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Factors Impacting Behavioral Intention to Use Online Learning of Junior College Students in a Private Vocational University in Chengdu, China

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Abstract

Purpose: This study aims to determine factors impacting behavioral intention of students painting majors in a private vocational university 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:** Quantitative methods were employed to survey a cohort of 500 participants. Prior to data collection, the study ensured the validity and reliability through the assessment of the Item-Objective Congruence (IOC) index and the calculation of Cronbach's Alpha during a pilot test involving 50 participants. Confirmatory factor analysis (CFA) and Structural Equation Modeling (SEM) were to assess and conduct statistical data processing. **Results:** perceived usefulness emerges as the most influential factor affecting behavioral intention. Furthermore, it is observed that perceived ease of use significantly contributes to perceived usefulness. Additionally, the study affirms the substantial impacts of reliability and responsiveness on the quality of the e-learning experience. Lastly, hedonic motivation, facilitating conditions, social influences, and the perceived quality of e-learning all collectively affect students' behavioral intentions in the online learning environment. **Conclusions:** The author elaborates on the relevant factors that affect the online learning behavior intention and how to improve their behavior intention, e-learning quality, and perceived usefulness.

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

JEL Classification Code: E44, F31, F37, G15

1. Introduction

With the development of the Internet and the improvement of digital technology, we have entered the era of big data. The entire education industry is no longer limited to traditional teaching methods but must develop new online virtual teaching modes (Hew & Kadir, 2017). Combine offline and online learning. With the popularization of the Internet, the emergence of online education has made it possible for students to stay in school during the pandemic. At present, network teaching has been in a rapid development stage. China's Ministry of Education has organized 22 online course platforms to offer free online courses to undergraduate and vocational schools. Online learning is not only a product of The Times but also a new model and teaching method that we need to develop modern education at that time.

The educational digital transformation of e-learning is not only the change of learning tools and means. What is more, the ideas of teachers and students about learning need to be changed, and how to maximize the critical thinking ability, initiative, and creativity of teachers and students has become an important subject. In the future, with the development of science and technology, education will be constantly reformed, and innovation will become an ecosystem. Teaching and learning in the future can be carried out at anytime and anywhere; teaching facilities are

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connected and recycled (Van den Broeck et al., 2019). Students will have access to various materials for their study topics, and academics will become freer and more flexible. At the same time, online courses are becoming more and more popular.

With the development of the digital Internet and the rise of the new e-learning online learning model, the modern teaching method has been greatly impacted, and online learning has become the modern universal bachelor's way. In higher education in the United States, including famous universities, there are online learning methods, and students can also learn all courses through online learning and finally obtain diplomas and degrees (Yusuf & AL-Banawi, 2013). In other words, American college education has expanded beyond traditional face-to-face teaching. Due to the continuous improvement and innovation of Internet technology and online teaching platforms, the online learning model in the United States is also developing rapidly in scale, level, and level. The full outbreak of COVID-19 in 2020 has affected learning, teaching, and learning in countries worldwide. Traditional teaching methods are difficult to reach currently. This is why UNESCO urgently supports countries with inclusive distance learning solutions, including recommending free digital education resources, and compiling a list of national learning platforms (Stoian et al., 2022).

The full outbreak of the novel coronavirus epidemic in 2020 also accelerated the development of online learning. The novel coronavirus epidemic prevented students from returning to school on time, and the traditional teaching method could not be completed during the emergency period while the Ministry of Education issued a series of policies of suspending classes but not schools (Dhawan, 2020). Online learning could be an effective way to enforce the no-suspension policy. Thus, it promotes the informatization reform of the education industry and the rapid development of online education. MOOC websites of Chinese universities have also provided nearly 8,000 high-quality courses for teachers and students of universities. Universities are also conducting online teaching on related online teaching platforms and high-quality online course platforms and have fully implemented the policy of suspending classes but not suspending classes. In the opening season of March 2020, online education scale and usage reached 422.96 million, up to 46.8%. Ushered in the new peak of online learning, but also promote the development of online learning model (Zhou et al., 2023).

