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A Study on Behavioral Intention to Use Online Learning of Undergraduate Students in Painting Majors in Chengdu, China

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Abstract

Purpose: This paper aims to study the impact factors of behavioral intention of students in painting majors in Chengdu, China. The conceptual framework contains perceived ease of use, responsiveness, reliability, perceived usefulness, e-learning quality, hedonic motivation, facilitation condition, social influence, and behavioral intention. **Research design, data, and methodology:** This study adopted quantitative methods to survey 500 participants. Before data collection, the index of item-objective congruence (IOC) and Cronbach's Alpha of pilot test (n=50) was used to ensure the validity and reliability. After collecting the data, the structural equation model (SEM) was used to verify the structure and relationship of variables, the validity and normality of research tools, data collection procedures, and statistical data processing. Structural equation modeling (SEM) and statistical tools are applied to hypothesis testing. **Results:** All eight hypotheses of this study are supported. Perceived usefulness has the most significant impact on behavioral intention. Perceived ease of use has a significant impact on perceived usefulness. Reliability and responsiveness significantly impact e-learning quality. Hedonic motivation, facilitating conditions, social influences, and e-learning quality impact behavioral intention. **Conclusions:** Developers of e-learning systems and senior managers of higher education institutions should improve learning systems so that students can learn online anytime, anywhere, retain recorded lessons, and accurately search for the content they want.

Keywords: E-Learning Quality, Perceived Usefulness, Perceived Ease of Use, Behavioral Intention

JEL Classification Code: E44, F31, F37, G15

1. Introduction

By May 2020, 1,454 universities nationwide had conducted online education during the pandemic. As many as 17.75 million college students have participated in online learning in China, which has received 2.3 billion visits. Network education is a symbol of the modernization of world education. Especially during the COVID-19 pandemic, people inevitably turn to homeschooling (Zhao et al., 2022). Finally, online learning has become a last resort for home learning, specifically designed to support the learning process. "Advances in information and communication technology (ICT), also known as technology, have opened up many possibilities for university communication, interactive and multimedia delivery systems. With the advent of the novel coronavirus, traditional face-to-face teaching is difficult to implement, and online learning will become one of the preferred teaching modes in colleges and universities. (UNESCO, 2020).

In the 21st century, the digital revolution has swept the world, rapidly impacting modern teaching methods. Meanwhile, online learning platforms have emerged continuously at the historic moment, opening new learning methods for college students of various majors. Students can choose learning content according to their interest in learning knowledge and online learning hardware facilities and can

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study anytime and anywhere, across time and space problems, more conveniently. Of course, the traditional way of education will also change, and how to adapt and change the way of teaching is also an important issue for teachers and students (Samaniego Erazo et al., 2015).

In the case of the rapid development of the network and the rapid impact of modern teaching methods, online learning has become common. In American higher education, there have been as many as 48,000 diploma and degree courses offered, among which the diploma and degree courses cover all disciplines and majors in American higher education institutions. Students use online learning to improve their degrees; over one million have taken courses to earn degrees. There are 22 countries or regions on the UNESCO list of recommended online learning platforms. The majority of these platforms are located in the United States (26 or 44%), while other countries are also starting to use online learning platforms for teaching and learning. Today, more than 800 universities around the world offer online degree programs over the Internet and widely use online education platforms to teach. Harvard University, MIT, and Cambridge University have agreed to allow international students to register for degree programs online and study at a distance. Online learning is also broadening people's horizons, improving the convenience of learning, and changing how people learn (UNESCO, 2020).

Nowadays, with the rapid development of Internet technology, including the new online learning system and the development of network technology. More and more people have access to online activities. Online learning has also become an achievable goal. With the development of Internet +, the rise of 5G technology, and the improvement of big data, the popularization of computer networks and digital learning terminals has been promoted, breaking the traditional learning mode and making students' learning more flexible. The Internet's popularity is becoming increasingly widespread, making online learning a trend (Dangi et al., 2022).

UNESCO (2020) also introduced relevant policies to strengthen the development and application of high-quality educational resources. It is suggested to strengthen the construction and development of network teaching resource systems, develop new network learning courses, and strengthen the application of information technology, which provided strong policy support for online learning and increased the social attention to online education—new ways of learning and teaching for more and more teachers and students.

