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Understanding Factors Impacting Behavioral Intention and Use Behavior of Online Art Exhibitions Among Art Student in Sichuan, China

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Abstract

This study aims to explore the factors impacting students in art majors in Chengdu universities to use online art exhibitions. The framework proposes seven variables of causal relationships, including subjective norms, perceived ease of use, perceived usefulness, behavioral intention, perceived behavioral control, social impact, and behavior. The researcher applied quantitative methods to distribute questionnaires to 517 participants. Before issuing the questionnaire, the validity and reliability of the data were tested using the Index of item objective congruence (IOC) and Cronbach's alpha for the pilot tests (n=50). The data are analyzed by confirmatory factor analysis (CFA) and structural equation model (SEM) to verify the model's goodness of fit and confirm the causal relationship between the hypothesis test variables. The results show that subjective norms have a significant impact on perceived usefulness, perceived ease of use has a significant impact on perceived usefulness, perceived ease of use has a significant impact on behavioral intention, perceived usefulness has a significant impact on behavioral intention, perceived behavioral control has a significant impact on behavioral intention, social impact has a significant impact on behavioral intention. The behavioral intention has a significant impact on behavior. The seven hypotheses have been proven to meet the research objectives. Therefore, the study of conceptual models can predict and explain the behavioral intention of using online art exhibitions in higher education.

Keywords : art college, online art exhibition, subjective norms, behavioral intention, use behavior

Introduction

In recent years, with the increasing number of multi-industry exhibitions such as various art exhibitions, industrial exhibitions, and agricultural exhibitions, the exhibition industry has become a new economic growth point of cities with great development potential. The development of the exhibition industry in a city can also reflect the city's cultural atmosphere, popularity, and comprehensive strength to a certain extent, with Beijing and Shanghai taking the lead in developing the exhibition industry. According to the relevant data collected by the Ministry of Commerce, the development of China's exhibition industry in 2019 is still the first in the world. The data shows that the total number of exhibitions and the total area of exhibitions in 2019 increased by more than 110 million and 4 million square meters, respectively, by 0.6% and 2% compared with 2018. It is also an important sign of China's exhibition industry's large-scale and centralized development. With the rapid development of global network and new media, online art exhibition has gradually become the main display form of art museums (CCPT, 2020).

Around 2010, China's online art exhibitions began to appear in domestic galleries. In April 2012, Google released a series of digital presentation art plans and established a cooperation mechanism with 151 art institutions to make their artworks into high-resolution images for people to browse. At the beginning of 2020, with the large-scale outbreak of COVID-19, the epidemic led to the emergence of the Internet plus model in the culture, exhibition, and conference industries, which is the centralized response of the government to the informatization support of public cultural places and is also the concentrated embodiment of art technology. The closure caused by the epidemic triggered a new model of digital museums, online exhibitions, and 3D text exhibitions to enter the public's view, allowing the public to experience a different kind of exhibition. It has further accelerated the development of domestic art galleries, traditional exhibition forms, and Internet and media technologies, bringing new presentations to online art exhibitions (Habelsberger & Bhansing, 2021).

Art museums, art fairs, galleries, and other art institutions worldwide have launched online exhibitions, including virtual exhibitions, webcasts, and social media interactions. At the same time, affected by the epidemic, many art schools in China have gradually turned to online art exhibitions. First, online art exhibition promotes online through new media technology, mainly through the combination of static two-dimensional plane and dynamic three-dimensional virtual. Publish the work's images, text, and videos in detail on the professional websites of university art museums, WeChat, and art media (Li & Wang, 2021).

The online art exhibition discussed in this article is also called virtual art exhibition, online exhibition room, online art exhibition, cloud art exhibition, etc. This means that the exhibition site is first in virtual cyberspace and then can be viewed indefinitely under the condition of website maintenance. The exhibition channels and information-receiving methods of the second exhibition should be based on the law of network communication. In the past 20 years, with the rapid development of digital information, museums and art galleries worldwide have established their own virtual exhibition world. Virtual means possibility," which is the opposite of certainty and reality. With the deepening of technology and the combination of context, it gradually presents an independent trend (Habelsberger & Bhansing, 2021).

The online art exhibition is based on information data architecture and interactive communication design, implying the interactive nature of inviting creators, planners, viewers, and other roles to participate. The network and audience can participate in cooperation and interaction. For example, Jon Kolko defines interaction designers as shapers of behavior. The core of interaction is to form a dialogue between products, systems, or services and people. The design aims to achieve better results - enhance the human experience, solve complex problems, and create works that resonate with the audience. The exhibition uses endless combinations of materials and creatively reconstructs content and ideas into external forms in unexpected ways, which is where the exhibition design is intriguing and charming (Liggett & Corcoran, 2020).