In China, In the 21st century, education changes constantly. New technologies and new ways of education keep emerging, especially with the rapid development of the Internet and information technology. With the vigorous development of open online courses, the learning mode of online learning has become normal in higher education. Significant changes have occurred in the learning styles, learning facilities, and learning conditions of higher education, as well as the cognitive mode. Some teaching methods will gradually change from face-to-face and traditional blackboard teaching to online learning. The learning process is shifting from simple classroom teacher-focused output learning to fragmented, multi-faceted, and multi-type learning, and students will have more choices and rich experiences in the change of learning style. However, there will be many problems in the early stage of development of China's online learning model, which need to be solved in time. How can the online learning mode of colleges and universities continue to develop healthily and steadily and optimize? This research will analyze the factors impacting e-learning quality. Perceived usefulness and behavior intention toward painting majors' junior college 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

The technical application of ease of use is perceived ease of use (Venkatesh et al., 2003). According to this study, use ease relates to how students think of online learning perceived ease of use. This relates to how students think of online learning perceived ease of use. Perceived ease of use in the perception of students could be both beneficial and bad for students' use of online learning (Al-Gahtani, 2016; Budu et al., 2018).

As stated by TAM theory, ease perception directly affects students' enthusiasm, thus affecting potential users' expectation of using the technology to be effortless (Davis, 1989). It can directly affect users' behavioral intentions towards technology, and they can directly and easily use technology, making them adopt it. Significantly, perceived ease of use by students greatly affects students' use of online learning and determines their behavioral intentions. As a result, applications that are perceived as easy to use tend to be used more widely and are considered more useful for accomplishing certain tasks or operations (Serenko, 2008).in perception, use ease relates to the easiness of system application (Venkatesh et al., 2003). besides, the impacts of use ease perception on behavioral intention made by some scholars are indirectly generated through perceived usefulness (Teo et al., 2019). To illustrate students' online learning adoption behaviors, former studies propose suggestions like the important link between perceived ease of use and learner satisfaction. Feng et al. (2022) pointed out that high expectations for a learning technique with less effort-making and improvement in learning lead to more satisfaction in learners. Thus, perceived ease of use is significant to students' behavioral intention to use online learning. From these supporting studies, we derive the following hypothesis:

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

2.2 Responsiveness

According to the relevant research of Cyr et al. (2009), users' perception and reaction to interactive media is responsiveness. In this paper, through online learning, students can feel the doubts of online teachers for students and the quick response of online learning systems for operation, which can bring convenience to students. Giving effective feedback is an important skill that teachers must have and need to develop continuously. Effective feedback guides students' learning and development, is crucial to students' learning, and provides timely feedback, which helps students' learning and encourages them.

Wu and Liu (2013) found that online learning efficiency, in-time response, and teacher feedback are positively related. If students are encouraged to learn and participate in classroom activities with credits and rewards, they will share ideas and learn with happiness. Bao (2020) conducted research and experiments on related online teaching and obtained similar results. Liao and Tsou (2009) found that users' high perception of response from teachers leads to the use of ease perception accordingly. In online learning, responsiveness is defined as learners perceiving responses from e-learning systems to be rapid, consistent, and largely reasonable (Lee et al., 2005). If students perceive the responses from an online learning system as fast, consistent, and reasonable, then the system response perception in students will be taken as easy and useful (Pituch & Lee, 2006). Bao (2020) investigated this issue. Teacher responsiveness is reflected through feedback and communication of the learning process, giving relevant responses to students' problems. Hu et al. (2016) found that feedback response was provided by giving students strategies for maintaining success and modifying unsuccessful strategies. From these supported studies, we derive the following hypothesis:

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

2.3 Reliability

Reliability means trustworthy or trustworthy. Whether it depends on the person's will, talent, or opportunity, if we think the person is reliable, then that person will be able to complete it, and for unreliable people, the result is often not complete. In the same way, an instrument is said to be reliable if it works when it is asked to. When asked to work, sometimes it works and sometimes it does not. It is called unreliable (Johnson et al., 2009). This refers to our online learning system: the longer the working time, the more reliable it will be, and it will be able to reach the speed of student use in the specified time. The learning system is easy to operate and provides students with reliable and useful information. Similarly, in the process of students' online learning, the teachers can provide good learning effects and teaching content, the teachers' ability is trustworthy, and they can timely give students feedback in the process of students' online learning and make reliable corrections and answers when necessary. In this study, reliability defines teachers' and system reliability of an effective teaching process that affects students' willingness to use online learning.