In the research background of colleges and universities, the rapid development of computer technology and network communication technology in recent years has formed more learning modes, from face-to-face teaching to online learning. Online learning integrates many advantages of online learning. It has become more convenient and diversified in the direction and subjects of learning, which has become the focus of higher education, training, and basic education research hotspots. Its development and application in higher education are particularly eye-catching (Pima et al., 2018). However, the overall digital education practice in China is progressing slowly. The development of China's education model of online learning started relatively late in the world and has not been applied to practice for a long time. Many online students need some help. Some students are less receptive to online learning, including some teachers who have many restrictions on the teaching mode of online learning compared with face-to-face teaching, and their teaching methods and contents should also be changed. This research will analyze the factors impacting e-learning quality. Perceived usefulness and behavior intention toward painting majors' students at a Private Vocational University in the influencing factors of Chengdu, China, are studied to study the relevant factors that affect online learning to promote students' learning behavior intention.

2. Literature Review

2.1 Perceived Ease of Use

Perceived ease of use means technological application in ease of use (Venkatesh et al., 2003), which refers to what degree a person has Perceived ease of use and effectiveness (Davis, 1989). Ease of use determines students' attitudes toward accepting and adopting online learning (Lee et al., 2009). Some studies have shown that TAM's empirical study has confirmed the strong effects of perceived ease of use on users' acceptance of applications (Ramayah, 2006).

If the perceived ease of use in the system is higher, users will be satisfied. As Shroff et al. (2011) argued, students' perceptions of the perceived usefulness and perceived ease of use of online learning. Students' perceptions of use ease and behaviors are in correlation. Students who feel online learning is easy and time-saving will have positive attitudes toward it. It is very useful for students. Learn online, which corresponds to ease of use in learning management systems, access to course materials, and communication with peers and faculty. The use ease perception and users' acceptance of using are positively correlated (Lee et al., 2005; Ramayah, 2006). Effectiveness is assumed with autonomous operation of behavior determinants (Chung, 2005). From these supported studies, we derive the following hypothesis:

H1: Perceived ease of use has a significant impact on perceived usefulness.

2.2 Responsiveness

In concept, responsiveness is the users' perception and response to the interactive medium (Cyr et al., 2009; Wu, 2016). In online retailing, responsiveness can improve product quality to create relevant customer results (Yoo & Yoo, 2010). In this paper, teachers respond to students' questions and related doubts in class in online learning. The rapid service and response provided by the e-learning page can also affect students' behavioral perception of online learning. As feedback from teachers is vital to processing learning, the effectiveness of feedback is the key to education (Leibold & Schwarz, 2015).

Teacher responsiveness, demonstrated by communication and feedback, is crucial in online education. Feedback with clearness, effectiveness, and meaningfulness is efficient for students' learning (Hattie & Timperley, 2007) and students' behavioral intention of online learning. Being responsive helps customers by immediately providing accessible services with convenience (Chung et al., 2020; Van den Broeck et al., 2019). This ability to use feedback with effectiveness and clarity fosters students' learning (Hattie & Timperley, 2007). In online learning, teachers make clear, effective, and meaningful responses to students' questions with answers and enlightenment, thus influencing students' behavioral intention and satisfaction with online learning. From these supported studies, we derive the following hypothesis:

H2: Responsiveness has a significant impact on e-learning quality.

2.3 Reliability

Reliability is defined as how the product performs its functions within certain conditions and time permits. Reliability measurement with probability is the reliability. Common reliability indicators include reliability, probability of failure and failure rate, average working time, maintenance time, and validity (Johnson et al., 2009).

Reliability related to a good teaching process involving the teacher and system is very important for online learning. It can influence students' interest and willingness to use the system of online learning mode. For students, reliable systems and teachers can make it easier for them to achieve the goal of online learning. Al-Kindi and Al-Suqri (2017) compared students' use of online learning systems and concluded that learning management systems are against online learning, while it fails to find related factors. Afterward, Hu et al. (2016) explored the learning management system of students and their views on accessing online learning systems and found that thanks to the availability and reliability problems of online learning systems, students' performances in learning systems did not get the best learning experience so lead to online learning interest is not big. From these supported studies, we derive the following hypothesis:

H3: Reliability has a significant impact on e-learning quality.

