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Predicting Factors of Undergraduate Art Students' Behavioral Intention to Use Online Education in Chengdu, China

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Abstract

Purpose: This study aims to explore the factors affecting online education behavior intention of fine arts students in three target universities in Chengdu, China. The conceptual framework proposes a causal relationship between perceived usefulness, perceived ease of use, attitude, facilitation condition, social impact, effort expectation, and behavioral intention. **Research design, data, and methodology:** The researchers used quantitative assessment techniques to conduct a statistical survey of 500 samples and identified undergraduate students at three target universities in Chengdu. The quantitative approach is used to distribute questionnaire to obtain survey data. The sampling techniques are purposive, quota, and convenience sampling. Confirmatory factor analysis (CFA) and structural equation model (SEM) were used for quantitative analysis, including model goodness of fit, correlation validity, and reliability test of each component. **Results:** Most variables had a significant effect on related latent variables, except that social influence had no significant effect on behavioral intention. In addition, perceived usefulness had the greatest effect on behavioral intention. **Conclusions:** Seven hypotheses were proved to achieve the research objectives. Therefore, the suggestion is to promote these aspects in the whole online education process to improve the online education behavior intention of fine arts students in Chengdu's target university.

Keywords: Facilitating Condition, Social Influence, Effort Expectancy, Behavioral Intention, Online Education

JEL Classification Code: E44, F31, F37, G15

1. Introduction

In early 2020, a sudden outbreak of novel coronavirus pneumonia spread rapidly. Following China's footsteps, many countries have imposed unprecedented lockdown and quarantine measures, requiring people to stay indoors if they do not have to, to stop the outbreak. The epidemic has greatly changed people's work and lives: China's Ministry of Education has extended the holidays, postponed the start of school, guaranteed the suspension of online education classes, and explicitly asked extracurricular training institutions to stop offline teaching. The epidemic in China has been effectively controlled through the efforts of the whole country, with enterprises gradually resuming work and people's lives gradually resuming. However, it can be predicted that online education will likely become a normal application in a long time (Meng & Wang, 2021).

Online education is a web-based teaching method. Through the Internet, students and teachers can carry out teaching activities even if they are far apart. In addition, with the help of online courseware, students can learn anytime, anywhere, breaking time and space limitations. Online distance education is the most convenient way for busy people with irregular learning times (Fang, 2015). The development of online education is an innovation of traditional education methods, and the previous online education is a supplement to school education. In 2018 and 2019, the online education industry developed rapidly, and the combination of AI, VR, AR, and other technologies restored the education scene and promoted the innovation of online education technology (Meng & Wang, 2021).

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Around 2010, the Internet penetrated every aspect of daily life, and the sudden emergence of mobile Internet has fundamentally changed how people connect to the Internet. It is estimated that more than 1.2 billion students in 180 countries and territories will need online education during the pandemic (Hang, 2021).

Online education for arts majors in Chinese universities can help teachers and students. Therefore, online education has been widely used today, sorting out the advantages and disadvantages of the education model. The online model emphasizes internal differences, resource skew, outcome orientation, and teacher teaching and student learning adjustment and improvement. To further achieve the purpose of improving the quality of education and promoting the sustainable development of education. Therefore, this study aims to explore the factors affecting online education behavior intention of fine arts students in three target universities in Chengdu, China.

2. Literature Review

2.1 Perceived Ease of Use

Perceived ease of use refers to a person's perception of whether a particular system is easy to use (Davis, 1989). Perceived ease of use is an individual's initial barrier to using the system (Venkatesh, 2000). PEOU was defined as the ease with which students use online education (Qin et al., 2019). Perceived ease of use is the degree to which an individual believes in using information technology to the point that no effort is required (Venkatesh & Bala, 2008). Perceived ease of use positively incentivizes the willingness to use technology (Chang et al., 2012). The degree to which the system is perceived to be easy to use is described as the perceived ease of use, and the sample believes that the use of the service of the target system will have a greater impact. PEOU refers to the user's belief that the future use of the technology is easy (Bashir & Madhavaiah, 2015). Perceived ease of use significantly affects willingness to use technology (Elkaseh et al., 2016). Perceived usefulness is the most important determinant of behavioral intention (Davis et al., 1989).