At the same time, Piccoli et al. (2001) suggested that the perceived reliability of technology and peer interaction would affect online learning efficiency. Because of the centrality of technology in online learning, the software and hardware used to support online learning environments must provide the functionality and reliability students expect. Online learning system has reliable technology and function, can be used by the learning, and cannot be bothered by the function and technical problems of the system, can be dedicated, pure online learning. With the drive of science and technology, the improvement of our existing technology, and the actual progress of things, students will have higher and higher requirements for technology. When they perceive the backward function of technology in the use process, they are more likely to have negative views on mitigation. It has never failed to apply current technologies or chosen to use others (Johnson et al., 2009). Since e-learning exists around high technology and systems of computers and relies on modern network systems, the reliability of technology is the source of everything (Sandholtz et al., 1992). Therefore, reliable online learning system technology and teachers are very important for online learning, which can give students recent learning experiences and attraction and influence the behavior intention of art and painting major students in online learning. From these supported studies, we derive the following hypothesis:

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

2.4 Perceived Usefulness

According to Davis (1989), an individual's belief about the impact of a specific system adoption on performance is perceived usefulness. Perceived usefulness predicts a user's willingness to act positively toward their behavior. In general, perceived usefulness boosts performance at work. As mentioned in the study, students believe they can achieve their goals through online learning, such as learning new knowledge, improving their grades, and so on. In most cases, the system's usefulness affects the learning efficiency (Virvou & Katsionis, 2008). Systems with perceived usefulness make users more productive. Usability is a quality that reflects how easy it is for humans to interact with computers. Iso 9241 defines perceived usefulness as the ease with which a product effectively, efficiently, and satisfactorily meets user objectives.

Alkis et al. (2014) conducted a qualitative study on online learning and found that students' perceived usefulness and ease of use would affect their use of online learning. A recent study by Hossain et al. (2017) objectively shows the impact of visualization on online learning, thereby showing that the useful knowledge of the system also contributes to students' behavioral willingness to learn online. From these supporting studies, we derive the following hypothesis:

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

2.5 E-Learning Quality

Web learning quality is used to measure Web service quality and has been developed in previous studies. It represents an overall perception of the quality, guideline clarity, information, and functionality of the features of an e-learning system (Mehta et al., 2019). Thus,

The author of the research defines e-learning quality as responsiveness and reliability. This includes the reliability

of the online learning system, the competence of responding quickly and the quality of service, the ability of teachers to respond quickly to students' questions and requests, and the quality of textbooks.

According to the relevant research of Loh et al. (2016). E-learning is a feasible alternative to the traditional face-to-face and offline teaching modes, and a new situation is emerging in teaching and learning. The quality of online learning will also affect students' learning behavior intention. According to the relevant research of Zhang et al. (2012), the quality of online learning can directly and indirectly affect students' willingness to continue to participate. Learning quality is related to students' learning quality, learning interest, and the degree of relevant use. Former researchers proved that e-learning quality and usefulness perception have a positive relation (Al-Busaidi, 2013; Mtebe & Raphael, 2018). The qualitative literature on online education procedures emphasizes that the quality of the platform correlates to students' demands in learning. The availability of providing better systems affects students' satisfaction with teaching (Alkhattabi et al., 2011). From these supporting studies, we derive the following hypothesis:

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

2.6 Hedonic Motivation

The pleasure or sense of pleasure generated using technology is known as hedonic motivation (Venkatesh et al., 2012). Tamilmani et al. (2019) found that hedonic motivation is a prerequisite to behavior intention in adopting various technologies. First, students find online learning interesting or enjoyable, which will encourage them to use it. When students are interested in using online learning, they will have intrinsic motivation for online learning participation. Guided by e-learning, students' perception of the system as entertaining and interesting will impact using willingness, thus being an important prerequisite.

Venkatesh et al. (2012) and Ainur et al. (2017) found that hedonic motivation is associated with the usefulness perception of users' pleasant experiences of using the system. In this study, students who feel pleasure or pleasure in using online learning as a learning mode will likely develop behavioral willingness to accept online learning systems. Previous studies have widely discussed the extent to which individuals learn online. According to many previous studies, hedonic motivation and an individual's behavioral intention of system acceptance are positive (Abu Gharrah & Aljaafreh, 2021; Nikolopoulou et al., 2020; Venkatesh et al., 2012). As Tamilmani et al. (2019) argued, individuals' relevant systematic behavioral intentions are determined by hedonic motivation. According to Ryan and Deci (2011), who have proposed the self-determination theory, El-Masri and Tarhini (2017) hypothesize that when students are interested in using online learning, they will be intrinsically motivated to participate in online learning. Students' perception of the system's entertainment and interest will affect their willingness to use it. From these supported studies, we derive the following hypothesis:

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

2.7 Facilitating Condition

According to Venkatesh et al. (2003), convenience is perceived by individuals who perceive the existence of organizations and technologies related to system infrastructure. When the infrastructure and online systems used are convenient, easy to operate, and can be used anytime, anywhere, it increases the willingness of students to learn online. If users feel their organization has sufficient resources for online learning, they will develop a behavioral willingness to use it. The convenience of e-learning provides hardware support, knowledge, etc., affecting students' use. (Salloum & Shaalan, 2018). In an online learning environment, convenience may include online learning systems and the convenience of taking classes anytime, anywhere, online learning systems.

Through the online learning platform, students' express ideas, ask questions, and share ideas at any time, promoting a sense of interaction and collective learning (Heggart & Yoo, 2018). Moreover, students can easily learn online at any time, such as MOOC, Google Class, etc. As Tamilmani et al. (2019) argued, individuals' relevant systematic behavioral intentions are determined by hedonic motivation. According to Ryan and Deci (2011), who have proposed the self-determination theory, El-Masri and Tarhini (2017) hypothesize that when students are interested in using online learning, they will be intrinsically motivated to participate in online learning. Students' perception of the system's entertainment and interest will affect their willingness to use it. 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 are when people or an individual believes that they are using and doing something, thereby influencing others (Venkatesh et al., 2003). Wu and Liu (2013) have found that SIs and students' acceptance of online learning are positively correlated. The same goes for social influences, which can motivate users to be more interested in technology, thus generating positive behavioral intentions. When students adopt online learning, society and the people around them will give them positive guidance and encouraging feedback, which will incentivize their use of online learning. In description, social influence refers to the degree to which individuals consider the opinions of others regarding the adoption of an innovative system, so social influence is assumed to be a major component that composes intention in behavior. Furthermore, social influence refers to students' perception of social pressure and expectation of participating in certain behaviors and the degree to which they feel the need to comply with these behaviors to carry out certain behaviors (Cheng et al., 2012). The definition of social influence in this paper is the student's perception that his related groups believe that online learning should be carried out.

Lecturers' or students', families, and friends' viewpoints and actions influence the intention of using online learning. For online- learning, social influence is crucial because learners' perception of approval from significant others influences their use of the system intentionally (Mehta et al., 2019). Venkatesh et al. (2003), who studied the development of UTAUT, found the greater impacts of social influence on coercive environments. Online learning is often a compulsory part of higher education courses. Online learning is often a compulsory part of courses for higher education. Hattie and Timperley (2007) found social influence a vital factor in technological use willingness in a society with the value of collectivism. Students may be influenced by other important people, such as lecturers, parents, school colleagues, school policies, and the use of online learning to come to school. Tarhini et al. (2017) also have a similar view. He advocates that students should be willing to use online learning to complete courses and mobilize their conscious initiative, which people around them may influence to use online learning. 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

In the past decade, online learning has experienced remarkable growth, making it imperative for educators, institutions, and policymakers to gain insights into students' behavioral intentions in this context. This literature review provides an overview of critical research findings regarding the factors that influence students' intentions to participate in online education.

The Technology Acceptance Model (TAM), initially introduced by Davis in 1989, has served as a foundational framework in the investigation of behavioral intention in online learning. According to TAM, the perceived ease of use and perceived usefulness of technology are fundamental in shaping individuals' intentions to adopt and employ it. Davis (1989) conducted research demonstrating the significant impact of students' perceptions of the ease of using online learning platforms on their behavioral intentions. Furthermore, Venkatesh et al. (2003) underscored the crucial role of perceived usefulness in forecasting online learning intention, emphasizing its contribution to facilitating learning and enhancing educational outcomes.

3. Research Methods and Materials

3.1 Research Framework

This study is based on the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), which serve as the theoretical foundations for the research model. The objective is to identify relevant factors that contribute to the application of technology within organizations, understand users' intentions and wishes objectively, and gain insights into user acceptance and behavior. The research model considers various factors such as performance expectations, effort expectations, social influence, and accessibility, which are known to play significant roles in determining user acceptance and behavior. Perceived usefulness, as a component of TAM, directly influences an individual's behavioral intention, providing insights into students' behavioral intentions when using online learning (Davis et al., 1989).