The research on factors impacting the behavioral intention and use behavior of online art exhibitions among art students in Sichuan, China holds considerable significance within the realms of art education, technology integration, and cultural preservation. The research extends its impact beyond the classroom. It influences art education practices, cultural preservation efforts, technological innovation, and art industry strategies. By uncovering the nuances of art students' interaction with online exhibitions, this study contributes to a more comprehensive understanding of the evolving dynamics between art, technology, and education.

This study aims to explore the factors impacting students in art majors in Chengdu universities to use online art exhibitions. Teachers can create personalized art exhibitions for educational purposes. This study's results highlight some areas that need further research. The suggestions will help guide the design and development of the online art exhibition system so that the online exhibition can promote social integration through wider use and encourage the public to carry out art awareness education by improving the availability and content of the exhibition. More research is needed to examine user needs.

Literature Review

Subjective Norms

Generally, a subjective norm is something important to a person or something that most people expect a person to do. When learners adopt and deploy BL (or do not adopt and deploy BL), Ajzen (2006) discusses the social pressure they face. Including a subjective normative structure enhances researchers' understanding of how social factors affect the purpose of purchasing products during difficult times. Ajzen (2006, p. 188) defines *subjective norms* as social pressures influencing consumers' online shopping decisions. (Maher & Mady, 2010). Subjective norm refers to the social pressure learners feel when they engage in or do not engage in BL. According to McKinnon and Igonor (2008), subjective norms refer to social pressure on a student to deploy BL from friends, lecturers, and classmates with whom he/she is close. The subjective norm is a belief that is based on expectations. (Cheon et al., 2012). The "subjective norm" states that if important people around an individual think a certain behavior is necessary, then the individual's intention to use it will be affected (Fishbein & Ajzen, 1975). In addition, individuals may view subjective norms as social pressures to participate or not to take specific actions (Ajzen, 2006). More crucial, subjective norms are students' opinions of the social norms that BL has established. In other words, expectations and normative judgments of others are tied to subjective norms (Yeou, 2016). Peer opinions are, therefore, crucial in influencing students' personal decisions to use BL for academic objectives (Wai & Seng, 2015). In comparing TRA and TAM experiences, Davis (1989) discovered that subjective norms affect perceived usefulness and intended use. Additionally, TAM2 was put forth by Venkatesh and Davis (2000), who claimed that subjective norms also influence use intention through perceived utility. By introducing the subjective norm structure, the researchers' understanding of how social factors affect consumers' willingness to purchase products in stressful situations is significantly improved. Social conformity influences customers' online purchase choices in a significant way (Maher & Mady, 2010). Therefore, this study indicates that:

Hypothesis 1: Subjective norms has a significant impact on perceived usefulness.

Perceived Ease of Use

A system's ease of use (PEOU) is defined as the extent to which a person believes that using a technology does not require effort. Many previous empirical studies have shown that PEOU has a positive correlation with BI, that is, directly (Davis, 1989; Venkatesh, 2000; Venkatesh & Davis, 2000;), through PU (Venkatesh, 2000) perceived ease of use refers to "ease of use related to system use" (Venkatesh et al., 2003, p. 450). Based on TAM, perceived ease of use is important for determining perceived usefulness and technology acceptance. PEOU is the degree to which an individual believes the system will be free. TAM shows that perceived ease of use can predict perceived usefulness and people's attitudes toward using information technology. PEOU is defined as that students expect to use ELS in an online learning environment that is cheap and easy. Clear and understandable student interaction with e-learning is present (Davis, 1989). According to studies (Lee & Lee, 2008; Sanchez & Hueros, 2010), students' behavioral intention to embrace and adopt less and mobile LMS is directly influenced by perceived ease of use (Han & Shin, 2016). On the other hand, other researchers have discovered that perceived usefulness mediates the indirect effect of perceived ease of use on behavioral purpose (Joo et al., 2016; Teo et al., 2019). The ease of perception in an electronic learning environment is the degree to which it is easy to use an electronic learning system. (Lin et al., 2011). The cognitive effort required to learn and use new technology is measured by perceived ease of use (Gefen, 2003). The degree to which a learner anticipates that using an ELS will be effortless and straightforward is known as PEOU in the background of online learning. The interactive way of students' online learning is clear and easy to understand (Davis, 1989). Ease of use in an e-learning environment is the degree to which people find it effortless to use e-learning systems (Lin et al., 2011). Previous research has demonstrated that the perceived usability of e-learning systems is positively correlated with perceived usefulness (Calisir et al., 2014; Roca & Gagne, 2008). Hence, the researcher hypothesizes that:

Hypothesis 2: Perceived ease of use has a significant impact on perceived usefulness.

Hypothesis 3: Perceived ease of use has significant impact on behavioral intention.