In previous studies, the study applied the Generic Extended Technology Acceptance Model for e-learning, and the results showed that subjective norms, experience, self-efficacy, and enjoyment had a positive impact on students' perceived ease of use, while self-efficacy and enjoyment have a positive and significant impact on students' perceived usefulness (Humida et al., 2021). Thereby, following hypotheses are posited:

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

H2: Perceived ease of use has a significant effect on attitude.

H4: Perceived ease of use has a significant effect on behavioral intention

2.2 Perceived Usefulness

Perceived usefulness is the degree to which students determine how a particular educational system contributes to their academic performance (Huang & Liaw, 2018). PU is considered the learner's perception of the expected benefits of using online learning (Li et al., 2021). The definition of perceived usefulness indicates that using online learning systems by college students will enhance their academic achievement (Vululleh, 2018). Perceived usefulness is the degree to which an individual believes that using the system will increase his or her performance productivity (Fokides, 2017). Perceived usefulness has a positive and sizable impact on user behavior and users' intent to use technology (Humida et al., 2021). In the context of e-learning, perceived ease of use, perceived usefulness, and intention exist to influence each other (Arbaugh & Duray, 2002; Pituch & Lee, 2006). Therefore, this study put forward a hypothesis:

H3: Perceived usefulness has a significant effect on behavioral intention.

2.3 Attitude

Attitude (ATT) is an individual's positive or negative feelings about executive behavior (Fishbein & Ajzen, 1975). Attitude is a psychological tendency to subjectively evaluate a certain object's favorable or unfavorable feelings to a certain extent (Eagly & Chaiken, 1993). ATT is different from instinct; attitude is not born. It is acquired through acquired learning. Without learning, innate behavioral tendencies are not attitudes. Individuals gradually form attitudes in their long-term lives through interaction with others and the constant influence of the surrounding environment (Arslan, 2022). Once an ATT is formed, it, in turn, affects the individual's reaction to the things around him and to others. In this interaction process, a person's attitude will gradually form an increasingly perfect attitude system through continuous circulation and revision. Attitude can be considered an effective domain factor that fosters learning motivation during teaching (Bajat, 2018). Attitude is formed based on needs after long-term perception and emotional experience, in which the emotional component occupies an important position and plays a powerful role. It makes one's attitude often emotionally strong, stable, and persistent. Because of this stability and persistence of attitudes, individuals can better adapt to the objective world (Shao, 2020).

Attitude is the main judgment point for students' willingness to use online educational technology in the learning process (Celik & Yesilyurt, 2013). Research shows positive changes in attitudes with age. However, the difference is not statistically significant, and attitudes are not innate but gradually formed in the acquired life environment through self and socialization (Arslan, 2022). Attitudes significantly impact behavioral intentions (Golnaz et al., 2010). Hence, this study concludes that:

H5: Attitude has a significant effect on behavioral intention.

2.4 Facilitating Condition

A facilitating condition is the availability of means and possessions to accomplish a task (Venkatesh et al., 2012). Facilitating condition is the factor responsible for external control and is associated with promoting resources (Taylor & Todd, 1995). Research argues that facilitating conditions are processes that help people by replacing outdated technologies with new ones when new ones become available (Teo & Noyes, 2014). The degree to which an individual feels that the organization supports using the system regarding relevant technology and equipment is defined as a facilitating condition (Chaka & Govender, 2017). Facilitating conditions are thought to have a single organization, and technology infrastructure can be used to support the use of trust level (Liestiawati & Agustina, 2018).

Studies have concluded that the lack of convenient infrastructure is a major factor affecting the implementation of online education systems (Engelbrecht, 2005). Facilitating conditions significantly positively impact students' acceptance of mobile learning (Mtebe & Raisamo, 2014). The study found that facilitating condition has a significant impact on behavioral intention (Yu et al., 2021). Accordingly, a hypothesis is set:

H6: Facilitating condition has a significant effect on behavioral intention.

2.5 Social Influence

The influence of others on the decision or influence of potential adopters to accept a new technology is known as social influence (Salloum & Shaalan, 2018). Researchers believe that the higher the user's desire for a specific activity, the more favorable the subjective criteria is social influence (Ajzen, 1991). Previous research defined social influence as students' decisions influenced by peers or others, such as teachers and parents (Chao, 2019). People can be influenced by what others believe and may engage in particular acts even if they do not want to, which is why social influence was discovered as a direct determinant of behavioral intention (Bardakcı, 2019). Due to interactions with others, SI changes one's thoughts, emotions, behavior, or behavior (Liestiawati & Agustina, 2018). Social influence is a common psychosocial phenomenon expressing human behaviors and attitudes influenced by social environments or social pressures (Teo & Noyes, 2014).

