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Factors Underlying Behavior Intention to Use Online Education of Art College Students in Xi'an, China

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Abstract

Purpose: This study aims to investigate the key factors affecting the online education behavior intention of fine arts students in three specific universities in Xi'an, China. The conceptual framework proposed includes perceived usefulness, perceived ease of use, attitude, facilitating condition, social influence, effort expectancy, and behavioral intention. **Research design, data, and methodology:** The researchers employed quantitative assessment techniques to conduct a statistical survey with a sample size of 502 undergraduate students from the three target universities in Xi'an, China. The survey data was obtained using a multi-stage selection method, which involved purposive, quota, and convenience sampling. Confirmatory factor analysis and structural equation modeling were used for quantitative analysis, including assessing model fit, testing correlation validity, and evaluating the reliability of each component. **Results:** Most latent variables exhibited significant effects on behavioral intention, except for facilitating condition and effort expectancy. Notably, Perceived usefulness had the greatest impact on behavioral intention. **Conclusions**: The study successfully validated six hypotheses, thus achieving the research objectives. Consequently, it is recommended to emphasize and promote these aspects throughout the entire online education process to enhance the online education behavior intention of fine arts students in the target university in Xi'an.

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

JEL Classification Code: E44, F31, F37, G15

1. Introduction

The new crown pneumonia epidemic outbreak has impacted the development of online education, laying the foundation for unprecedented large-scale online education practice (Li et al., 2021). More than 200 million Chinese students are learning through online education thanks to online platforms and digital learning materials. More importantly, this practice has a significant impact on future education reform, enabling educators and students to realize that online education is not only a way to solve the educational problems of the current era but also a trend to promote the reform of education, teaching, and educational organization in the new era (Chen et al., 2021).

Online education, also known as distance education and online learning, refers to a new type of education mode that uses the Internet to disseminate educational resources. To a certain extent, online education solves the temporal and spatial limitations of high-quality resource transmission, makes teaching methods more flexible, and meets individual needs (Hang, 2021).

Online education plays an irreplaceable role in maintaining normal teaching progress and plays a clear advantage in responding to the uncertainties caused by global emergencies, so global education has maintained a steady increase during turmoil. Therefore, higher education,

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which has the second largest market share in the global education market, should also return to a rational focus on the value of education, adopt a prudent attitude to understand the current development status of higher education, and think about the future direction of the online education model of higher education, to maximize its advantageous role (Li et al., 2021).

The research on online education of art majors in Chinese universities and colleges can not only help educators better understand the reality of online education but also help the students to correctly see the education methods, including online education under the influence of the objective force majeure environment. Because of the practical problems encountered in the process, the effectiveness of the degree of further optimization to promote the balance of education structure. Thus, this study aims to investigate the key factors affecting the online education behavior intention of fine arts students in three specific universities in Xi'an, China.

2. Literature Review

2.1 Perceived Ease of Use

Perceived ease of use was described as the intensity at which users believe they can run a particular setting without effort, and considering effort is a limited resource, an application is more acceptable to users (Davis et al., 1989). The concept of perceived ease of use originated from TAM, and some studies define perceived ease of use as the use of it to measure user acceptance of innovative technologies (Elkaseh et al., 2016). PEOU is also understood as a perception of how people believe services provided through the target system will be more successful (Arshad & Akram, 2018). PEOU indicates how certain people are about how simple the entire system will be (Chauhan, 2015). Perceived usefulness and behavioral intent are influenced by perceived ease of use (Altin et al., 2008). Numerous studies have also shown that perceived ease of use positively impacts use attitudes and behavioral intentions and that perceived ease of use is a significant determinant of student-teacher attitudes and intentions to use technology (Luan & Teo, 2009).

Research suggests that the Perceived ease of use of online learning affects behavioral intentions (Masrom, 2007). Studies have shown that PEOU significantly impacts PU (Haugstvedt & Krogstie, 2012). Studies have shown that PEOU significantly affects behavioral intent (Venkatesh & Bala, 2008). 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 defined as the degree to which a person believes that using a particular system will improve their job performance, and a particular system is highly perceived as useful because users believe there is a positive user-performance relationship (Davis, 1989). PU is a metric that predicts student adoption of new educational technologies (Elkaseh et al., 2016). Researchers believe that perceived usefulness refers to the belief that system users will get better results from using a service (Humida et al., 2021). Perceived usefulness and perceived ease of use are considered high and low levels of identity, respectively (Venkatesh & Davis, 2000). Research suggests that the impact of perceived ease of use on perceived usefulness will be stronger because users can assess their likelihood of achieving perceived usefulness based on information gained from their experience with perceived ease of use (Venkatesh & Bala, 2008).

