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Influencing Factors of Behavior Intention of Master of Arts Students Towards Online Education in Chengdu Public Universities, China

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Abstract

Purpose: This study aims to investigate influencing factors of behavioral intentions to use online education of Master of Arts students from three public universities in the Chengdu region of China. The conceptual model contains perceived ease of use, perceived usefulness, social influence, effort expectancy, self-efficacy, perceived satisfaction, and behavioral intention. **Research design, data and methodology:** The researchers employed a quantitative approach of survey distribution to 501 participants. The sample techniques involve judgmental, quota and convenience sampling. The content validity method of Item Objective Congruence (IOC) Index was used, resulting all measuring items reserved by three experts. Pilot testing of 30 participants was approved under Cronbach's Alpha reliability test at a score of 0.7 or over. Confirmatory Factor Analysis (CFA) and Structural Equation Model (SEM) were performed for data analysis, including goodness of model fits, validity, and reliability testing. **Results:** Perceived ease of use had the strongest influence on perceived usefulness toward behavioral intention. Furthermore, perceived usefulness, social influence, self-efficacy, perceived satisfaction, except effort expectancy, significantly impacted behavioral intention. **Conclusions:** The findings lead to the recommendations that educational administrators at public universities to enhance the behavioral intention to use online education by providing well-design online learning system and promote various benefits of using.

Keywords : Online Education, Perceived Ease of Use, Perceived Usefulness, Self-Efficacy, Behavioral Intention

JEL Classification Code: E44, F31, F37, G15

1. Introduction

Since 2018, the rapid development of internet technology, the comprehensive promotion of big data applications and mobile learning applications have enabled online education to enter the fast lane of rapid expansion. In addition, due to the impact of the epidemic, online education has faced an exponential growth in 2020, driving the urgent market demand for quality online education (Gong & You, 2021).

Online education is a learning method that undertakes internet technology as the carrier and spreads content responsively through digital application. As early as the mid-1990s, with the continuous development of China's social economy, especially the progress of internet

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technology, China began to implement information-based teaching in university education. In the context of COVID-19, many traditional art colleges and universities in China have launched online education for students majoring in art (Gong & You, 2021).

With the continuous development of electronic learning, creating an intelligent education environment for art majors in Chinese universities will be the next important development direction of education reform. Online education is a concentrated manifestation which has been studied widely through the recent research and academic study. During the period of the outbreak, Chinese college students of art have been forced to use online education. The effective internet technology and digital platform allows teachers and students to engage online teaching and learning process.

Online education can provide students and teachers with interactive classes, after-class practice and self-paced learning. Artificial intelligence technology is combined with measured data to delivering individualized teaching (Jiang, 2021). The physical classroom has been shifted to virtual format. For students majoring in art, the knowledge has been broadened with the practices, and the combination of art, and technology has been deepened to assist the art or painting practices. In this study, art programs usually involve fine arts and art design. The art profession, whether art design or fine art, is largely visual in nature (Basse & William, 2021). Art majors in Chinese universities generally refer to fine arts and art design, and the two majors are usually combined. For example, the College of Fine Arts and Design of Chengdu University.

In the context of COVID-19, the research of online education of art schools in Chinese universities and colleges can not only help educators better understand the reality of online education, but also help the students to clearly see the how technology could help them learn more conveniently and effectively, focusing on online education under the influence of pandemic situation. In view of the practical problems encountered in the process, the effectiveness of technology can be extended to the degree of further optimization in balancing online education structure.

1.1 Objectives of this Research

a) To investigate influencing factors of behavioral intentions to use online education of Master of Arts students from three public universities in the Chengdu region of China.

b). To examine the causal relationships from perceived ease of use, perceived usefulness, social influence, effort expectancy, self-efficacy, perceived satisfaction towards behavioral intention.

c) To provide recommendations for subsequential improvement of online education's implementation and optimize arts students' learning performance.

1.2 Conceptual Framework

The conceptual framework was constructed from reviewing previous literatures, based on technology acceptance model (TAM) and unified theory of acceptance and use of technology (UTAUT) theories. Shin and Kang (2015) developed theoretical framework in considering with three major variables from TAM, including perceived ease of use (PEOU), perceived usefulness (PU), and behavioral intention (BI). Based on UTAUT, Venkatesh et al. (2003) validated the effects of self-efficacy (SE) and effort expectation (EE) on behavioral intention (BI). Cheung and Vogel (2013) demonstrated the direct relationship between self-efficiency (SE), effort expectancy (EE), and behavioral intention (BI). Cigdem and Ozturk (2016) confirmed the impact of perceived ease of use, perceived usefulness, and perceived satisfaction (PS) on behavioral intentions (BI).