2.4 Perceived Usefulness

Perceived usefulness refers to an individual's belief in the effects of a particular system adoption on performance. (Davis, 1989), Alternatively, users' thoughts on improving work performance when using a particular system are subjective. The concept of perceived usefulness was first proposed in the technology acceptance model, meaning that a person can imagine using the system or infrastructure to improve work efficiency and development (Davis, 1989). besides, scholar Davis et al. (1989) illustrated that perceived usefulness could directly affect the positive attitude of users towards what he has done, thus predicting their intention to use. Based on the Research done by Davis et al. (1989).

In other words, the concept of "Perceived usefulness" relates to users' degree of belief in the positive effects of the used technology on their performances in both work and study. (Akbar, 2013; Venkatesh et al., 2003). Perceived usefulness can predict technology adoption intentions in various contexts (Hendro, 2021). Research has found that usefulness is perceived when users find technology easy and effective (Brandon-Jones & Kauppi, 2018; Mohammadi, 2015). thus, this concept refers to the individual's viewpoints of how a system affects performances positively (Davis, 1989). Meanwhile, Davis (1989) found in his Research that Research has found that when users find technology easy and effective, usefulness is perceived and Perceived ease of use to its use at present or in the future. The importance of visual acuity is further emphasized in his later Research. Compared to the simple perception of use, perceived usefulness correlates more with future use behavior. Through this study, we can know that the willingness of users to adopt a new system may positively affect their performance. From these supported studies, we derive the following hypothesis:

H4: Perceived usefulness has a significant impact on behavioral intention.

2.5 E-Learning Quality

The e-learning quality estimates its service quality accordingly. Miranda et al. (2017) believed it represents an e-learning system in quality, guideline clarity, and information perception. Studies have found that well-designed online courses are vital to shaping students' readability and teacher's use of technologies related to e-learning (Peltier et al., 2007; Rocca et al., 2016).

E-learning quality is a significant aspect of students' online Learning, followed by the tutors for e-learning quality and course materials, management, and service support (Pham et al., 2019). Of course, it also includes the responsiveness and reliability of Online Learning, which is the key to the whole e-learning quality. Some institutions have made efforts to improve e-learning quality. For example, the global organization Quality Matters (QM) has been studying how to confirm and ensure online learning quality. They developed rules and standards for the management and improvement of online Learning. Aurora Institute has studied online education transformation for high online Learning (INACOL, 2020). Therefore, the quality of e-service is an important factor affecting students' online learning behavior intention. From these supported studies, we derive the following hypothesis:

H5: E-learning quality has a significant impact on behavioral intention.

2.6 Hedonic Motivation

Hedonic motivation refers to users' pleasure in system usage, which is vital to creating the behavioral intention of people to perform certain behaviors. Hedonic motivation refers to the pleasure or pleasure generated by technological use (Venkatesh et al., 2012). according to Venkatesh et al. (2012), hedonic motivation can predict technological intent and is very effective. In the UTAUT2 model, hedonic motivation is considered the most important, and a measure of the emotional component of technological adoption can be obtained through hedonic motivation (Tamilmani et al., 2019).

Hedonic motivation refers to the enhanced enjoyment users gain through experience (Kohler et al., 2011). Interactive learning for online students is a source of entertaining, engaging, and interesting experiences. Hedonic motivation excluded in the UTAUT2 model is considered the most important. Overall, like technology, hedonic motivation has been affected (Tamilmani et al., 2019). Hedonic motivation predicts students' intention to use online learning (Samsudeen & Mohamed, 2019). From these supported studies, we derive the following hypothesis:

H6: Hedonic motivation has a significant impact on behavioral intention.

2.7 Facilitating Condition

Facilitating convenience refers to individuals who perceive the existence of organization and technology related to system infrastructure (Venkatesh et al., 2003). These are perceived behavioral controls and compatibility that try to make technology easy to use. (Venkatesh et al., 2003). Convenience in the TRA model refers to the skills, support, and opportunities for outcome achievements. Through relevant experimental studies, it is found that convenient teams affect how students use e-learning (Abbad et al., 2009). Especially in the current pandemic, convenient teaching methods are very important because there is no way to gather for offline classes. All these will affect students' behavioral intention to use online learning (Salloum & Shaalan, 2018).