Perceived usefulness can greatly impact an individual's behavior (Altin et al., 2008). Behavioral intentions are directly influenced by perceived usefulness and ease of use (Neo et al., 2015). PEOU and perceived usefulness are key determinants of behavioral intention for students and teachers using technology for online learning in higher education (Elkaseh et al., 2016). Therefore, this study put forward a hypothesis:

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

2.3 Attitude

Attitude is thoughts and feelings about a person and an individual's behavior toward the object of the attitude (Orakci et al., 2022). Attitude is a stable mental intention of a person toward a specific object or system, and attitude is a tendency to react pro or con to the use of technology (Ajzen, 1991). Attitude, as a psychological phenomenon, relates to people's interior experiences and behavioral inclinations. People's words, actions, and behaviors mostly reflect their hidden attitudes. People, events, nations, groups, systems, concepts, and so on are all examples of objects of people's views. People accept or approve of certain attitude objects.

In contrast, others express rejection or opposition, and this psychological evaluative tendency, such as acceptance, approval, rejection, and opposition, is referred to as an attitude. Therefore, attitude can be seen as a state of psychological preparedness that governs people's choices of observation, memory, and thinking and also determines what people hear, see, think, and do (Zhong et al., 2022). Attitude is a key indicator of an individual's acceptance of educational technology and reflects an individual's preference for technology (Shao, 2020). Attitude is an internal structure;

although it contains a tendency to act, it is not equal to behavior, so the attitude cannot be directly observed (Arslan, 2022).

Strong attitudes can drive behavior, and a positive learning attitude may contribute to the effective use of learning strategies. Moreover, one's attitude toward online education and technology is directly related to learning (Orakci et al., 2022). TAM uses the constructs of PU, PEOU, and ATT to explain and predict the adoption of technological systems (Davis, 1989). However, some studies have shown that attitudes do not significantly affect behavioral intentions (Mohamed Riyath et al., 2022). Hence, this study concludes that:

H5: Attitude has a significant effect on behavioral intention.

2.4 Facilitating Condition

Research defines the extent to which individuals believe in organizational and technological infrastructure that supports system use as a facilitating condition (Venkatesh et al., 2003). According to some studies, facilitation conditions are also defined as enabling environmental factors that affect PEOU and teachers' propensity to use technology in TAM (Teo, 2011). Effort expectations are defined as the ease-of-use concept of how individuals feel about the system (Chao, 2019). The availability of perceptible organizational and technical infrastructure allows the identified and used facilitation system to be defined as facilitating conditions (Mtebe & Raisamo, 2014). A facilitating condition is defined as an environmental factor or behavioral, physical setting that promotes a user to perform a task and the extent to which individuals believe that technology and organizational infrastructure can sustainably strengthen them. (Salloum & Shaalan, 2019).

The study stated that the facilitating condition was hypothesized to affect perceived usefulness, attitudes, and intentions separately, and the facilitating condition was found to significantly affect perceived usefulness, attitudes, and intentions related to consumer acceptance of mobile wallet services (Chawla & Joshi, 2019). Studies have observed that facilitating condition is a significant factor in predicting attitudes and intentions of online technology adoption (Karjaluoto et al., 2002). Accordingly, a hypothesis is set:

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

2.5 Social Influence

Social Influence also refers to the degree to which individuals perceive that other significant people think they should use a hybrid social labeling approach (Qin et al., 2019). Some studies define social Influence as the acceptance or support of behavioral activation by potential individuals (Bashir & Madhavaiah, 2015). SI is the extent to which individuals know how others believe they should use a new information system (Salloum & Shaalan, 2019). Social Influence refers to social forces, including subjective norms and individual images, on an individual's perceived usefulness and willingness to use new systems. In contrast, subjective norms refer to an individual's perception of expectations or pressures on important reference objects and personal image, which in turn refers to an individual's desire to shape a good image by following subjective norms in order to improve membership as a member of the inner circle (Doo, 2021).