Perceived Usefulness

Perceived usefulness is the degree to which a person believes using technology will help him or her achieve better work or school performance (Akbar, 2013; Venkatesh et al., 2003). A PU is the degree to which users believe that using a particular system can improve their performance. (Davis, 1989). The cognitive utility of e-learning can be defined as the extent to which users perceive e-learning as motivating them to achieve their goals. (Lin et al., 2011). The term perceived utility (Davis, 1989) refers to the degree to which a person believes that engaging in and using technology can improve his or her performance at work. PU is the degree to which an individual thinks using a certain system will improve operational performance. In actuality, the perceived utility hugely favors internet purchases (Chiu et al., 2005). Additionally, it significantly and favorably affects the behavioral purpose of utilizing Google Classroom (Al-Maroof & Al-Emran, 2018). Students' perceptions that wearing smartwatches will enhance their academic performance are what make this study helpful. Several earlier investigations have confirmed the relationship between PU and behavioral intention (Al-Emran & Teo, 2020; Kamal et al., 2020; Rafique et al., 2020). It is a good indicator of people's purpose in using technology in several settings (Avci & Askar, 2012). The study also discovered a substantial difference between pupils adopting and moving LMS regarding perceived utility (Hsu, 2012). (Joo et al., 2016; Teo et al., 2019). Studies have demonstrated that perceived utility favors students' ongoing purpose in utilizing e-learning systems (Li et al., 2012; Roca & Gagne, 2008). Additionally, the perception of utility influences the impact of perceived usability on the persistence of intention to utilize e-learning systems (Li et al., 2012; Roca & Gagne, 2008). Students are more likely to utilize the platform regularly if they believe MOOCs are a helpful tool that can increase their learning effectiveness and allow them to communicate with teachers, teaching assistants, and other students more effectively (Lee et al., 2011). The perceived utility and adaptability of new technologies in many situations, such as e-banking technology, e-commerce, etc., were found to be strongly correlated in earlier studies (Gefen, 2003; Venkatesh & Davis, 2000). Accordingly, a hypothesis is developed:

Hypothesis 4: Perceived usefulness has a significant impact on behavioral intention.

Perceived Behavioral Control

The notion of self-efficacy and the perceived behavioral control element of the theory of scheduled behavior are comparable (Ajzen, 2006). Perceived behavioral control is a person's awareness of the difficulty or simplicity of certain behavior. According to TPB, there is a correlation between perceived behavioral control and the propensity to seek advice from others. Beliefs concerning control effects that might prevent or facilitate the deployment of BL are linked to perceptions of behavioral control (Tselios et al., 2011). According to its definition, the concept of perceived behavioral control refers to the extent to which a person views the performance of a given activity as easy or difficult, referring to the consciousness of control he or she has over the conduct (Ajzen, 2006).

On the other hand, perceived behavioral control is the perceived ease or challenge of executing the behavior, and it is predicted to represent experience as well as expected obstructions and difficulties (Ajzen, 2006). The phrase people's sense of ease or difficulty in doing the behavior of interest describes perceived behavioral control (Ajzen, 2006, p. 183). Additionally, previous experience as well as predicted impediments and repercussions were reflected in it (Ajzen, 2006). Perceived behavioral control is made up of two components (such as control belief and perceived facilitation), and a person's impression of the existence or absence of external limitations also affects his behavioral intention (Ajzen, 2006). Therefore, a person's propensity to co-create is determined by how much control they have over a particular online behavior (Chu et al., 2016). According to research, perceived behavioral control positively impacts adolescents' intentions to act in a pro-environmentally friendly way. Additionally, it describes the ease or difficulty with which people do their desired activities (Valtonen et al., 2015). According to the study, it imagines past events and predicted barriers and results (Ajzen, 2006). Consequently, a hypothesis is suggested:

Hypothesis 5: Perceived behavioral control has a significant impact on behavioral intention.