When it becomes easier to make students feel the objective conditions of technology, their behavioral intentions improve. In this study, if students felt that their school had sufficient and proper infrastructure in organization and technology, thus supporting e-learning use, they generated behavioral willingness to adopt e-learning for the academy. Abu Gharrah and Aljaafreh (2021) argued that convenience conditions positively correlate with users' behavioral willingness to accept online learning. It can make learners feel that the objective conditions of using online learning are easy to obtain, such as relevant training, technical support, and easy manipulation of the online learning platform. This facilitates students' willingness to use e-learning behavioral intention. From these supported studies, we derive the following hypothesis:

H7: Facilitating condition has a significant impact on behavioral intention.

2.8 Social Influence

Social influences refer to an individual's intention of believing in using and doing things, thus affecting others (Venkatesh et al., 2003). it also refers to how individuals think things are meaningful to others, like students' use of the system in relevant groups like teachers, parents, friends, and people around them. Social influence about intent behaviors is generated due to other's opinions affecting students' participation in certain behaviors, just as students' behavioral intent in online learning does.

If individuals have the perception from others about their intention of using a technology or an object, the degree of technology or system in use is considered a social influence (Venkatesh & Davis, 2000). Studies show that social influence significantly affects students' intention and practical use of online learning (Akbar, 2013). it is possible that social influences behavioral intentions due to impacts from others' opinions and certain behaviors. People will listen to the opinions of others psychologically, even if they have their own ideas in mind, but different opinions also need to be referred to. Nevertheless, the link connecting social influence and online learning willingness is important, and social influence can determine willingness to use online learning (Tarhini et al., 2017). From these supported studies, we derive the following hypothesis:

H8: Social influence has a significant impact on behavioral intention.

2.9 Behavioral Intention

Online learning has witnessed significant growth over the past decade, and understanding students' behavioral intention in this context is crucial for educators, institutions, and policymakers. This literature review synthesizes key research findings on behavioral intention within the domain of online learning, exploring factors that influence students' intentions to engage in online education. The Technology Acceptance Model (TAM), initially proposed by Davis in 1989, has been extensively applied to investigate online learning behavioral intention. TAM posits that perceived ease of use and perceived usefulness are pivotal in shaping individuals' intention to use technology. Research by Davis (1989) found that students' perceptions of the ease of using online learning platforms significantly influence their behavioral intention. Moreover, Venkatesh and Davis (2000) emphasized the importance of perceived usefulness in predicting online learning intention, highlighting its role in facilitating learning and improving educational outcomes.

3. Research Methods and Materials

3.1 Research Framework

The research model proposed in this study is based on the Technology acceptance model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). The aim is to find out some relevant reasons why the technology can be applied to the organization, understand the intention of use in use, and thus understand the user's wishes more objectively. We also understand through models that they play an important role in determining user acceptance and behavior—expectations of performance and effort, social impact, and accessibility. In perceived usefulness, TAM directly affects an individual's behavioral intention. Using perceived usability to know that perceived usefulness affects individuals' behavioral intentions objectively can better understand students' behavioral intentions when using online learning (Davis et al., 1989).

In the research model of this study, three theoretical frameworks are adopted for research. The first one is proposed by Hu et al. (2016), which provides perceived usefulness, perceived ease of use, and behavioral intention; the second theoretical framework is adopted by Muqtadiroh et al. (2020). Reliability, responsiveness, e-learning quality, and behavioral intention are provided among them. Finally, in the third theory, based on the relevant research of Rudhumbu (2022), it is proposed that hedonic motivation, facilitating conditions, and social influences can determine students' behavioral intention in online learning. The conceptual framework of this study is shown in Figure 1.