Social influence is that not all activities are self-activating to determine whether or not a human does something (Vululleh, 2018). Former students or others can influence the opinions of college students, for example, lecturers or family members (Chao, 2019). Social influence significantly impacts students' acceptance of mobile learning (Mtebe & Raisamo, 2014). Based on the previous literatures, a hypothesis is indicated:

H7: Social influence has a significant effect on behavioral intention.

2.6 Effort Expectancy

Effort expectations also indicate the level of comfort and ease associated with positioning, accepting, and using technology, and the ease with which technology can be used determines effort expectations (Venkatesh et al., 2003). Effort expectations are also an aspect of expectation theory and are related to how much effort an individual wishes to scale up to complete a task (Isaac et al., 2001). Effort expectations are also defined as students' perceptions of the use and effectiveness of online learning (Ssekakubo et al., 2011). Simultaneous effort expectations are identified as the ease with which a particular educational system is utilized (Bardakcı, 2019). Effort expectations are the degree to which students utilize e-learning systems (Mtebe & Raisamo, 2014).

Previous academic researchers have demonstrated that effort expectations are an important determinant of behavioral intent (Bardakcı, 2019). Effort expectations have no significant effect on younger users but have a significant effect on older users (Teo & Noyes, 2014). The study also found that effort expectations did not significantly affect the willingness to use mobile learning services (Joo et al., 2014). Subsequently, a hypothesis is suggested:

H8: Effort expectancy has a significant effect on behavioral intention.

2.7 Behavioral Intention

Behavioral Intention is the subjective probability of how a person will perform the behavior (Fishbein & Ajzen, 1975). BI was defined as the Intention to perform a specific behavior (Davis, 1989). Researchers define behavioral intent as the level of an individual's intentional strategy to perform or not perform some upcoming behavior (Humida et al., 2021). Behavioral Intention is the cognitive representation of an individual's readiness to perform a given behavior and is a prerequisite for behavior (Asadi et al., 2016). Research has found that behavioral intentions are derived from a psychological theory that focuses on completed behaviors, describing how individuals behave when they accept a system (Chauhan, 2015). The degree to which an individual subjectively plans to achieve or not to achieve a specific future behavior is defined as behavioral Intention (Bashir & Madhavaiah, 2015). In previous studies, behavioral intentions have been shown to affect perceived usefulness, ease of use, satisfaction, effort expectations, convenience, and social influence (Qin et al., 2019). According to previous research, behavioral intent relates to actual behavior (Davis et al., 1992; Min et al., 2022).

3. Research Methods and Materials

3.1 Research Framework

The conceptual framework is developed based on previous research frameworks. It is adapted from three theoretical models. The first framework was published by Venkatesh and Bala (2008) and was titled "TAM 3 and the Intervention Research Agenda." The results of the research framework show that PEOU has an impact on perceived usefulness, perceived usefulness has an impact on behavioral intention, and perceived ease of use significantly impacts behavioral intention. The second framework was published by Qin et al. (2019) as a user adopting a hybrid social tagging approach in online knowledge communities. The results of the framework study show that perceived ease of use has a positive impact on user attitude, perceived usefulness has an impact on behavioral intention, attitude has a significant impact on behavioral intention, and social influence has a significant impact on behavioral intention. The third framework was published by Venkatesh et al. (2003). The third framework adopts an approach to technology acceptance and unified theory. The third framework adopts a unified theory approach to technology acceptance and use. The paper also makes several recommendations for future research, including further understanding the dynamic impact of the study in this paper, improving the measurement of core structures used in UTAUT, and understanding the use of organizational outcomes associated with new technologies. The results of the framework study show that effort expectation has a positive impact on behavioral intention, social influence has a significant impact on behavioral intention, and convenience has a significant impact on behavioral intention.