Social Influence

Social influence is the degree to which a person recognizes that other significant individuals think he or she should take a particular action, such as using a system or technology (Kitcharoen & Vongurai, 2021). It symbolizes the level to which a person recognizes how important others believe they should use the new system (Venkatesh et al., 2003, p. 451). In the UTAUT model, social influence (SI) is defined as the degree to which consumers consider using a technology essential if their important others (i.e., friends, family) believe it is essential. It was recommended subjective norm is to describe social influence in TRA (Venkatesh et al., 2003, 2012). The SI model of technology use assumes that media representations of people are partially socially constructed, meaning that these representations are shaped by the attitudes, deeds, and statements of other participants in the social environment in which they are found. As was previously noted, behavioral intention refers to how much a person intends to carry out or refrain from carrying out a function in the future (Venkatesh et al., 2003). Studies examining the effect of SI on the adoption of information technology show that SI has a substantial impact (Eckhardt et al., 2009; Hsu & Lu, 2004). The intents of any technology are influenced positively or negatively by professional coworkers, siblings, friends, and peers (Alalwan et al., 2015; Tandon & Kiran, 2019; Teo & Noyes, 2014). Adopting online delivery is often influenced by superior/lecturer pressure (El-Masri & Tarhini, 2017; Pynoo et al., 2011; Tosuntas et al., 2015; Tseng et al., 2019). In addition, the perceived usefulness of a technology or system may also be influenced by parties other than the user himself, including the user's peers (Teo et al., 2012). In recent years, researchers have incorporated social influence into the TAM framework. Past research has shown that social influences have positive and negative effects on behavioral intentions. Thus, a hypothesis is formulated:

Hypothesis 6: Social Influence has a significant impact on behavioral intention.

Behavioral Intention

The TPB model's most important predictor of behavior is the behavioral intention, which is linked to an individual's willingness to try to carry out a behavior (Ajzen, 2006). The most accurate predictor of any planned future conduct is intention (Krueger et al., 2000). Numerous empirical studies have shown that intention can predict conduct (Cronan et al., 2015; Stone et al., 2010). Based on TPB, subjective norm, PBC, and attitude, the intention may be affected, influencing behavior (Ajzen, 2006). According to Ajzen (2006), students' behavioral intentions—their willingness to engage conduct—directly cause their actual behavior.

In contrast to earlier studies, the present study included the behavioral intention to utilize library public computing resources as the dependent variable. It did not distinguish between user behavior and intention on different dimensions. This was demonstrated by Mathieson (2006) study.

According to Chau and Hu (2002), the cognitive act of visualizing a person's acceptance (or use) of technology is revealed as behavioral intention. The higher education community has committed to ongoing innovation in teaching and learning. Chau and Hu (2002) claimed that the definition of behavioral intention is seeing a person undertaking a cognitive act to engage in (or utilize) a technology. Understanding the causes of intention can improve our comprehension of intentional action. The most accurate indicator of any intended future conduct is intention. We can comprehend deliberate conduct more fully if we have a clearer understanding of the causes of intention (Krueger et al., 2000). The theory of planned conduct states that individual attitudes, subjective norms, and perceived behavioral control all impact intentions, which in turn impact future behavior (Ajzen, 2006). Advice-seeking behavior is made easier by learners' intentions, which helps them pick the right college or university

(Navratilova, 2013). Several speculative conclusions may be drawn from adopting the TPB model as the foundation for a sibylline model of weblog learning. Hence, a hypothesis is proposed:

Hypothesis 7: Behavioral intention has a significant impact on behavior.

Behavior

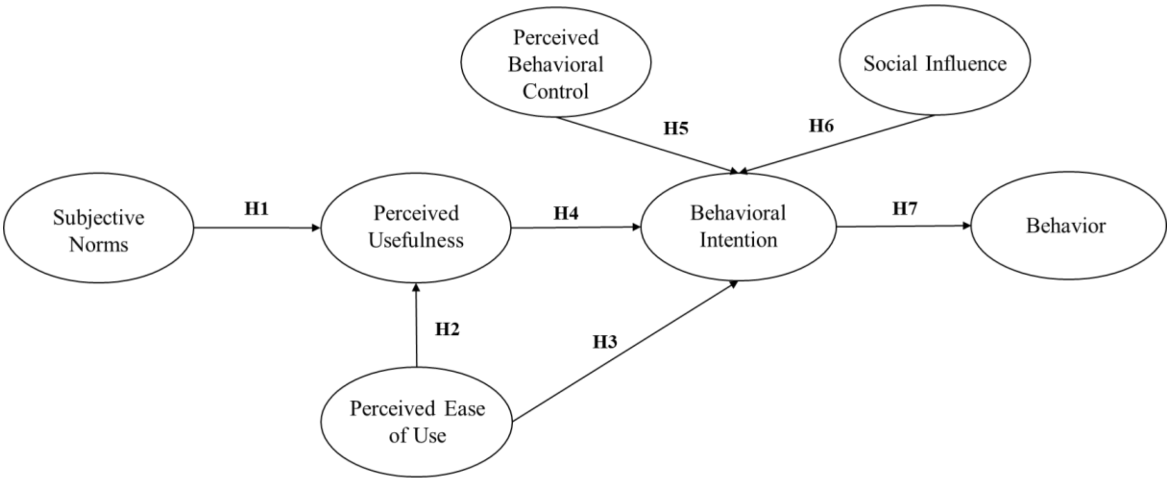
The way a person acts and interacts with others and with events is referred to as their behavior. The TPB (Ajzen, 2006) states that behavioral intents, subjective norms, and attitudes toward behavior all guide human conduct (Venkatesh et al., 2003). A conduct's social exposure, described as the combination of how individuals perceive that behavior in its social, physical, and symbolic contexts, can be a source of a legal consequence (Mead et al., 2014). Vigor (Patterson et al., 2006) refers to a user's level of energy, effort, and time given to a participation focus beyond purchase, while behavioral activation (Hollebeek et al., 2014) illustrates the user's intentions to participate in specific brand-related acts (Dessart et al., 2015). In the intention-based approach, behavior is a clear, single-act requirement carried out (not carried out) concerning a specific aim in a given situation at a certain point in time (Fishbein & Ajzen, 1975). PBC describes beliefs about having access to the tools and opportunities required to act, according to Ajzen (2006). In various contexts, including technology (Cheon et al., 2012), The degree to which a person likes or dislikes an action is highlighted by their attitudes. Subjective norms reflect a person's opinion of how seriously others take to conduct. Perceived behavioral control represents a person's propensity for and aptitude for behavior. The paper briefly describes these three constructs and their connections to this investigation in the next few words. The behavior that results in goal achievement comprises subgoals and issues with their implementation (Ajzen, 2002). As was previously indicated, as the period between intention measurement and behavior observation lengthens, the accuracy of behavior prediction typically declines. Additionally, it motivates customers to carry out non-transactional actions (Hollebeek et al., 2017).