The conceptual framework of this study consists of seven variables that can be classed as independent variables or dependent variables. The conceptual framework generalizes the research model (Hair et al., 2013). Each structural pathway has been evidenced from previous studies (Clark & Ivankova, 2016). This research captures the impact of behavioral intentions towards online education among Master of Arts students at Chengdu Public Universities in China as illustrated in Figure 1.

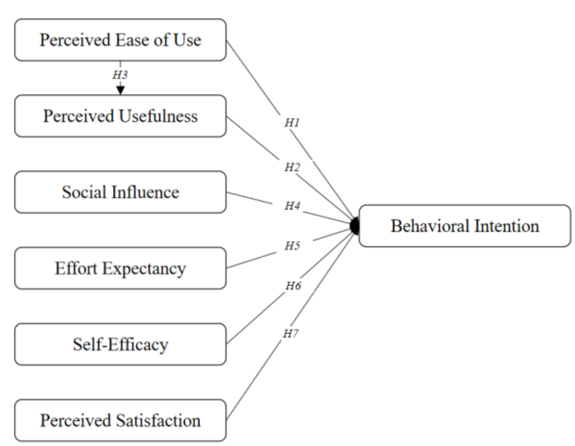

Figure 1: Conceptual Framework
Source: Created by the author

1.3 Significance of the Study

The successful technology adoption can serve the purpose of the system implementation, which incurs investment, time and manpower. The expectation of online education is to investigating whether or not students adopt an online learning system and what degree for them to achieving their academic goals. Furthermore, the students' behavior intention to use online education impacts institution's potential and opportunity to further improve the system for better learning efficiency. This study will point out the significance of each factor that driving the online education acceptance.

This quantitative research lays out the mechanism of behavior intention among Master of Arts students in China's Chengdu region towards online education. Teaching art via virtual platform is a big challenge due to the program chrematistics are based on active and physical practices more than traditional lecturing. Consequently, this paper will be beneficial to front-line instructors to adapting their teaching style and materials in responding to such challenge. Government and academic affairs offices could be guided in to focus on the important factors to build more comprehensive and reasonable learning methods and processes for online art education, as well as to develop suitable teaching project to cope with the challenges.

2. Literature Review

2.1 Perceived Ease of Use

Perceived ease of use pertains to a person's view that using a specific technology requires minimum or no effort (Davis, 1989). It was the degree to which students believe that using an online education system was easy and convenient (Qin et al., 2019). Perceived ease of use is termed as a person's perception that using a system was simple. The perception of how straightforward the technology will be to use was measured by perceived ease of use (Venkatesh et al., 2003). The extent to which a person believes using a certain technological breakthrough makes a task easier can be classified as perceived ease of use, and this was how far students, as users, could perceive the usefulness of online education technology with more efficiently and conveniently in developing their behavioral intention to use it (Neo et al., 2015). Accordingly, two hypotheses are projected:

H1: Perceived ease of use has a significant impact on behavioral intention to use online education among Master of art students in Chengdu.

H3: Perceived ease of use has a significant impact on perceived usefulness of online education among Master of art students in Chengdu.

2.2 Perceived Usefulness

According to comprehensive research, perceived usefulness has a significant influence on the use of behavioral intention (Altin et al., 2008). This concept indicates how far university's students who employed an e-learning system would improve their academic performance (Vululleh, 2018). Any kind of system technology supposes to alleviate emotional tension of people (Davis, 1989). The belief that technology will be used to improve outcomes was defined as perceived usefulness which indicates an individual's conviction that employing a hybrid education system will enhance his or her learning's productivity (Fokides, 2017). The perception on the benefits of students influences their desire to use online education. The research is backed up with the most accepted theories and data analysis in presenting the strong impact of the perceived usefulness has a favorable impact on behavioral intention to use a system technology (Fan et al., 2021; Neo et al., 2015). Hence, the second hypothesis is constructed:

H2: Perceived usefulness has a significant impact on behavioral intention to use online education among Master of art students in Chengdu.

2.3 Social Influence

Social influence was characterized as the impact of family and friends, professional colleagues, media, and other information in convincing a user to adopt a system technology (Salloum & Shaalan, 2019). Social influence is defined as the establishment and response to social norms inside groups (Joo et al., 2014). Social influence can be extended to which individuals believe their system usage is meaningful to others in a situation where society's attitude about system use is strongly linked with decision making (Hosizah et al., 2016). Social influence was a typical social psychology phenomenon characterized by human behavior and attitudes influenced by the social environment or social pressure (Teo & Noyes, 2014). People can be influenced by what others believe and may perform or act even if they do not want to, which is why social influence has been identified as a direct predictor of behavioral intention (Bardakcı, 2019). Based on these assumptions, it can produce a hypothesis:

H4: Social influence has a significant impact on behavioral intention to use online education among Master of art students in Chengdu.