This study adopts three theoretical frameworks for research. The first framework, proposed by Hu et al. (2016), includes perceived usefulness, perceived ease of use, and behavioral intention. The second framework, based on the work of Muqtadiroh et al. (2020), incorporates reliability, responsiveness, e-learning quality, and behavioral intention. Lastly, the third framework, influenced by the research of Rudhumbu (2022), suggests that hedonic motivation, facilitating conditions, and social influences contribute to students' behavioral intention in online learning. Figure 1 illustrates the conceptual framework of this study.

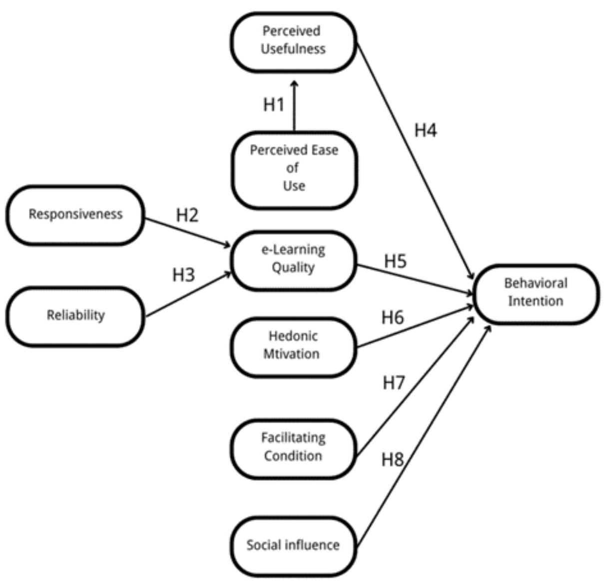

Figure 1: Conceptual Framework

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 study adopts a quantitative research method and collects relevant sample data through a questionnaire survey. This study aims to explore the influencing factors of online learning behavioral willingness of students majoring in painting at universities in Chengdu. In this study, an online structured questionnaire was used to collect data. The questionnaire was conducted online by Tencent's Wenxing to ensure the convenience and efficiency of issuing and collecting the whole questionnaire and the safety and effectiveness of the questionnaire content.

Before distributing the questionnaire related to the target population, 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.

This study used CFA to test data. Then, SEM was used to study the importance of the conceptual model test in the relationship between the structures of this study and the model test to explore the causal relationship between each variable and the related effects proposed. The relevant method mentioned above is the SEM method that Anderson and Gerbing (1988) proposed to analyze sample data.

3.3 Population and Sample Size

The target population of this study is college students majoring in painting at Chengdu Vocational University of the Arts, and all subjects have more than one month of online learning experience. The prior sample size calculator of Widaman and Thompson (2003) SEM was used for data sample size. Entering the relevant data information for this study into the prior sample size calculator shows that the expected level of statistical power is 0.8, the number of potential variables is 9, and the recommended minimum sample size is 460. Therefore, the sample size of this study is 500, which is suitable for structural equation modeling (SEM) statistical techniques.

3.4 Sampling Technique

This study used sampling methods such as judgment, convenience, and stratified sampling to select the sample range. The judgment sampling method was used to select the students of Chengdu Vocational University of the Arts with more than one month of online learning experience.

According to Lavrakas (2008), stratified sampling was used to divide the target population into multiple groups. Therefore, the stratified sampling method is adopted in this study to stratify four different painting majors and determine the number of samples in each 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, and the summary of maintenance hole statistics is shown in Table 2 below. Of the respondents, 315 were women, and 185 were men, accounting for 63% and 37% respectively. Among the respondents, 134 were aged 16-18 (26.8%), 167 were aged 19-20 (33.4%), 56 were aged 21-23 (11.2%), 92 were aged 24-26 (18.4%), and 51 were over 26 (10.2%). As shown in Table 2 below.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	315	63%
	Female	185	37%
Age	16-18 years old	134	26.8%
	19-20 years old	167	33.4%
	21-23 years old	56	11.2%
	24-26 years old	92	18.4%
	Over 26 years old	51	10.2%