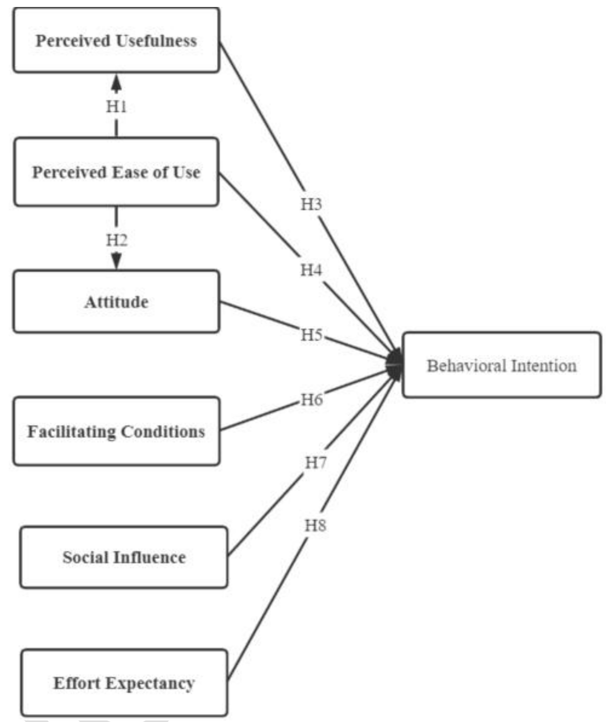

Figure 1: Conceptual Framework

H1: Perceived ease of use has a significant effect on perceived usefulness.
H2: Perceived ease of use has a significant effect on attitude.
H3: Perceived usefulness has a significant effect on behavioral intention.
H4: Perceived ease of use has a significant effect on behavioral intention
H5: Attitude has a significant effect on behavioral intention.
H6: Facilitating condition has a significant effect on behavioral intention.
H7: Social influence has a significant effect on behavioral intention.
H8: Effort expectancy has a significant effect on behavioral intention.

3.2 Research Methodology

Using a quantitative non-probabilistic sampling method, the researchers distributed questionnaires online and in paper form. The target groups are fine arts students from the three target universities: Sichuan Normal University (SNU), Chengdu University (CDU), and Sichuan Conservatory of Music (SCM) in Chengdu. Collect data and analyze key factors that significantly impact Behavioral Intention in online education. The survey was divided into three parts. First, the screening questions are used to identify the characteristics of the respondents. Second, five proposed variables were measured using a 5-point Likert scale ranging from strongly disagree (1) to agree (5) for all four hypotheses. Finally, demographic issues are gender, age, and educational background.

Before the data collection, the index of item-objective congruence (IOC) was evaluated by experts and tested by the objective consistency index. The results pass threshold of 0.6 and were consequently excluded from further analysis. The reliability of Cronbach's Alpha method was tested in the pilot test (n=30). A Cronbach's alpha values exceed 0.7 serves as the acceptable threshold (Nunnally & Bernstein, 1994).

After the reliability test, the questionnaire was distributed to the target respondents, and 500 accepted responses were obtained. The researchers used SPSS AMOS software to analyze the collected data. Then, confirmatory factor analysis (CFA) is used to test and verify the convergence accuracy. The model fit measure is calculated by testing the whole of the given data to ensure the validity and reliability of the model. Finally, the structural equation model (SEM) was used to examine the influence of the variables.

3.3 Population and Sample Size

The target population of this paper is the three target universities in Chengdu Sichuan Normal University (SNU), Chengdu University (CDU), Sichuan Normal University (SNU), and Chengdu University (CDU). Sichuan Conservatory of Music (SCM) students majoring in fine arts. Some researchers say a reasonable sample size is about 150 respondents without data loss, while others recommend a minimum sample size of 200 (Taherdoost, 2017). The survey 796 respondents. After data screening, 500 questionnaires were used in this study.

3.4 Sampling Technique

The researchers adopted the non-probability sampling method and judgment sampling method to target art students in three target universities in Chengdu. Then, using a quota sample, 1,179 graduate art students with at least one month of online education experience were identified from three public universities with fine arts majors in Chengdu, China. In addition, as shown in Table 1, 500 participants were designated as the final sample using three different subsegments of the quota. Convenience sampling was implemented by the online survey distributed to the target group.