Research assumes that social Influence is based on systematic acceptance (Mtebe & Raisamo, 2014). Some researchers believe that social factors have good and bad influences on people's behavioral intentions (Vermeir & Verbeke, 2006). However, some studies suggest that social Influence is not a major predictor of BI in a voluntary setting but becomes crucial in a coercive setting (Venkatesh et al., 2003). 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 are the ease associated with information systems and their use (Salloum & Shaalan, 2019). Researchers believe that effort expectancy is related to the perceived simplicity of the system and the information it contains (Fakhoury & Aubert, 2017). Previous research has shown a positive effect on effort expectations and behavioral intentions (Alharbi & Drew, 2014). Effort expectation is understood as the degree of expectation of individuals who possess the ease of use of technology, and the effort expectation construction in each model is important (Liestiawati & Agustina, 2018).

Researchers believe that effort expectancy is the main reason students voluntarily adopt ubiquitous learning (Honarpisheh & Zualkernan, 2013). Effort expectations significantly impact student acceptance of mobile learning (Mtebe & Raisamo, 2014). The study concluded that since online education is still in its early stages, effort expectations are an important factor influencing the behavioral willingness to use it. (Salloum & Shaalan, 2019). Subsequently, a hypothesis is suggested:

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

2.7 Behavioural Intention

Behavioral intention is considered to be how much effort an individual is willing to put in to accomplish a task or how much effort an individual is willing to put in to achieve a desired behavior (Ajzen, 1991). 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).BI is how eager a person is to complete the desired activity (Cigdem & Ozturk, 2016). The definition of behavioral intent is the degree to which a person deliberately plans to perform or not perform a given future activity. Many aspects influence a learner's behavioral intent to use technology in the learning process (Davis et al., 1992). Previous research has defined behavioral intention as a learner’s decision to continue using technology, a phrase that drives technology use (Venkatesh et al., 2012).

Research has found a moderating role in the relationship between perceived ease of use and behavioral intent (Venkatesh & Bala, 2008). Behavioral intentions are an important determinant of the effects of technology or system use (Bardakcı, 2019). Previous studies have shown that behavioral intentions directly impact the actual use of electronic systems, especially e-learning systems, and there is a considerable positive correlation between the two (Salloum & Shaalan, 2019).

3. Research Methods and Materials

3.1 Research Framework

The conceptual framework of this study is built upon previous research frameworks, drawing inspiration from three theoretical models. The first framework, titled "TAM 3 and the Intervention Research Agenda," was published by Venkatesh and Bala in 2008. The findings of this framework reveal that perceived ease of use influences perceived usefulness, perceived usefulness impacts behavioral intention, and perceived ease of use significantly affects behavioral intention.

The second framework, proposed by Qin et al. (2019) in their study on user adoption of a hybrid social tagging approach in online knowledge communities, indicates that perceived ease of use positively influences user attitude, perceived usefulness impacts behavioral intention, attitude significantly influences behavioral intention, and social influence has a significant impact on behavioral intention.

The third framework, presented by Venkatesh et al. (2003), adopts a unified theory approach to technology acceptance and use. This framework also suggests future research directions, including a deeper understanding of the dynamic impact explored in this study, improved measurement of the core structures used in UTAUT, and comprehension of the organizational outcomes associated with new technologies. The results of this framework study demonstrate that effort expectancy positively impacts behavioral intention, social influence significantly influences behavioral intention, and convenience significantly affects behavioral intention.