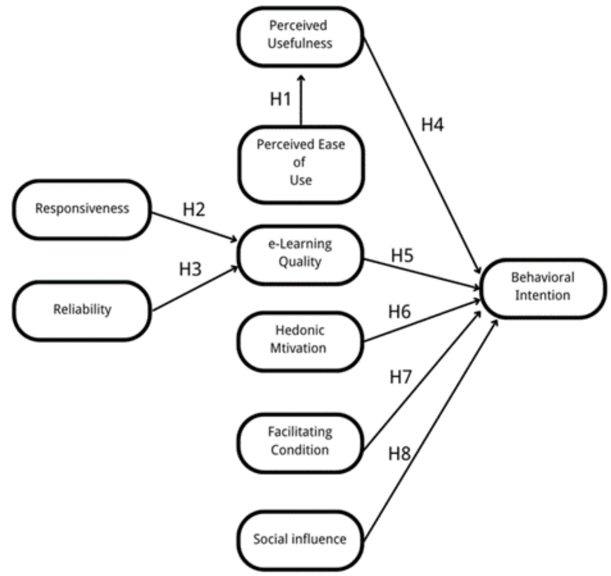

Figure 1: Conceptual Framework

H1: Perceived ease of use has a significant impact on perceived usefulness.
H2: Responsiveness has a significant impact on e-learning quality.
H3: Reliability has a significant impact on e-learning quality.
H4: Perceived usefulness has a significant impact on behavioral intention.
H5: E-learning quality has a significant impact on behavioral intention.
H6: Hedonic motivation has a significant impact on behavioral intention.
H7: Facilitating condition has a significant impact on behavioral intention.
H8: Social influence has a significant impact on behavioral intention.

3.2 Research Methodology

This chapter includes research methods and tools, including the target population selection, the reasons for selecting sampling units, and the selection of sample size. This study used quantitative methods and questionnaires to collect the data of relevant survey objects. Before data collection and questionnaire distribution, three experts were asked to perform the index of item-objective congruence (IOC) to test the content validity. Cronbach's Alpha pilot test was used to ensure the validity of the questionnaire content. IOC results pass at all items score over 0.6. According to George and Mallery (2003), Cronbach's should have an alpha value of 0.7 or higher to indicate acceptable reliability.

Therefore, the pilot test (n=50) was assessed by Cronbach's Alpha with all constructs had their values over 0.7. After completing the reliability and validity test, the questionnaire was distributed to undergraduates in Chengdu Vocational University of the Arts painting, and the respondents had more than one month of online learning experience. In this study, the SEM method proposed by Anderson and Gerbing (1988) was used to analyze sample data. First, JAMOVI and AMOS were used to verify the convergence validity of CFA test data. Then, SEM was used to study the importance of conceptual model testing in the relationship between the structures of this study and propose hypotheses between variables.

3.3 Population and Sample Size

The target population is 1195 students in painting majors in a university in Chengdu, China. The minimum sample size should be around 200 participants. Thus, the researcher considered to collect 500 sample for statistical analysis.

3.4 Sampling Technique

This study used sampling methods such as judgment, convenience, and stratified sampling to select the sample range. The sample of fine Arts undergraduates from Chengdu Vocational University of the Arts with more than one month of online learning experience is selected by judgment sampling. Stratified random sampling is considered to divide the target population into multiple groups. Samples were randomly selected from the study group or study group (Lavrakas, 2008). In this study, the levels of four undergraduate students majoring in painting at Chengdu Art Vocational College were selected by stratified sampling to determine the sample size of the sample layer, as shown in Table 1 below.

Table 1: Sample Units and Sample Size

Major	Population Size	Proportional Sample Size
Oil painting	499	205
Chinese painting	148	65
Printmaking	287	122
Other majors	261	108
Total	**1195**	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

The total number of respondents in this study is 500; the maintenance hole statistics are summarized in Table 2 below. Among the interviewees are 367 women and 133 men, accounting for 73.4% and 26.6% respectively. Among the respondents, 55 were aged 16-18 (11%), 145 were aged 19-20 (29%), 186 were aged 21-23 (37.2%), 72 were aged 24-26 (14.4%), and 42 were over 26 (8.4%).

