Pedroso, R., Zanetello, L., Guimaraes, L., Pettenon, M., Goncalves, V., Scherer, J., Kessler, F., & Pechansky, F. (2016). Confirmatory factor analysis (CFA) of the crack use relapse scale (CURS). *Archives of Clinical Psychiatry, 43*(3), 37-40.

Pituch, K. A., & Lee, Y.-K. (2006). The influence of system characteristics on e-learning use. *Computers & Education, 47*(2), 222-244. https://doi.org/10.1016/j.compedu.2004.10.007

Rizana, A. F., Hediyanto, U. Y. K. S., Ramadhan, F., & Kurniawati, A. (2020). E-learning success determinants in higher education: a systematic literature review from users' perspective. *IOP Conference Series: Materials Science and Engineering, IOP Publishing, 830*(3), 032012.

Robinson, H., Al-Freih, M., & Kilgore, W. (2020). Designing with care: towards a care-centered model for online learning design. *The International Journal of Information and Learning Technology, 37*(3), 99-108.

Roca, J. C., Chiu, C. M., & Martınez, F. J. (2006). Understanding e-learning continuance intention: an extension of the technology acceptance model. *International Journal of Human Computer Studies, 64*(8), 683-696.

Roy, D., Tripathy, S., Kar, S. K., Sharma, N., Verma, S. K., & Kaushal, V. (2020). Study of knowledge, attitude, anxiety & perceived mental healthcare need in Indian population during COVID-19 pandemic. *Asian Journal of Psychiatry, 51,* 102083.

Sallaku, R., & Vigolo, V. (2022). Predicting customer loyalty to Airbnb using PLS-SEM: the role of authenticity, interactivity, involvement and customer engagement. *The TQM Journal*, Vol. ahead-of-print No, ahead-of-print. https://doi.org/10.1108/TQM-12-2021-0348

Sari, F. M., & Oktaviani, L. (2021). Undergraduate Students' Views on the Use of Online Learning Platform during COVID-19 Pandemic. *Teknosastik, 19,* 41-47.

Sharma, S., Mukherjee, S., Kumar, A., & Dillon, W. (2005). A simulation study to investigate the use of cutoff values for assessing model fit in covariance structure models. *Journal of Business Research, 58*(7), 935-943. https://doi.org/10.1016/j.jbusres.2003.10.007

Shattuck, K., Zimmerman, W. A., & Adair, D. (2014). Continuous improvement of the QM rubric and review processes: scholarship of integration and application. *Internet Learning, 3*(1), 25-34.

Shiau, W. L., & Chau, P. Y. K. (2016). Understanding behavioral intention to use a cloud computing classroom: a multiple model comparison approach. *Information and Management, 53*(3), 355-365.

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 Science Publishers.

Soper, D. S. (2022, May 24). *A-priori Sample Size Calculator for Structural Equation Models.* Danielsoper. www.danielsoper.com/statcalc/default.aspx

Urbach, N., & Müller, B. (2012). The updated DeLone and McLean model of information systems success. In Y. K. Dwivedi, M. R. Wade, & S. L. Schneberger (Eds.), *Information Systems Theory: Explaining and Predicting Our Digital Society* (pp. 1-18). Springer. https://doi.org/10.1007/978-1-4419-6108-2

Wang, T., Lin, C. L., & Su, Y. S. (2021). Continuance intention of university students and online learning during the COVID-19 pandemic: a modified expectation confirmation model perspective. *Sustainability, 13,* 45-86.

Wu, J. H., & Wang, Y. M. (2006). Measuring KMS Success: A Respecification of the DeLone and McLean's Model. *Journal of Information & Management, 43,* 728-739. http://dx.doi.org/10.1016/j.im.2006.05.002

Xu, F., Tian, M., Xu, G., Ayala, B. R., & Shen, W. (2017). Understanding Chinese users' switching behaviour of cloud storage services. *The Electronic Library, 35*(2), 214-232.

Yang, H. L., & Lin, S. L. (2015). User continuance intention to use cloud storage service. *Computers in Human Behavior, 52*, 219-232.

Zhang, L., Zhang, X., Duan, Y., Fu, Z., & Wang, Y. (2010). Evaluation of learning performance of e-learning in China: a methodology based on change of internal mental model of learners. *The Turkish Online Journal of Educational Technology, 9*(1), 70-82.

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