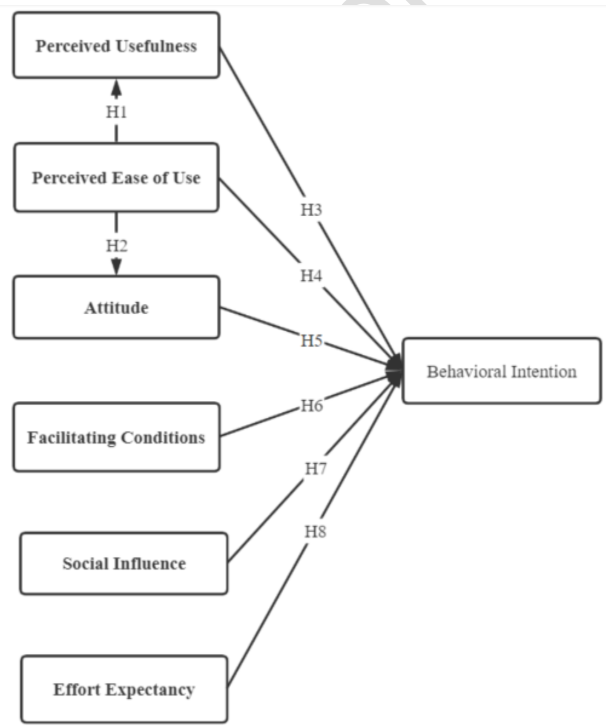

Figure 1: Conceptual Framework

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 method of non-probabilistic sampling, the researchers collected data to analyze the key factors that significantly impact Behavioral Intention in online education. The survey was distributed online and in paper form to the target population consisting of students from Shaanxi Normal University (SNNU), Northwest University (NU), and Xi'an Academy of Fine Arts (XAFA). The survey questionnaire comprised three parts. Firstly, screening questions were included to gather information on the respondents' characteristics. Secondly, the five proposed variables were measured using a 5-point Likert scale, ranging from strongly disagree (1) to agree (5), to assess all four hypotheses. Lastly, demographic information such as gender, age, and educational background was collected.

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, resulting in 502 valid and accepted responses. The collected data was analyzed using SPSS AMOS software. Confirmatory factor analysis (CFA) was employed to test and verify the accuracy of convergence. The model fit measure was calculated to ensure the validity and reliability of the model. Lastly, the structural equation model (SEM) was utilized to examine the influence of the variables.

3.3 Population and Sample Size

This paper analyzes the target population of Shaanxi Normal University (SNNU), Shaanxi Normal University (SNNU), Northwest University (NU) and Xi'an Academy of Fine Arts (XAFA). 500 is the minimum sample size required for complex models compared to simple models (Williams et al., 2010). The survey surveyed 1,750 respondents. After data screening, 502 questionnaires were used in this study.

3.4 Sampling Technique

The researchers adopted the non-probability and judgment sampling methods to target the fine arts students in the three target universities in Xi 'an. Then, using a quota sample, 1,750 graduate art students with at least one month of online education experience were identified from three public universities with fine arts majors in Xi 'China. In addition, as shown in Table 1, 502 participants were designated as final samples 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 Xi'an	Population Size	Proportional Sample Size
Sichuan Normal University (SNU)	145	41
Chengdu University (CDU)	149	43
Sichuan Conservatory of Music (SCU)	1456	418
Total	**1750**	**502**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

Demographic data were targeted at 502 participants; the results are shown in Table 2. Male respondents represented 46.6%, and female respondents 53.4%. In terms of age group, respondents aged 19-23 accounted for the largest proportion, accounting for 73.3%, followed by those aged 18 at 25.7% and those over 24 at 1%. According to the academic qualifications of the respondents, the number of second-year undergraduate students accounted for 46.6%, followed by the number of first-year undergraduate students accounted for 25.8%, the number of third-year undergraduate students accounted for 23.8%, and the number of fourth-year undergraduate students accounted for at least 3.8%.

Table 2: Demographic Profile

Demographic and General Data (N=502)		Frequency	Percentage
Gender	Male	234	46.6%
	Female	268	53.4%
Age	Below 18 years of age	129	25.7%
	19 to 23	368	73.3%
	above 24	5	1%
Year of Study	Freshman	130	25.8%
	Sophomore	233	46.6%
	Junior	119	23.8%
	Senior	20	3.8%

Source: Constructed by author

4.2 Confirmatory Factor Analysis (CFA)

CFA refers to a set of advanced factor analysis methods commonly used in social science research to help determine the factor structure that researchers believe phenomena follow (Huang, 2020). CFA gives more cost-impact explanations and better model flexibility (Bollen, 2002).

The factor load value should be greater than or equal to 0.50, but greater than 0.70 is preferred (Hair et al., 2010). In this study, convergence validity was examined using the mean-variance extraction (AVE) measure, with a minimum AVE >0.50 (Hair et al., 2016).

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 (Sarmento & Costa, 2016). The convergence and discriminant validity values, as shown in Table 3, exceed the acceptable thresholds, thus confirming both convergence validity and discriminant validity.

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	0.843	0.567-0.876	0.855	0.547
Perceived Ease of Use (PEOU)	Davis et al. (1989)	6	0.881	0.600-0.920	0.888	0.575
Attitude (ATT)	Davis (1989)	4	0.850	0.624-0.942	0.864	0.619
Facilitating Conditions（FC）	Ajzen (1991)	5	0.872	0.514-0.889	0.882	0.607
Social Influence (SI)	Mtebe and Raisamo (2014).	3	0.903	0.822-0.893	0.903	0.756
Effort Expectancy (EE)	Moore and Benbasat (1996)	4	0.851	0.578-0.875	0.856	0.603
Behavioral Intention (BI)	Asadi et al. (2016)	4	0.905	0.814-0.876	0.906	0.708

As of Table 4, these model measurements not only validate the discriminant validity but also support the subsequent validation of the estimated validity of the structural model. 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).