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	367	73.4%
	Female	133	26.6%
Age	16-18 years old	55	11%
	19-20 years old	145	29%
	21-23 years old	186	37.2%
	24-26 years old	72	14.4%
	Over 26 years old	42	8.4%

Source: Constructed by author

4.2 Confirmatory Factor Analysis (CFA)

According Table 3 can be obtained. Statistical analysis of survey data is known as confirmatory factor analysis, and CFA is the starting point and critical first step in SEM (Hair et al., 2010). According to Byrne (2010), CFA has proved to be SEM's starting point and key factor. The reliability and validity between the two variables can be measured using CFA. The convergent validity of a variable can be measured by Cronbach's Alpha reliability, AVE, and CRL. According to the related study by Hair et al. (1998), factors with values above 0.50 have a significant impact. According to this study's values, all variables' load values are greater than 0.50 and greater than 0.70. As shown in Table 3 below, the CR value of all variables is greater than or equal to 0.70, and the AVE value is greater than or equal to 0.4. As shown in Table 3, the CR values of the variables in this study are all over 0.7, and the AVE values are over 0.5, so the estimates of all variables are significant. According to George and Mallery (2003), Cronbach's should have an alpha value of 0.7 or higher to indicate acceptable reliability. Cronbach's Alpha values of all factors in this study are greater than or equal to 0.7, so it can be shown that all variables are acceptable and reliable.

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
Behavioral intention (BI)	Rudhumbu (2022)	3	0.851	0.781-0.827	0.851	0.656
E-learning quality (ELQ)	Herdiyanti and Puspitasari (2020)	4	0.855	0.733-0.834	0.845	0.572
Perceived usefulness (PU)	Hu and Lai (2019)	3	0.829	0.746-0.816	0.853	0.658
Perceived ease of use (PEU)	Hu and Lai (2019)	4	0.839	0.713-0.785	0.840	0.567
Responsiveness (RES)	Herdiyanti and Puspitasari (2020)	4	0.859	0.737-0.823	0.850	0.586
Hedonic motivation (HM)	Rudhumbu (2022)	3	0.822	0.737-0.839	0.827	0.615
Facilitating condition (FC)	Rudhumbu (2022)	3	0.811	0.750-0.787	0.802	0.575
Reliability (REL)	Herdiyanti and Puspitasari (2020)	4	0.863	0.738-0.827	0.871	0.629
Social influence (SI)	Rudhumbu (2022)	3	0.808	0.718-0.828	0.815	0.596

Table 4 below shows all goodness-of-fit indicators. The values of GFI, AGFI, NF, CMIN/DF, RMSEA, CFA, TLI, and CFI of the variables are all acceptable values, which can prove the model's goodness of fit in this study.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/ DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	2.435
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.900
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.911
NFI	≥ 0.80 (Wu & Wang, 2006)	0.852
CFI	≥ 0.80 (Bentler, 1990)	0.931
TLI	≥ 0.80 (Sharma et al., 2005)	0.895
RMSEA	< 0.08 (Pedroso et al., 2016)	0.430
Model Summary		**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

As shown in Table 5 below, it is significant that the AVE square root of all variables is greater than the factor correlation value to judge the effectiveness of factors.

Table 5: Discriminant Validity

	PEU	RES	REL	HM	FC	SI	PU	ELQ	BI
PEU	**0.752**								
RES	0.204	**0.765**							
REL	0.230	0.141	**0.793**						
HM	0.249	0.251	0.136	**0.784**					
FC	0.169	0.198	0.155	0.164	**0.758**				
SI	0.149	0.195	0.158	0.134	0.114	**0.772**			
PU	0.241	0.147	0.192	0.220	0.134	0.203	**0.811**		
ELQ	0.220	0.322	0.303	0.214	0.209	0.243	0.267	**0.756**	
BI	0.316	0.305	0.251	0.283	0.287	0.344	0.445	0.461	**0.810**

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

4.3 Structural Equation Model (SEM)

From Table 6, According to Salloum and Shaalan (2018), relevant theoretical research uses the structural equation model to test the causal relationship between variables. Compared with other traditional models, SEM can better show the multiple relationships between independent variables and dependent variables. In this study, the structural equation model (SEM) was used to analyze the collected data, and goodness of fit of the structural model was measured, as shown in Table 5 below. The statistical values were CMIN/DF = 1.429, GFI = 0.933, AGFI = 0.916, NFI=0.923, CFI = 0.975, TLI = 0.971 and RMSEA = 0.290, respectively. All the values of the fit index are greater than the acceptable values, thus affirming the model's goodness of fit.