Conceptual Framework

The conceptual framework is developed from studying previous research frameworks. It is adapted from three theoretical models. The behavioral intention of "digital natives" toward adapting the online education system in the Rise of online education. Ya-Ching (2006). An empirical investigation into factors influencing the adoption of an e-learning system. Patrick et al., (2016). An integrative adoption model of video-based learning. The conceptual framework of this study is proposed in Figure 1.

Figure 1

Conceptual Framework



Note: Constructed by author

Research Methodology

Research Design

This study uses quantitative methods and questionnaires as data collection tools. Participants had to fill out a separate questionnaire. In order to improve the validity and reliability of the questionnaire, objective consistency (IOC) was used to evaluate the questionnaire. Specialists from various fields were solicited to determine the validity of the questionnaire items. The 7 structures were divided into 33 items, among which 5 items had a validity of 0.33, and less than 0.67, which did not meet the requirements of content validity. Therefore, 28 items in this study meet the requirements and can be tested for reliability. Based on the education EI model, the researchers used a multi-item scale to measure seven variables. Five-point Likert the questionnaire was divided into two parts. Section 1 includes questions on the details of the demographic structure of respondents, while section 2 covers scale items for the main structures included in the proposed model.

Cronbach's Alpha method was tested for effectiveness and reliability. The pilot test (n=50) by the Cronbach alpha coefficient reliability test resulted that all items have strong internal consistency equal to or above 0.7 (Hair et al., 2003). After the reliability test, the questionnaire was distributed to the target interviewees, and 517 accepted responses were obtained. The researchers analyzed the collected data through SPSS AMOS 26.0. Then, confirmatory factor analysis (CFA) is used to test the convergence Accuracy and validation. Given the data, the model fit is calculated through comprehensive testing to ensure the effectiveness and reliability of the model. Finally, the researchers applied structural equation modeling (SEM) to examine the impact of variables.

Research Population and Sample

After the investigator had inputted all the essential knowledge into the calculator, including the expected outcome size (0.2), the expected level of statistical significance (0.8), the number of prospective variables (7), the number of observed variables (21) and the statistical likelihood size (0.05), the calculator indicated a small sample size. The minimum number of observations required by the model structure is 200, while the minimum recommended observations are 425. In addition, Analyses can be carried out to allow for further rigorous major impact assessments. Therefore, the researchers collected samples from three universities in Chengdu, China, for better statistical results. After distribute questionnaires to over 1,000 students, 517 were qualified for the data analysis.

Data Analysis

There are three steps in this present study's sampling procedures: purposive or judgmental sampling and convenience sampling. Students from three art colleges in three different regions of Chengdu, China, who have experience using online art exhibitions, will be targeted. First-year students did not use online art exhibitions, which were not used as demographic samples for a stratified sampling of sophomores, juniors, and seniors. It is convenient to use sampling, and students of sophomores, juniors, and seniors can be randomly selected for direct sampling. The data are analyzed by confirmatory factor analysis (CFA) and structural equation model (SEM) to verify the model's goodness of fit and confirm the causal relationship between the hypothesis test variables.