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/ DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	1155.240/413 or 2.797
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.881
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.857
NFI	≥ 0.80 (Wu & Wang, 2006)	0.884
CFI	≥ 0.80 (Bentler, 1990)	0.922
TLI	≥ 0.80 (Sharma et al., 2005)	0.912
RMSEA	< 0.08 (Pedroso et al., 2016)	0.060
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.

To assess the convergence validity in this study, the mean-variance extraction (AVE) measure was employed. It was ensured that the minimum AVE value was above 0.50, as recommended by Hair et al. (2016). Furthermore, the values of discriminant validity, as presented in Table 5, surpassed the critical value. Therefore, both the convergence validity and discriminant validity of this study are confirmed and guaranteed.

Table 5: Discriminant Validity

	PU	PEOU	ATT	FC	SI	EE	BI
PU	**0.740**						
PEOU	0.428	**0.758**					
ATT	0.373	0.275	**0.787**				
FC	0.315	0.236	0.308	**0.779**			
SI	0.363	0.278	0.255	0.211	**0.869**		
EE	0.265	0.234	0.203	0.177	0.256	**0.777**	
BI	0.363	0.316	0.273	0.167	0.252	0.156	**0.841**

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

4.3 Structural Equation Model (SEM)

After conducting the Confirmatory Factor Analysis (CFA), the Structural Equation Model (SEM) was employed in this study to estimate a specific system of linear equations and evaluate the fit of the model. The measurement model was utilized to analyze the relationship between potential and measured variables, while the structural model focused on examining the correlation between endogenous and exogenous variables (Ramlall, 2017).

Table 6 presents the fitness index of the structural model, including values for CMIN/DF, GFI, AGFI, NFI, CFI, TLI, and RMSEA. The results of these indices indicate that the SEM validation in this study has a satisfactory Goodness of Fit.

Table 6: Goodness of Fit for Structural Model

Index	Acceptable	Statistical Values
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	1270.444/421 or3.018
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.854
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.828
NFI	≥ 0.80 (Wu & Wang, 2006)	0.873
CFI	≥ 0.80 (Bentler, 1990)	0.911
TLI	≥ 0.80 (Sharma et al., 2005)	0.902
RMSEA	< 0.08 (Pedroso et al., 2016)	0.063
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 significance of each variable was determined by calculating the regression weights and R2 variances. The outcomes of these calculations are presented in Table 6.

Perceived Ease of Use was found to significantly influence Perceived Usefulness, with a standardized path coefficient (β) of 0.428 (t-value = 7.836*). Furthermore, Perceived Ease of Use exhibited the greatest impact on Attitude, with a standardized path coefficient (β) of 0.308 (t-value = 6.564*). Perceived Usefulness influenced Behavioral Intention, with a standardized path coefficient (β) of 0.187 (t-value = 3.464*). Attitude also significantly influenced Behavioral Intention, with a standardized path coefficient (β) of 0.165 (t-value = 3.415*). Similarly, Perceived Ease of Use was found to impact Behavioral Intention, with a standardized path coefficient (β) of 0.173 (t-value = 3.209*). Social Influence was found to have an impact on Behavioral Intention, with a standardized path coefficient (β) of 0.110 (t-value = 2.392*).

On the other hand, Facilitating Conditions had an impact on Behavioral Intention with a standardized path coefficient (β) of 0.021 (t-value = 0.467), and Effort Expectancy had an impact on Behavioral Intention with a standardized path coefficient (β) of 0.017 (t-value = 0.375). However, it is worth noting that these impacts were not statistically significant, as their p-values were greater than 0.05.