Source: Constructed by author

4.2 Confirmatory Factor Analysis (CFA)

Statistical analysis of survey data is called confirmatory factor analysis, and CFA is the starting point and critical first step of SEM (Hair et al., 2010). In related research experiments, CFA tests the degree of agreement between the relationship between a factor and the corresponding measure and the theoretical relationship of the research design and is used to verify the measurement model (Khan & Qudrat-Ullah, 2021). The convergence validity of a variable can be measured by Cronbach's Alpha reliability, AVE, and CRL. Hair et al. (2003) showed that factors with a value above 0.50 had a significant impact. According to Table 3 can be obtained. All the values in this study have load values greater than 0.50 and 0.70 for each variable. As shown in Table 3 below, the CR value of each variable 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 value of each variable in this study is greater than 0.7, and the AVE value is greater than 0.5, so the estimated values of each variable 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	0.833	0.773-0.805	0.833	0.625
E-learning quality (ELQ)	Herdiyanti and Puspitasari (2020)	4	0.867	0.745-0.836	0.868	0.623
Perceived usefulness (PU)	Hu and Lai (2019)	3	0.834	0.783-0.804	0.834	0.626
Perceived ease of use (PEU)	Hu and Lai (2019)	4	0.855	0.721-0.823	0.814	0.594
Responsiveness (RES)	Herdiyanti and Puspitasari (2020)	4	0.870	0.755-0.834	0.864	0.614
Hedonic motivation (HM)	Rudhumbu (2022)	3	0.820	0.736-0.869	0.825	0.612
Facilitating condition (FC)	Rudhumbu (2022)	3	0.818	0.736-0.797	0.819	0.601
Reliability (REL)	Herdiyanti and Puspitasari (2020)	4	0.862	0.755-0.815	0.871	0.628
Social influence (SI)	Rudhumbu (2022)	3	0.816	0.662-0.888	0.821	0.609

Table 4 presents the goodness-of-fit indicators for the variables. The values of GFI, AGFI, NFI, CMIN/DF, RMSEA, CFA, TLI, and CFI all meet the acceptable criteria, indicating a good fit of the model 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)	2.634
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.905
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.931
NFI	≥ 0.80 (Wu & Wang, 2006)	0.889
CFI	≥ 0.80 (Bentler, 1990)	0.895
TLI	≥ 0.80 (Sharma et al., 2005)	0.921
RMSEA	< 0.08 (Pedroso et al., 2016)	0.040
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

Table 5 below demonstrates that the square root of the Average Variance Extracted (AVE) for all variables is greater than the factor correlation value, which is a significant finding for assessing the effectiveness of the factors.

Table 5: Discriminant Validity

	PEU	RES	REL	HM	FC	SI	PU	ELQ	BI
PEU	**0.770**								
RES	0.180	**0.783**							
REL	0.236	0.146	**0792**						
HM	0.234	0.233	0.123	**0.782**					
FC	0.103	0.163	0.124	0.159	**0.775**				
SI	0.099	0.220	0.171	0.090	0.084	**0.780**			
PU	0.248	0.152	0.224	0.152	0.081	0.192	**0.791**		
ELQ	0.217	0.362	0.289	0.192	0.174	0.259	0.270	**0.789**	
BI	0.301	0.303	0.259	0.272	0.332	0.332	0.450	0.481	**0.790**

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., The structural equation model was used to test the causal relationship between variables. Compared with traditional models, SEM can better demonstrate the multiple relationships between independent and dependent variables (Salloum & Shaalan, 2018). Ainur et al. (2017) proposed that the absolute fitting measure defined the fitness of the model designed by the research data. Meanwhile, the correlation index of absolute fit measure contains four indices: the first is chi-square (χ2), the second is adjusted goodness of fit index (AGFI), the third is goodness of fit index (GFI), and the fourth is approximate root mean square error (RMSEA). According to the relevant study of Folkes (1988), after measuring the goodness of fit value of the structural model at 0.70 or above, the mean-variance extraction (AVE) is suggested to be greater than or 0.4. Table 3 below shows that all estimates are significant, with CR values over 0.7 and AVE values over 0.5 in this study. In this study, the structural equation model (SEM) was used to analyze the collected data and measure the goodness of fit of the structural model, as shown in Table 5. The statistical values were CMIN/DF = 1.676, GFI = 0.923, AGFI = 0.904, NFI=0.914, CFI = 0.963, TLI = 0.957, RMSEA = 0.037. The values of all fitting indexes are greater than the acceptable values, which confirms that the model fits well.