Demographics of Participants

Demographic information collected from respondents is about gender and the year of study. The first set of questionnaires was distributed to students in three selected higher education institutions in the form of 517 copies Institution. Arts College of Sichuan University, Academy of Fine Arts Sichuan Conservatory of Music, Art School of Southwest Minzu University. The respondents included 289 women and 228 men, accounting for 55.9% and 44.1% respectively. In this academic year, there were 160 sophomores, accounting for 30.9%, 203 junior students, accounting for 39.3%, and 154 senior students, accounting for 29.8%.

Table 1

The demographic data

Demographic and General Data (n=517)	Category	Frequency	Percentage
Gender	Male	228	44.1%
	Female	289	55.9%
Grade	Sophomore	160	30.9%
	Junior	203	39.3%
	Senior	154	29.8%

Results and Discussion

Convergent validity means that the classification obtained is highly correlated when two different measuring tools are used to measure the same concept. This study tested the convergence validity by constructing reliability (CR) and mean-variance extraction (AVE). The construction reliability is generally greater than 0.7, and AVE is greater than 0.5.

The confirmatory factor analysis results of the overall scale are shown in the table. The standardized factor loads of items under the seven variables of subjective norms, perceived usefulness, perceived ease of use, behavioral intention, perceived behavioral control, social impact, and behavior are all above 0.5, indicating that each observation variable can largely explain its latent variables. The combination reliability CR is greater than 0.8, significantly higher than the standard 0.7, so the observation variables under each dimension can explain this well. The convergent validity of each dimension is reflected by the average variance extraction (AVE) value, which is usually used to reflect the convergent validity of the scale. It can directly show how much of the variance explained by the potential variable is from the measurement error. The larger the AVE value, the larger the percentage of the variance explained by the potential variable, the smaller the relative measurement error, and the general value requirement is above 0.5. It can be seen from the above table that the AVE values are above the standard value of 0.5, which indicates that the scale in this paper has good convergent validity.

Cronbach's alpha (CA) is a statistical test to assess the internal consistency of the items within the construct (Killingsworth et al., 2020)—the larger value of Cronbach's alpha, the higher reliability of items. Cronbach's alpha value is from 0 to 1 and is acceptable or good at 0.7 to 0.8. A value between 0.8 to 0.9 is considered very good, and 0.9 or higher is considered excellent (Hair et al., 2003).

Table 2

Confirmatory Factor Analysis Result, Composite Reliability (CR) and Average Variance Extracted (AVE)

Variables	Source of Questionnaire	No. of Item	CA	Factors Loading	CR	AVE
Subjective Norms (SN)	Huang (2011)	3	0.815	0.773-0.801	0.818	0.600
Perceived Usefulness (PU)	Teo et al. (2012)	4	0.854	0.737-0.852	0.858	0.602
Perceived Ease of Use (PEOU)	Lin (2006)	4	0.828	0.715-0.800	0.830	0.551
Behavioral Intention (BI)	Venkatesh and Davis (1996)	4	0.844	0.724-0.865	0.850	0.588
Perceived Behavioral Control (PBC)	Lu et al. (2009)	3	0.820	0.772-0.787	0.824	0.609
Social Influence (SI)	Fishbein and Ajzen (1975)	3	0.817	0.732-0.831	0.823	0.608
Behavior (B)	Ajzen (2006)	4	0.863	0.732-0.838	0.865	0.616

Discriminant validity is confirmed when the AVE's square root is larger than any intercorrelated construct's coefficient (Fornell & Larcker, 1981). As illustrated in Table 3, the square root of AVE for all constructs at the diagonal line was greater than the inter-scale correlations. Hence, the discriminant validity was guaranteed.

Table 3

Square roots of AVEs and correlation matrix

	SN	PU	PEOU	PBC	SI	BI	B
SN	**0.774**						
PU	0.378	**0.776**					
PEOU	0.403	0.482	**0.742**				
PBC	0.488	0.480	0.502	**0.780**			
SI	0.530	0.487	0.496	0.629	**0.780**		
BI	0.355	0.421	0.449	0.488	0.470	**0.767**	
B	0.370	0.242	0.196	0.315	0.338	0.184	**0.785**

Note: The diagonally listed value is the AVE square roots of the variable

When judging whether the structural equation model is acceptable, it is mainly measured by measuring some relevant indicators, among which CMIN/df is generally required to be less than 3, GFI is the fitness index, AGFI is the adjusted fitness index, NFI standard fitness index, and CFI comparative fitness index. Generally, these values must be greater than 0.9, indicating that the model has good adaptability, but greater than 0.8 indicates that the model is acceptable. RMSEA should be less than 0.08, meaning the fit energy and model fit are good. It can be seen from the following table CMIN/df is 2.406 less than 3, GFI is 0.915 more than 0.8, AGFI is 0.891 more than 0.8, NFI is 0.907 close to 0.9, CFI is 0.943 more than 0.9, TLI is 0.933 more than 0.9, RMSEA=0.052 less than 0.08. It shows that the fitting degree of the model is good and that the model is acceptable. According to the standard of model fitting indicators, the fitting indicators of the model meet the requirements, so the model's path is analyzed.