Table 1: Sample Units and Sample Size

Three public universities in Chengdu	Population Size	Proportional Sample Size
Sichuan Normal University (SNU)	308	193
Chengdu University (CDU)	199	125
Sichuan Conservatory of Music (SCU)	290	182
Total	**797**	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

The demographic target is 500 participants, and the results are shown in Table 2. Male respondents represented 38.8%, and female respondents 61.2%. Regarding age group, respondents aged 19-23 accounted for the largest proportion, accounting for 73.0%, followed by those below 18 years old, accounting for 27.0%, and over 24 years old, accounting for 0%. According to the academic qualifications of the respondents, the number of second-year undergraduate students accounted for 46.6%, the number of first-year undergraduate students accounted for 32.4%, the number of third-year undergraduate students accounted for 15.6%, and the number of fourth-year undergraduate students accounted for 5.4%.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	194	38.8%
	Female	306	61.2%
Age	Below 18 years of age	135	27%
	19 to 23	365	73%
Year of Study	Freshman	162	32.4%
	Sophomore	233	46.6%
	Junior	78	15.6%
	Senior	27	5.4%

Source: Constructed by author

4.2 Confirmatory Factor Analysis (CFA)

CFA is a multivariate analytical tool used to test multiple hypotheses simultaneously, which are combined to produce an evaluation matrix (Lewis-Beck et al., 2004). Confirmatory factor analysis experiments conceptual validity (Brown, 2015). In this study, CFA was used after the data collection phase. Arbuckle and Wothke (2008) defines formal CFA as a statistical research method to estimate hypothetical variables of mutual characteristics between students. CFA evaluates whether the structure and loading of each observed variable are compatible with the hypothesis (Malhotra et al., 2004).

Based on earlier studies, researchers established a factor loading threshold 0.5 (Truong & McColl, 2011). According to Kline (2016), the minimum values for the goodness of fit metric were as follows: Chi-square ($p > 0.05$), CFI (>0.95), AGFI (>0.90), and RMSEA (<0.06). It was permissible to use a chi-square index criterion of less than or equal to 3.00 (Hair et al., 2010).

According to the statistical results summarized in Table 3, all Cronbach's Alpha values greater than 0.80, factor loadings greater than 0.30, p-value less than 0.50, composite reliability (CR) greater than 0.70, and average variance extracted (AVE) greater than 0.50 were significant (Byrne, 2010). Furthermore, this study's convergent and discriminant validity was ensured

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
Perceived Usefulness (PU)	Davis (1989)	5	0.858	0.535-0.944	0.864	0.574
Perceived Ease of Use (PEOU)	Davis et al. (1989)	6	0.874	0.533-0.914	0.881	0.560
Attitude (ATT)	Davis (1989)	4	0.843	0.578-0.880	0.854	0.600
Facilitating Conditions（FC）	Ajzen (1991)	5	0.877	0.607-0.913	0.884	0.610
Social Influence (SI)	Mtebe and Raisamo (2014).	3	0.868	0.820-0.840	0.868	0.687
Effort Expectancy (EE)	Moore and Benbasat (1996)	4	0.897	0.684-0.919	0.904	0.704
Behavioral Intention (BI)	Asadi et al. (2016)	4	0.901	0.801-0.878	0.902	0.698

The convergence and differential validity are verified to be greater than the acceptable values in Table 4. Thus, convergence validity and discriminant validity are guaranteed. In addition, these model measurements validate the discriminant validity and subsequent validation of the estimated validity of the structural model.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/ DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	1197.329/413 or 2.899
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.878
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.853
NFI	≥ 0.80 (Wu & Wang, 2006)	0.883
CFI	≥ 0.80 (Bentler, 1990)	0.920
TLI	≥ 0.80 (Sharma et al., 2005)	0.910
RMSEA	< 0.08 (Pedroso et al., 2016)	0.062
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.

Proposed a criterion indicating that a construct's validity can be deemed satisfactory if the coefficients between interrelated constructs are less than the square root of the Average Variance Extracted (AVE). The square root of AVE for each construct is detailed in the diagonal of Table 5. Significantly, these figures surpass the correlation coefficients observed between distinct constructs, underscoring the robustness of discriminant validity and its alignment with the suggested standards (Hair et al., 2016).

Table 5: Discriminant Validity

	PU	PEOU	ATT	FC	SI	EE	BI
PU	**0.758**						
PEOU	0.271	**0.748**					
ATT	0.306	0.239	**0.775**				
FC	0.347	0.244	0.334	**0.781**			
SI	0.391	0.371	0.286	0.305	**0.829**		
EE	0.433	0.244	0.226	0.335	0.347	**0.839**	
BI	0.287	0.194	0.196	0.231	0.238	0.207	**0.835**

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

4.3 Structural Equation Model (SEM)

Following the CFA method, the structural equation model (SEM) was used to estimate a specific system of linear equations and validate the model's fit. Structural equation models were a multivariate statistical approach that uses factor analysis to examine possible or causal links between variables (Klem, 2000). Table 6. shows the adjusted results, including all CMIN/DF, GFI, AGFI, CFI, TLI, and RMSEA values. As a result, each indicator of goodness of fit in SEM verification for this study was satisfactory.