Table 6: Goodness of Fit for Structural Model

Index	Acceptable	Statistical Values
CMIN/ DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	1.429
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.933
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.916
NFI	≥ 0.80 (Wu & Wang, 2006)	0.923
CFI	≥ 0.80 (Bentler, 1990)	0.975
TLI	≥ 0.80 (Sharma et al., 2005)	0.971
RMSEA	< 0.08 (Pedroso et al., 2016)	0.290
Model Summary		**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

The correlations between the independent and dependent variables presented in the hypotheses in this study were measured using regression coefficients or standardized path coefficients, as shown in Table 7 below.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-Value	Result
H1: PEU→PU	0.306	5.669*	Supported
H2: RES→EQ	0.307	6.126*	Supported
H3: REL→EQ	0.348	6.885*	Supported
H4: PU→BI	0.402	8.005*	Supported
H5: ELQ→BI	0.372	7.589*	Supported
H6: HM→BI	0.132	2.849*	Supported
H7: FC→BI	0.193	4.060*	Supported
H8 SI→BI	0.231	4.815*	Supported

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

As shown in Table 7 above, the eight hypotheses in this study all support the strong influence of e-learning quality, perceived usefulness, and behavioral intention. Behavioral intention is significantly affected by perceived usefulness and e-learning quality, respectively.

The greatest influence on behavioral intention is perceived usefulness, as shown in **H4,** where the standardized path coefficient is 0.402, and the T-value is 8.005. This conclusion supports the study of Davis et al. (1989), which shows that perceived usefulness is crucial to behavioral intention variables. In related studies, customers directly exposed to electronic systems that perceive usefulness have a greater impact on their behavioral intentions (Castaneda et al., 2007). Similarly, Wu (2016) found that perceived usefulness significantly affects behavioral intent compared to the initial adoption stage, especially in the post-use stage. All perceived usefulness can improve students' behavioral intention to use online learning.

Similarly, e-learning quality has the second largest impact on behavioral intention, **H5** with its standardized path coefficient of 0.372 and T-value of 7.589. This conclusion is consistent with the relevant research conclusion of Zhang et al. (2012), who found that the quality of e-learning can directly and indirectly affect students' willingness to continue to participate. E-learning is widely accepted by e-learners, e-university students, employees, and the public, and e-learning quality affects users' behavioral intentions. Therefore, e-learning quality can determine students' behavioral intentions.

Perceived ease of use significantly affects the perceived usefulness of **H1,** whose standardized path coefficient is 0.306 and T-value is 5.669. This result is consistent with the results confirmed by Lee et al. (2005). Studies have shown that perceived usefulness and ease of use affect learners' satisfaction with the system. The higher the former, the higher the satisfaction in users. Perceived ease of use. They are using the system. The higher the former, the higher the satisfaction in users. Perceived ease of use. Then, relative can enhance the perceived usefulness of students.

Reliability has a significant impact on e-learning quality. In **H2,** the standardized path coefficient is 0.307, and the T-value is 6.126. This result supports the relevant studies of Hu et al. (2016), DeRouin et al. (2005), and Baylari and Montazer (2009). When students feel reliable, e-learning quality will improve, and vice versa.

Responsiveness, another important factor affecting e-learning quality, In **H3,** had a standardized path coefficient of 0.348 and a T-value of 6.885. This effect is the same as that of Pituch and Lee (2006), Muqtadiroh et al. (2020), and Chung et al. (2020). Concise, effective, and meaningful responsiveness has a powerful effect on students' e-learning quality.

H6, Hedonic motivation has a significant impact on behavioral intention. The standardized path coefficient is 0.132, and the value is 2.849. In line with Kohler et al. (2011), Abu Gharrah and Aljaafreh (2021), Tamilmani et al.(2019) conducted a review and concluded that systematic behavioral intention is generated through hedonic motivation. So, hedonic motivation and the behavioral willingness of the individual to accept the system are significantly correlated.

An important influencing factor in Behavioral intention is facilitating conditions, whose standardized path coefficient is 0.193 and T-value is 2.849. **H7** is consistent with the findings of Abbad et al. (2009), Abu Gharrah and Aljaafreh (2021), and Mehta et al. (2019). The convenience of these resources may include hardware support, knowledge, convenience of online learning systems, etc., which can affect students' behavioral willingness to learn online (Salloum & Shaalan, 2018). Therefore, the H7 results of this study are supportive.