2.4 Effort Expectancy

According to numerous researchers, the key rationale for students' voluntary acceptance of online learning is effort expectancy (Honarpisheh & Zualkernan, 2013). The usage of online learning among students was marked by effort anticipation because they believe it can help to improve their learning performance (Salloum & Shaalan, 2019). Students expect that online education should be easy and simple. Because many students in developing countries have not been exposed to a diversity of online learning platforms, their expectation of the use is very limited (Ssekakubo et al., 2011). The level of easiness associates with the use of a specific educational system (Bardakcı, 2019). The system should not be complicated, and should be functionally work with not much effort needed (Joo et al., 2014). Subsequently, a below hypothesis is framed:

H5: Effort expectancy has a significant impact on behavioral intention to use online education among Master of art students in Chengdu.

2.5 Self-Efficacy

Self-efficacy is defined as the degree to which students believe in their ability to achieve the learning objectives, as well as the key mechanism for determining the purpose of human activity and behavior (Chiu & Wang, 2008). Following this, self-efficacy is usually interpreted as people's belief in their capacity to use objects such as computers and information technology (Eom, 2012). This term has also been described as an exceptional assessment of his or her capacity to complete a certain study project with a specific goal (Fokides, 2017). Self-efficacy is determined as the forecast of how individuals would have a control over various information technology apps (Kim et al., 2010). Many studies found a significant positive link between the self-efficacy and behavioral intention to use a system technology (Compeau & Higgins, 1995). Henceforth, a following hypothesis is explicated:

H6: Self-efficacy has a significant impact on behavioral intention to use online education among Master of art students in Chengdu.

2.6 Perceived Satisfaction

Perceived satisfaction is how students are satisfied with their learning experience. The level of satisfaction is a judgement of a system success or failure, as well as their level of comfort with systems (Liaw ,2008). Perceived satisfaction is projected to be a measure of enjoyment, matching with consumer expectations. Various studies reported that perceived satisfaction with online learning can predict a behavioral intention (Johnson et al., 2008). In the context of online education, perceived satisfaction is an important indicator to measure the successful technology adoption, and it may emerge as a barrier to the system's acceptance (Damnjanovic et al., 2013). Therefore, the final hypothesis is set:

H7: Perceived satisfaction has a significant impact on behavioral intention to use online education among Master of art students in Chengdu.

2.7 Behavioral Intention

Behavioral intention has been derived from a psychology theory that focuses on completed action. It can be conceptualized as an individual's behavior in adopting a certain system (Chauhan, 2015). An individual's behavioral intention can be defined as their cognitive presentation of whether or not they intend to employ a specific technology (Qin et al., 2019). Behavioral intention refers to an individual's goal in selecting whether or not to perform a given activity now and in the future (Cigdem & Ozturk, 2016). Experience is found in moderating the effects of effort expectancy and social norms on behavioral intentions, as well as the effect of ease on usage (Phyu & Vongurai, 2020). Some researchers revealed an interesting interaction between perceived norm and the behavioral intention of diplomatic or undiplomatic clients to use the target system (Kalinic & Marinkovic, 2016). The findings of scientific research show that positive attitudes of their peers or teachers encouraged students' acceptance of e-learning. To put it another way, social influence has a great impact on students' desire to accept and use e-learning (Vululleh, 2018).

3. Research Methods and Materials

3.1 Research Methodology

The researchers employed a nonprobability sampling strategy to distributing questionnaires to 501 Master of art students in three colleges in Chengdu. This work summarizes and investigates the data from Chengdu University (CDU), Sichuan University (SCU), and Sichuan Normal University (SNU). Three sections are in the design of questionnaire, involving screening questions for identifying qualified respondents (Voß et al., 2021), demographic information such as gender and year of study for better understanding the characteristics of respondents (Mertens, 2015), and five-point Likert scale for the measuring items' evaluation (Salkind, 2017).