Table 6: Goodness of Fit for Structural Model

Index	Acceptable	Statistical Values Before Adjustment	Statistical Values After Adjustment
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	1556.428/426 or 3.654	1225.407/414 or2.960
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.816	0.856
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.785	0.827
NFI	≥ 0.80 (Wu & Wang, 2006)	0.848	0.881
CFI	≥ 0.80 (Bentler, 1990)	0.885	0.917
TLI	≥ 0.80 (Sharma et al., 2005)	0.874	0.907
RMSEA	< 0.08 (Pedroso et al., 2016)	0.073	0.063

Index	Acceptable	Statistical Values Before Adjustment	Statistical Values After Adjustment
Model Summary		**In harmony with Empirical data**	**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 significance for each variable was calculated using the standardized path coefficient value and t-value. Table 6 shows the calculated outcomes for each calculation. Perceived Ease of Use has the greatest impact on Attitude, which with the standardized path coefficient (β) result as 0.246 (t-value = 5.053*), and Perceived Ease of Use influenced Perceived Usefulness with β as 0.170 (t-value = 3.407*), Perceived Usefulness has influenced Behavioral Intention with β as 0.128(t-value = 2.637*), Facilitating Conditions has impacted Behavioral Intention with β as 0.118 (t-value = 2.510*), Attitude has influenced with Behavioral Intention with β as 0.117 (t-value = 2.359*), Perceived Ease of Use has influenced with Behavioral Intention with β as 0.101 (t-value = 2.056*), Effort Expectancy has impacted with Behavioral Intention with β as 0.095 (t-value = 2.028*), and Social Influence has impacted with Behavioral Intention with β at -0.023(t-value = -0.572). Therefore, except Social Influence, all other assumptions are significantly supported with p value less than 0.05.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-Value	Result
H1: PEOU→PU	0.170	3.407*	Supported
H2: PEOU→ATT	0.246	5.053*	Supported
H3: PU→BI	0.128	2.637*	Supported
H4: PEOU→BI	0.101	2.056*	Supported
H5: ATT→BI	0.117	2.359*	Supported
H6: FC→BI	0.118	2.510*	Supported
H7: TS→JS	-0.023	-0.572	Not Supported
H8: EE→BI	0.095	2.028*	Supported

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

According to the information in Table 7, it may be possible to obtain the following extensions.

H1 has confirmed that perceived ease of use is an important component in perceived usefulness, with the standardized route coefficient value in the structural approach being 0.170. It is found that perceived ease of use significantly impacts perceived usefulness (Teo, 2009).

H2 has confirmed that perceived ease of use is the largest component in attitude, with the standardized route coefficient value in the structural approach being 0.246. Attitude is significantly influenced by perceived ease of use (Nagy, 2018).

The correlational statistics result for **H3** validated the hypothesis for the strong impact of perceived usefulness on behavioral intention, which was described by the standard coefficient value of 0.128. Perceived usefulness positively and considerably impacts user behavior with the user's intent to use technology (Humida et al., 2021).

H4 discovered that perceived ease of use influences behavioral intention, with a standard coefficient of 0.101. According to the findings, perceived ease of use significantly impacts behavioral intent (Venkatesh & Bala, 2008).

Attitude reinforced behavioral intention, as evidenced by the statistic value of 0.117 on the standard coefficient examining the active impact of **H5.** The models studied state that behavioral imagery relies primarily on attitudes (Perry, 2017).

H6 has confirmed that facilitating conditions are an important component in perceived usefulness, with the standardized route coefficient value in the structural approach being 0.118. Facilitation conditions had a significant effect on the prediction of behavioral intention to use e-learning, and facilitation conditions had a significant moderating effect on students' behavioral intention to use e-learning (Humida et al., 2021).

In addition, **H7** shows that social influence has no significant influence on behavioral intention in this study, and the standard coefficient value is -0.023. The social influence of art students in the three target universities in Chengdu has no significant effect on the behavioral intention of learning and putting it into practice.