Social influences also significantly affect behavioral intention in **H8,** especially when the standardized path coefficient is 0.231 and the T-value is 4.815. This result is consistent with the findings of Hossain et al. (2017), Abbad et al. (2009) and Venkatesh et al. (2003). Abu Gharrah and Aljaafreh (2021) study found that social influence significantly impacts students' behavioral willingness to use online learning.

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

This study analyzes the factors affecting the e-learning quality, perceived usefulness, and behavioral intention of college students majoring in painting after editing relevant questionnaires and doing the IOC and small-range reliability tests. Undergraduate students majoring in painting with more than one month of online learning experience were selected as the data collection research objects. After the completion of relevant data collection, CAF and SEM were used to analyze the reliability and validity of the conceptual model of this study. In this study, a total of 8 hypotheses were proposed, all supported to be valid and satisfy the hypotheses.

The results of this study are as follows:

Perceived usefulness has the strongest impact on behavioral intention. In related research, customers directly exposed to electronic systems that perceive usefulness have a greater impact on their behavioral intentions (Castaneda et al., 2007). Wu (2016) found that perceived usefulness significantly affects behavioral intent compared to the initial adoption stage, especially in the post-use stage. Therefore, establishing a system based on goal-related performance can effectively motivate students' behavioral intentions.

Students' behavioral intention is also greatly influenced by the quality of e-learning. Relevant studies have found that the quality of e-learning can directly and indirectly affect students' willingness to continue to participate (Zhang et al., 2012). The high quality of e-learning can exert students' positive behavioral intention of online learning.

According to reliability, a related variable mentioned above, responsiveness significantly impacts e-learning quality. Chung et al. (2020) study showed that concise, effective, and reliable responses significantly impact students' e-learning quality. It can improve the quality of students' e-learning by improving reliability and responsiveness.

At the same time, improving perceived ease of use-related factors can bring better-perceived usefulness to students, thus improving their behavioral intention of online learning. Hedonic motivation, facilitating conditions, and social influences can also have significant influences. When students feel that online learning is interesting and convenient, and people around them think they should use it, their behavioral intentions can be significantly influenced.

5.2 Recommendation

This study determined the e-learning quality (ELQ) of Chengdu Art Vocational University painting major undergraduate students. Perceived usefulness (PU), perceived ease of use (PEU), responsiveness (RES), hedonic motivation (HM), Key factors for facilitating condition (FC), reliability (REL), social influence (SI), and behavioral intention (BI).

According to previous studies, perceived usefulness is the most significant factor affecting behavioral intention. Therefore, improving the perceived ease of use of online systems can improve the operation of online learning systems. Features and related technologies make online learning easy to use and help students achieve better results. By making students feel that the online learning system is useful, they can enhance their behavioral intention of online learning.

E-learning is also one of the factors that significantly affect behavioral intentions. E-learning quality and reliability are also significantly affected, and the responsiveness and reliability of online learning are improved, including teachers' training on online teaching and how to respond quickly to classroom lessons—even dealing with student problems and interacting with students online. Improve the responsiveness of the online learning system so that the learning system can be reliable and fast to use and respond to student operations.

Hedonic motivation is also influenced by social influence, facilitating conditions, and facilitating conditions. Among them, it can be communicated through the media and trained so that important relatives and friends of students can understand the advantages of online learning and promote its use. Optimizing the interface, operation, and some auxiliary functions of the learning system can make people more interested in using it. Developers of e-learning systems and senior managers of higher education institutions should improve learning systems so that students can learn online anytime, anywhere, retain recorded lessons, and accurately search for the content they want.

5.3 Limitation and Further Study

There are some limitations in this study. First, this study is only based on students majoring in painting at a university in Chengdu, Sichuan Province. As the research object, the scope and quantity of all samples are limited, which may not apply to the study of other groups. Secondly, the background of this research is China's online education platform, which is the peak of the rise of the online education model, and the research results may be different in different times and social cultures. Finally, this study is aimed at undergraduate students majoring in painting, and the research conclusions may differ for interviewees with different cultural levels and occupations. In the follow-up further research, respondents with different educational levels and social backgrounds can be selected from different universities and some social institutions, and different groups of people can be included in the research.

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