Table 6: Goodness of Fit for Structural Model

Index	Acceptable	Statistical Values
CMIN/ DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	1.676
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.923
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.904
NFI	≥ 0.80 (Wu & Wang, 2006)	0.914
CFI	≥ 0.80 (Bentler, 1990)	0.963
TLI	≥ 0.80 (Sharma et al., 2005)	0.957
RMSEA	< 0.08 (Pedroso et al., 2016)	0.037
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 relationships between the independent and dependent variables, as stated in the hypotheses of this study, were assessed using regression coefficients or standardized path coefficients. These coefficients are presented in Table 7 below.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-Value	Result
H1: PEU→PU	0.307	6.786*	Supported
H2: RES→EQ	0.278	5.712*	Supported
H3: REL→EQ	0.388	7.792*	Supported
H4: PU→BI	0.420	8.212*	Supported
H5: ELQ→BI	0.393	7.956*	Supported
H6: HM→BI	0.170	3.653*	Supported
H7: FC→BI	0.142	3.022*	Supported
H8 SI→BI	0.217	4.606*	Supported

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

According to Table 7, all eight hypotheses in this study are supported. Behavioral intention is strongly influenced by perceived usefulness. Secondly, perceived usefulness is strongly influenced by perceived ease of use. E-learning quality was affected by responsiveness, and behavioral intention was affected by e-learning quality.

In **H4,** behavioral intention is strongly influenced by perceived usefulness, where the standardized path coefficient is 0.420, and the T-value is 8.212. This conclusion supports the work of Davis et al. (1989), which showed that perceived usefulness is critical to behavioral intention variables. The expectation-confirmation model assumes that users' willingness to continue using IS/IT depends on their perception of usefulness, degree of confirmation, and satisfaction with IS/IT (Bhattacherjee, 2001). Moon and Kim (2001) found that perceived usefulness positively guides students to adopt relevant technologies. Similar results were obtained by Haryanto and Kaltsum (2016) and Salloum et al. (2019). Perceived usefulness can improve students' behavioral willingness to use online learning.

E-learning quality is subject to responsiveness, as shown in **H3.** The standardized path coefficient is 0.388, and the T-value is 7.792. It is concluded that e-learning quality is related to responsive factors (Muqtadiroh et al., 2020). Wu and Liu (2013) found that students' e-learning efficiency was positively correlated with teachers' timely feedback. So, the responsiveness level is higher, and the e-learning quality is higher.

E-learning quality significantly impacts behavioral intention; **H5,** the standardized path coefficient is 0.393, and the value is 7.956. Chung et al. (2020) put forward the hypothesis of communication technology advancement brought about by the Internet and the World Wide Web. The emergence of the whole Internet system has also brought new ways of learning. Meanwhile, Muqtadiroh et al. (2020) found that online learning quality positively correlates with students' behavioral intention to learn online.

Perceived ease of use is an important influencing factor of perceived usefulness. In **H1,** the standardized path coefficient is 0.307, and the T-value is 6.786. TAM's empirical research confirms that perceived ease of use is crucial for users to use a certain technology (Lee et al., 2005). Shroff et al. (2011) studied students' perceptions of online learning. They found that their perception of the system's ease of use significantly affected their attitude, thus indicating the importance of students' perception of ease of use in useful knowledge. When the system was supposed to save time and energy, students were interested in it. So, perceived ease of use has a significant impact on perceived usefulness.

Reliability has a significant impact on e-learning quality. In addition, it can be seen from **H2** that its standardized path coefficient is 0.278, and its value is 5.712. Meanwhile, Hu et al. (2016) investigated students' use of the learning management system and their views. They found that students' access to the online learning system can be improved due to the availability and reliability of online learning systems. Students need the best learning experience when using online learning systems, resulting in low interest in online learning. Therefore, reliability affects the quality of students' online learning. The results support the H2 hypothesis in this study.

Social influences have a significant impact on behavioral intention. The standardized path coefficient of **H8** is 0.217, and the T-value is 4.606. The results are consistent with Abu Gharrah and Aljaafreh (2021) findings that social influences significantly impact students' behavioral willingness to use online learning. When a student learns what online learning means to them and thus considers the views of those around them about adopting the system, the whole process influences their awareness and makes them accept the adoption.

Hedonic motivation has a significant impact on behavioral intention. In **H6,** the standardized path coefficient is 0.170, and the T-value is 3.653. Consistent with the conclusion of Tamilmani et al. (2019), systematic behavioral intention is generated through hedonic motivation. Hedonic motivation is very important for students to learn online. Increased interest can stimulate students' behavioral intentions for online learning.