Therefore, except for Facilitating Conditions and Effort Expectancy, all other assumptions were significantly supported, with p-values below 0.05.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-Value	Result
H1: PEOU→PU	0.428	7.836*	Supported
H2: PEOU→ATT	0.308	6.564*	Supported
H3: PU→BI	0.187	3.464*	Supported
H4: PEOU→BI	0.173	3.209*	Supported
H5: ATT→BI	0.165	3.415*	Supported
H6: FC→BI	0.021	0.467	Not Supported
H7: TS→JS	0.110	2.392*	Supported
H8: EE→BI	0.017	0.375	Not Supported

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

The results in Table 7 can be refined as follows:

The correlational statistics result for **H1** validated the hypothesis for the strong impact of perceived ease of use on attitude, described by the standard coefficient value of 0.428. Perceived ease of use significantly impacts PU (Wang et al., 2016).

H2 has confirmed that perceived ease of use is the largest important component in attitude, with the standardized route coefficient value in the structural approach being 0.308. Researchers found that perceived usability has a more significant impact on individual attitudes than perceived usefulness (Shih & Fang, 2004).

H3 discovered that perceived usefulness influences behavioral intention, with a standard coefficient of 0.187. Perceived usefulness can predict students' behavioral intentions in online education (Abdullah et al., 2016).

The correlational statistics result for **H4** validated the hypothesis for the strongly perceived ease of use impact on behavioral intention, which was described by the standard coefficient value of 0.173. It is found that perceived ease of use significantly affects behavioral intention (Marakarkandy et al., 2016).

Attitude reinforced behavioral intention, as evidenced by the statistic value of 0.165 on the standard coefficient examining the active impact of **H5.** Research suggests that attitudes directly affect behavioral intent (Unal & Uzun, 2020).

In addition, **H6** shows no significant facilitating conditions influencing behavioral intention in this study, and the standard coefficient value is 0.021. The facilitating conditions of art students in the three target universities in Xi 'an have no significant effect on the behavioral intention of learning and putting into practice.

H7 has confirmed that social influence is an important component in perceived usefulness, with the standardized route coefficient value in the structural approach being 0.110. Some researchers have demonstrated that SI positively affects behavioral intent and that social influence is one of the most important determinants of behavioral intent (Jairak et al., 2009).

Finally, **H8** the statistical results of this study do not support the notion that effort expectancy affects behavioral intentions, according to the H8 hypothesis, and its standard coefficient value is 0.017. Among the relevant elements of online education for Xi 'students majoring in fine arts, effort expectancy has little effect on students' behavioral intention of learning online.

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 the three target universities in Xi 'an. 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 questionnaires were distributed to 502 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 perceived ease of use has the greatest impact on perceived usefulness and attitude. In contrast, perceived usefulness has the strongest direct impact on the behavioral intention of online education, which is the same as previous research results. Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Attitude (ATT), and Social Influence (SI) have a significant effect on the online educational behavior intention of fine arts majors in the three target universities in Xi 'an. In this study, Facilitating Condition (FC) and Effort Expectancy (EE) is not a significant determinant of behavioral intention.

Convenience and expectation of effort are only some of the important factors influencing the choice of fine arts majors in the three target universities in Xi 'an. This result can be attributed to the difficult access to learning resources in online education, the need for learning resources, and the incompatibility with other systems. According to the inquiry and analysis of the target population, online education has become an important learning tool in the context of the epidemic, and it is difficult for the target population to find the detailed learning resources they need. At the same time, considering the resources, opportunities, and knowledge required for online education, it takes work for the target population to use online education. Therefore, the target population's convenience and effort expectations could be clearer. Students majoring in art have a strong ability to accept new things, and professional courses have been produced with new media technology, which is also the direction of the development of this discipline. TAM model theory introduced in this study is generally aimed at public exploration and investigation. However, the effect of employment expectation on behavioral intention in this study has yet to be verified in this unique sample population because college students majoring in art may not have abundant learning resources and have too simple learning methods due to the particularity of their majors.

5.2 Recommendation

The researchers found that in Xi 'a Target University, the key factors affecting the online education behavior intention of fine arts students are Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Attitude (ATT), and Social Influence (SI) have significant influence on behavioral intention (BI). In this study, Facilitating Condition (FC) and Effort Expectancy (EE) were not significant determinants 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 Xi 'a target University.

First, 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.

Second, the technical support is diversified. 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.

Finally, 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.

5.3 Limitation and Further Study

The study has several limitations. First, the demographic and sample were limited to students majoring in fine arts from the three target universities in Xi 'China. Future studies may expand the geographical scope of the study to include other regions of China. Secondly, future researchers should consider prospective variables such as satisfaction, trust, and performance expectations. Finally, qualitative methods, such as interviews or focus groups, should be extended to provide a more critical analysis of the findings.

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