Table 4

Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/df	<3.00 (Hair et al., 2010)	2.406
GFI	>0.90 (Bagozzi & Yi, 1988)	0.915
AGFI	>0.80 (Filippini et al., 1998)	0.891
NFI	>0.80 (Hair et al., 2010)	0.907
CFI	>0.90 (Hair et al., 2010)	0.943
TLI	>0.90 (Hair et al., 2010)	0.933
RMSEA	<0.08 (Hu & Bentler, 1999)	0.052
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,

Structural Equation Modeling (SEM)

Structural equation modeling (SEM) has also become structural equation analysis. It is a statistical method to analyze the relationship between variables based on the covariance matrix of variables, so it is also called covariance structure analysis. SEM is a multivariate statistical analysis technology that organically combines multiple regression and factor analysis methods to evaluate a series of interrelated causal relationships automatically. Structural equation modeling has similar uses to multiple regression but has more powerful functions. It applies to modeling under complex conditions such as implicit variables, independent variables correlation, variable errors, multiple dependent variables, etc. The structural equation is a statistical analysis tool based on sample data to evaluate whether the theoretical model proposed by researchers is acceptable.

The structural model was modified by correlating the measurement error between items in the constructs. The goodness-of-fit indices were recalculated in Table 5 based on the modified structural model. The results of statistical values were CMIN/DF = 2.667, GFI = 0.904, AGFI = 0.881, NFI=0.893, CFI = 0.930, TLI = 0.920, and RMSEA = 0.057. The fitness of the structural model is confirmed.

Table 5

Goodness of Fit for Structural Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/df	<3.00 (Hair et al., 2010)	2.667
GFI	>0.90 (Bagozzi & Yi, 1988)	0.904
AGFI	>0.80 (Filippini et al., 1998)	0.881
NFI	>0.80 (Hair et al., 2010)	0.893
CFI	>0.90 (Hair et al., 2010)	0.930
TLI	>0.90 (Hair et al., 2010)	0.920
RMSEA	<0.08 (Hu & Bentler, 1999)	0.057
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

Hypothesis Outcomes

The correlation magnitude among the independent and dependent variables proposed in the hypothesis is measured by regression coefficients or standardized path coefficients. Table 6 shows that seven out of eight proposed hypotheses were supported. Behavioral intention to use online art exhibitions was strongly impacted by perceived usefulness, followed by attitude toward using. The perceived usefulness of online art exhibitions was significantly driven by service, information, and system quality, respectively.

Table 6

Summary of hypothesis tests

Hypothesis	Standardized path coefficient (β)	t-value	Testing result
H1: Subjective norms has a significant impact on perceived usefulness.	0.235	4.427**	Supported
H2: Perceived ease of use has a significant impact on perceived usefulness	0.408	7.333**	Supported
H3: Perceived ease of use has a significant impact on behavioral intention.	0.180	2.770*	Supported
H4: Perceived usefulness has a significant impact on behavioral intention.	0.158	2.946**	Supported
H5: Perceived behavioral control has a significant impact on behavioral intention.	0.226	3.304*	Supported
H6: Social influence has a significant impact on behavioral intention.	0.179	2.665**	Supported
H7: Behavioral intention has a significant impact on behavior.	0.212	4.130**	Supported

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

Discussion

H1: The standardized path coefficient from subjective norms to perceived usefulness is 0.235 (t value=4.427, p=0.000<0.01), indicating that subjective norms have a significant positive impact on perceived usefulness, that is, the higher the subjective norms, the higher the perceived usefulness, so the hypothesis is valid.

H2: The standardized path coefficient from perceived ease of use to perceived usefulness is 0.408 (t value=7.333, p=0.000<0.01), indicating that perceived ease of use has a significant positive impact on perceived usefulness, that is, the higher the percei ved ease of use, the higher the perceived usefulness, so the hypothesis is valid.

H3: The standardized path coefficient from perceived ease of use to behavioral intention is 0.180 (t value=2.770, p=0.006<0.05), indicating that perceived ease of use has a significant positive impact on behavioral intention, that is, the higher perceived ease of use, the higher behavioral intention, so the hypothesis is valid.

H4: The standardized path coefficient from perceived usefulness to behavioral intention is 0.158 (t-value=2.946, p=0.000<0.01), indicating that perceived usefulness has a significant positive impact on behavioral intention, that is, the higher perceived us efulness, the higher behavioral intention, so the hypothesis is valid.