Item Objective Congruence (IOC) Index was used, resulting all measuring items reserved by three experts. The results of IOC showed that all items were approved at a score of 0.6 or above. The sample size for the pilot study should be between 25 and 100 persons (Fink, 2003). Pilot testing of 30 participants was approved under Cronbach's Alpha reliability test (Lodico et al., 2006), resulting in all constructs passing a score of 0.7 or above (Nunnally & Bernstein, 1994). 501 graduate students are selected and were analyzed by IBM SPSS and AMOS. CFA was used to measuring factor loadings, t-value, comprehensive reliability (CR), average variance extraction (AVE), and discriminant validity. The direct, indirect, and total effect, and hypotheses are tested by using structural equation modeling (SEM).

3.2 Population and Sample Size

Master of Arts students from three public universities in Chengdu are including Chengdu University (CDU), Sichuan University (SCU), and Sichuan Normal University (SNU). The researchers chose these three universities four reasons. First of all, these three higher education institutions are representatives of different regions located in Chengdu. Secondly, these universities have been established more than 40 years. Thirdly, every university has more than 20,000 students. Lastly, all three universities offer online education in the same period of time. According to Israel (1992), the minimum sample size for the complex assessment framework in structural equation model should be 200-500 people. From 713 answers, 501 students were chosen as the final sample using judgmental sampling and quota selection.

3.3 Sampling Techniques

The researchers applied multiple approaches of sampling strategy. Initially, the researchers used judgmental sampling to select 713 Master of Arts students from the three public universities in China who have at least one month of online education experience. Next, 501 participants were designated as the final sample selected from is subgroup, using quota sampling as shown in Table 1. Finally, the survey was distributed via offline and online by convenience sampling method.

Table 1: Sample Units and Sample Size

Target Universities	Sampling Units	First Stage Sample Size Total = 713	Proportional Sample Size Total = 501
Chengdu University	First year of graduate school	114	80
	Second year of graduate school	83	58
	Third year of graduate school	68	48
Sichuan University	First year of graduate school	105	74
	Second year of graduate school	101	71
	Third year of graduate school	100	70
Sichuan Normal University	First year of graduate school	43	30
	Second year of graduate school	48	34
	Third year of graduate school	51	36

Source: Created by the author.

4. Results and Discussion

4.1 Demographic Information

The demographic profile of 501 participants is that male respondents make up 22.80 %, while female respondents are 77.20 %. According to Table 2, the first year of graduate school accounts for 36.70%, the second year of graduate accounts for 32.50 %, and the third year of graduate accounts for 30.80%.

Table 2: Demographic Profile

Demographic and General Data (N=501)		Frequency	Percentage
Gender	Male	114	22.80%
	Female	387	77.20%
Year of Study	First year of graduate school	184	36.70%
	Second year of graduate school	163	32.50%
	Third year of graduate school	154	30.80%

Source: Created by the author

4.2 Confirmatory Factor Analysis (CFA)

Confirmatory factor analysis (CFA) was utilized to assess the measurement model (Brown, 2015). The significance of each item's factor loading and acceptable values show the goodness of fit (Hair et al., 2006). CFA can be used to analyze both the reliability and validity (Byrne, 2010). CFA determines whether the structural and load quantities of each observed variable are consistent with the hypothesis (Malhotra et al., 2004). In this work, the average variance extracted (AVE) measure was utilized to investigate convergent validity, with a minimum value of AVE >.50. (Hair et al., 2016).

The results by SPSS and AMOS statistical software were adjusted, resulting the chi-square value to the degree of freedom (CMIN/DF) was 1.122, which lower than 5.00 (Hair et al., 2010), the goodness-of-fit index (GFI) was 0.941, which is greater than 0.85 (Sica & Ghisi, 2007), the adjusted goodness-of-fit index (AGFI) was 0.929 which more than 0.80 (Sica & Ghisi, 2007), the comparative fit index (CFI) was 0.994 which over 0.80 (Hair et al., 2006), the normalized fit index (NFI) was 0.950 which was greater than 0.80 (Hair et al., 2006), and the root mean square error of approximation (RMSEA) was 0.016 shown less than 0.08 (Pedroso et al., 2016). As a result, all these indicators for the goodness of fits were approved in measurement model.

According to the statistical results summarized in Table 3, there were Cronbach's Alpha values of greater than 0.70, factor loadings od greater than 0.30, t-value of greater than 1.98, p-value of less than 0.50, composite reliability (CR) of greater than 0.60, and average variance extracted (AVE) of greater than 0.50 (Sarmento & Costa, 2016).

Therefore, CFA results were validated to confirm the convergent and discriminant validities.