Facilitating conditions has a significant impact on behavioral intention. Then, in **H7,** the standardized path coefficient is 0.142, and the T-value is 3.022. Convenience involves user support for system performance, which exists in the infrastructure associated with the organization and technology, so adequate support for system use will affect its behavioral intent (Mehta et al., 2019). So, convenience has a significant effect on behavioral intention.

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

This study analyzed the factors affecting painting majors' online learning quality, perceived usefulness, and behavioral intention. After compiling relevant questionnaires, IOC tests and small-range reliability tests were conducted. After the questionnaires passed the reliability and reliability tests, majors with more than one month of online learning experience in painting majors were selected as data collection objects. Data collection of respondents was completed, and CAF and SEM were used to analyze the reliability and validity of the conceptual model of this study. A total of 8 hypotheses were proposed in this study, all of which were supported as valid and satisfying hypotheses for this study.

Based on the hypothesis and relevant research results, the following conclusions are made:

Behavioral intention is most strongly influenced by perceived usefulness, which is crucial to behavioral intention variables and an important way to influence behavioral intention (Gefen et al., 2003). Moon and Kim (2001) found that perceived usefulness positively leads students to adopt relevant technologies and is positively correlated with behavioral intention. Therefore, the perceived usefulness of the system can motivate students' behavioral intentions.

Reliability and responsiveness also have an impact on the quality of e-learning. Wu and Liu (2013) found that students' e-learning efficiency was positively correlated with teachers' timely feedback. Therefore, the higher the response level, the higher the e-learning quality. At the same time, reliability can improve students' use of online learning systems, thus improving the quality of e-learning.

Perceived ease of use has a significant impact on perceived usefulness. Moreover, perceived usefulness can significantly affect behavioral intent. Improving perceived usability can also affect perceived usefulness, enabling students to feel that online learning is useful for improving life and learning, thus influencing students' behavioral intentions.

E-learning quality also has a significant impact on behavioral intention. According to the relevant literature of Muqtadiroh et al. (2020), online learning quality positively correlates with students' behavioral intention to learn online.

Hedonic motivation, facilitating conditions, and social influences also significantly affect behavioral intention. When students learn online, they think it is convenient to improve their behavioral intentions. When the people they value around them think they should learn online, they will also improve their behavior intentions. Similarly, students' perception that online learning is fun positively correlates with behavioral intentions.

5.2 Recommendation

This study assessed the online learning quality (ELQ) of painting majors in Chengdu Vocational University of the Arts. Perceived usefulness (PU), perceived ease of use (PEU), responsiveness (RES), hedonic motivation (HM), facilitative key factors (FC), Reliability (REL), social impact (SI), and behavioral intention (BI).

According to this study, perceived usefulness is the strongest factor affecting behavioral intention, so improving perceived usefulness can enhance students' behavioral intention. Improving the learning system, improving the fluency of the learning system, making it easy to operate and convenient to use, and improving Perceived ease of use can enhance students' perceived usefulness, enable students to learn things through online learning, and improve their learning, life, and other aspects, to enhance students' behavioral intention.

E-learning quality can be greatly affected by Reliability and responsiveness. In online learning, e-learning quality can be influenced by the rapid response of teachers and the learning system, as well as students' answers, efficiency, and Reliability.

E-learning quality, hedonic motivation, facilitating conditions, and social influences also significantly affect behavioral intention. The improvement of the quality of e-learning, the technological upgrading of the interface operation of the system, and the fun of online learning can make students feel happy about online learning and, at the same time, make important people around students understand the benefits of student learning and have a comprehensive understanding of what online learning is, and provide convenience in the course setting so that students can learn anytime and anywhere. Moreover, it provides convenient learning hardware. Students' behavioral intention to actively use online learning can be enhanced through the above.

In this study, the author elaborates on the relevant factors that affect the online learning behavior intention, e-learning quality, and perceived usefulness of painting majors, and how to improve their behavior intention, e-learning quality, and perceived usefulness, and gives some suggestions.

5.3 Limitation and Further Study

Some aspects could be improved in this study. As for the research object of this study, only the junior college students majoring in painting at a university in Chengdu, Sichuan Province, are taken as the research object, and the sample size of the selected research object and scope is limited. Secondly, this research is based on the research background of online education in China. During the research period, online education in China is in a state of rapid rise, and the research results will be different in different cultures and social conditions. In further research, teachers and education practitioners from different identities can be added as research objects, and qualitative research and interviews can be added to summarize the same questions better to understand the respondents' behavioral intentions for online learning, thus increasing the comprehensiveness of the research.

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