H5: The standardized path coefficient from perceived behavioral control to behavioral intention is 0.226 (t value=3.304, p=0.000<0.05), indicating that perceptual, behavioral control has a significant positive effect on behavioral intention, that is, the higher the perceptual, behavioral control, the higher the behavioral intention, so the hypothesis is valid;

H6: The standardized path coefficient of social influence on behavioral intention is 0.179 (t value=2.665, p=0.008<0.01), indicating that social impact has a significant positive impact on behavioral intention. That is, the higher the social impact is, the higher the behavioral intention is, so the hypothesis is valid.

H7: The standardized path coefficient from behavioral intention to behavioral intention is 0.212 (t value=4.130, $p=0.000<0.01$), indicating that behavioral intention has a significant positive impact on behavioral intention, that is, the higher behavioral intention, the higher behavioral intention, so the hypothesis is valid.

Conclusion

This paper focuses on investigating the intention and behavior of online art exhibitions, as well as the factors that affect the behavior of the students of the Sichuan Academy of Arts in China. It selects three universities in Chengdu as samples: the School of Arts of Sichuan University, the Chengdu Academy of Fine Arts of Sichuan Conservatory of Music, and the School of Arts of Southwest Minzu University. A survey questionnaire was prepared and sent to the target students. Through data analysis, this paper discusses the factors that affect the intention and behavior of online art exhibitions of college students at Sichuan Art Institute and uses confirmatory factor analysis to measure the validity and reliability of the conceptual model. Therefore, by applying structural equation (SEM), this paper analyzes online art exhibitions' intention and behavior factors. The research results of this study are described as follows. Subjective norms have a significant positive impact on perceived usefulness, perceived ease of use has a significant positive impact on perceived usefulness, perceived ease of use has a significant positive impact on behavioral intention, perceived behavioral control also has a significant positive impact on behavioral intention, and social influence has a significant positive impact on behavioral intention. Regression or standardized path coefficients measure the correlation between the independent and dependent variables proposed in the data hypothesis. Seven of these hypotheses are supported. These can determine the important factors that should be emphasized when influencing the behavior intention of online art exhibitions of college students in three art universities in Sichuan, China. Focus on improving college students' usefulness and positive understanding of using online art exhibitions. It is important to encourage the use of online art exhibitions to learn the process. Not only for the digital era we are currently in but also as a substitute to ensure that we continue to learn in any situation that may affect the interruption of learning (such as during COVID-19).

Recommendations

The researchers determined that such key factors as subjective norms, perceived usefulness, perceived ease of use, behavioral intention, perceived behavioral control (PBC), social impact, and behavior have an impact on the behavioral intention of three art universities in Sichuan to use online art exhibition. The above key factors should be developed and promoted to gain the willingness to adopt online art exhibitions in higher education, except for the trust caused by the importance of online art exhibitions. In this study, perceived usefulness is the strongest predictor of attitudes toward using online art exhibitions and behavioral intentions of using online art exhibitions. Therefore, it is necessary to emphasize the usefulness of promoting the system. This means that if undergraduates think that an online art exhibition system is a useful tool to improve their academic performance, they are willing to use online art exhibitions. The functions provided by online art exhibitions should be interactive, flexible, accurate, and relevant to their research. This function should include high-quality technical assistance, so adequate training should be carried out to improve the service level of engineers and service administrators to help learners use online art exhibitions more effectively and improve learners' willingness to accept online art exhibitions. Once the quality characteristics are guaranteed, the usefulness of the system, operating procedures, and other facilities supported should be promoted to students, such as training or media exchanges, to enhance their awareness and recognition. These can stimulate or increase positive attitudes and the possibility of using online art exhibitions in the learning process.

In conclusion, this study explains in detail the factors that affect undergraduates' willingness to use online art exhibitions. It allows developers of online art exhibitions and senior managers of higher education institutions to identify variables that affect undergraduates' willingness to use online art exhibitions. These variables can be applied to projects, investments, and the full use of online art exhibitions.

Limitations and Further Study

This study has some limitations that need to be noted, and the following are suggestions for further research. Firstly, this study only focuses on art universities and collects data from three selected universities in Sichuan, resulting in a limited scope and sample size. Secondly, the theme of this study is only based on an online art exhibition. Further research can be conducted on other types of online display systems or systems used for other purposes, exploring the potential for different types and purposes of the online display to lead to different discoveries, improve the universality of research models, and obtain more universal results. Thirdly, the survey is limited to students.

Further research may add teachers to the respondents to understand their views on the behavioral intentions of using online art exhibitions. In future research, researchers can use experimental methods to control for other variables that may confuse causal relationships, such as defining a specific quality factor to observe this independent variable's impact on the dependent variable's behavioral intention. In addition, qualitative research can be added to understand better undergraduates' behavioral intentions using online presentations.

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