Finally, the statistical results of this study do support the notion that effort expectancy affects behavioral intentions, according to the **H8** hypothesis, and its standard coefficient value is 0.095. The theoretical matrix of the unified theory of technology acceptance and use suggests that effort expectation is one of the direct determinants of behavioral intent, and many previous academic researchers have demonstrated that effort expectation is a fundamental determinant of behavioral intent (Bardakcı, 2019).

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

This study aims to verify the significant influence of behavioral intention on fine arts majors in three target universities in Chengdu. This study uses hypothesis as the conceptual framework. Discuss Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Attitude (ATT), Facilitating Condition (FC), The significant impact of Social Influence (SI) and Effort Expectancy (EE) on behavioral intention (BI) of online education. Under the conceptual framework, a hypothesis was put forward, and the questionnaire was distributed to 500 fine arts students with at least one month of online teaching experience. Confirmatory factor analysis (CFA) was used to analyze the validity and reliability of the concept matrix. Then, an equation model (SEM) is constructed to determine the main influencing factors affecting the behavior intention.

It is found that the perceived ease of use has the greatest impact on attitude. In contrast, the perceived usefulness of online education has the strongest direct impact on behavioral intention, consistent with previous research results. Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Attitude (ATT),

Facilitating Condition (FC) and Effort Expectancy (EE) significantly influence the online educational behavior intention of fine arts majors. In this study, Social Influence (SI) was not a significant determinant of behavioral intention. This suggests that the social impact of using online education is only one of the important factors influencing college student's choice of study. This result can be attributed to the independent learning nature of online education. According to the inquiry and analysis of the target group, as contemporary college students have independent thoughts, will not be easily influenced by the outside world, and have their decision-making ability, online education has become an important learning tool in the era of big data, and the target audience will choose the online education suitable for them according to their needs. Therefore, the target population's social influence does not significantly impact the behavioral intention of online education. In particular, students majoring in art have a strong ability to accept new things and will find a suitable one in various online education options. TAM model theory introduced in this study is generally aimed at public exploration and investigation. However, the effect of social influence on behavioral intention in this study has not been verified in this unique sample population, and other factors, except social influence, have significant effects on behavioral intention in online education.

5.2 Recommendation

The researchers found that in the target universities in Chengdu, the key factors affecting the behavioral intention of fine arts students in online education are Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Attitude (ATT), Facilitating Condition (FC) and Effort Expectancy (EE) have significant influence on behavioral intention (BI). In this study, Social Influence (SI) was not a significant determinant of behavioral intention. Therefore, the suggestion is to promote these aspects in the whole online education process to improve the online education behavior intention of fine arts students in Chengdu target university.

First, improve the function of the online education platform and pay attention to course design. When students use online learning, the system's usefulness and ease of use directly affect their behavioral intention towards online education, and this attitude has a positive impact on the final use of online education. Therefore, it is very important to choose online education for teaching, and it is necessary to choose the appropriate online learning platform based on the platform's functions, operability, and friendliness. At the same time, the construction of course content should be strengthened to improve students' sense of identity for online learning. Improvements can be made in course design and content selection. For example, the design of courses should be student-led, and forms such as independent exploration and passing through examinations should be added to make students feel that online learning platforms are conducive to improving knowledge learning. To improve the target students' behavioral intention of online education.

Secondly, simplify the operation process, increase the interface guidance, and strengthen the convenience conditions. In developing online education functions, the design should be centered on students as the main body, simplify the operation process, have better interface guidance, improve the platform's compatibility, and improve the target students' recognition of the ease of use of the online learning platform.

Finally, diversify technical support. There was no significant effect of promoting factors on behavioral intention use of online education. The reason may be that with the current Internet technology and 5G, artificial intelligence, and other aspects of popularization, most students have a relatively high degree of information teaching, Internet technology, and proficiency, so online learning such technology has been able to be mastered well. However, you can use the form of short video help documents from technical support, and you can more intuitively grasp the use of methods to improve the impact of promoting factors.

5.3 Limitation and Further Study

The disadvantage of the study is that the demographics and sample are limited to college students majoring in fine arts from the three target universities in Chengdu, China. Future research could look at two approaches. One option is to expand the study to other parts of China. Secondly, within the research framework, we can further study the prospective use of attitude variables such as trust, psychological expectation, learning motivation, performance expectation, and satisfaction.

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