Table 3: Confirmatory Factor Analysis Result, Composite Reliability (CR) and Average Variance Extracted (AVE)

Latent Variables	Source of Questionnaire	No. of Items	Factors Loading	Cronbach's Alpha	CR	AVE
Perceived Ease of Use (PEOU)	Cheung and Vogel (2013)	5	0.575-0.920	0.853	0.669	0.565
Perceived Usefulness (PU)	Cigdem and Ozturk (2016)	6	0.616-0.924	0.887	0.897	0.597
Social Influence (SI)	Mtebe and Raisamo (2014)	4	0.634-0.916	0.842	0.854	0.599
Effort Expectancy (EE)	Mtebe and Raisamo (2014)	4	0.618-0.856	0.856	0.862	0.613
Self-Efficacy (SE)	Fokides (2017)	4	0.676-0.868	0.870	0.875	0.639
Perceived Satisfaction (PS)	Shin and Kang (2015)	4	0.690-0.890	0.887	0.893	0.677
Behavioral Intention (BI)	Venkatesh et al. (2003)	4	0.722-0.886	0.874	0.877	0.643

Source: Created by the author

Convergent validity is determined when CR is larger than AVE and AVE is more than 0.50. (Hair et al., 2009). Furthermore, the values of discriminant validity were investigated and demonstrated in Table 4, which exceeded the critical point values. As a result, the convergent and discriminant validities of this study were ensured.

Table 4: Discriminant Validity

	PEOU	PU	SI	EE	SE	PS	BI
PEOU	**0.752**						
PU	0.391	**0.773**					
SI	0.341	0.202	**0.774**				
EE	0.309	0.266	0.290	**0.783**			
SE	0.376	0.215	0.241	0.206	**0.800**		
PS	0.304	0.259	0.257	0.224	0.212	**0.823**	
BI	0.335	0.270	0.262	0.235	0.264	0.254	**0.802**

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. Researchers used SEM to study the causal relationship between various constructs made up of independent and dependent variables (Erasmus et al., 2015). Table 5 shows the adjusted results from SPSS and AMOS statistical programs, 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 5: Goodness of Fit for Structural Model

Index	Criterion	Source	After Adjustment Values
CMIN/DF	< 5.00	Hair et al. (2010)	1235.883/420 or 2.943
GFI	≥ 0.85	Sica and Ghisi, (2007)	0.857
AGFI	≥ 0.80	Sica and Ghisi, (2007)	0.831
NFI	≥ 0.80	Arbuckle (1995)	0.872
CFI	≥ 0.80	Hair et al. (2006)	0.912
TLI	≥ 0.80	Hair et al. (2006)	0.902
RMSEA	< 0.08	Pedroso et al., (2016)	0.062

Source: Created by the author.

4.4 Research Hypothesis Testing Result

The significance for each variable was calculated using the regression weights and R2 variances. Table 6 shows the calculated outcomes for each structural pathway.

Perceived ease of use had the strongest impact on perceived usefulness, with the standardized path coefficient (β) result of 0.373 (t-value = 7.203***).

Perceived satisfaction significantly impacted behavioral intention, with β as 0.151 (t-value = 3.190**).

Self-efficacy had a significant impact on behavioral intention, with β as 0.144 (t-value = 2.947**).

Perceived usefulness significantly impacted behavioral intention, with β as 0.141 (t-value = 2.766**).

Social influence had a significant impact on behavioral intention with, β as 0.138 (t-value = 2.891**).

Perceived ease of use had a significant impact on behavioral intention, with β as 0.128 (t-value = 2.518*)

Effort expectancy had no significant impact on behavioral intention, with β at 0.087 (t-value = 1.184).

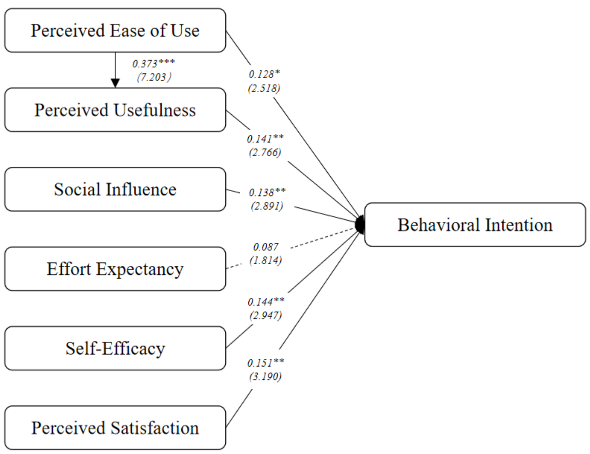

Figure 2: Structural Equation Model (SEM)
Note: *** p<0.001, ** p<0.01, * p<0.05
Source: Created by the author

Table 6: Hypothesis Result of the Structural Equation Modeling

Hypothesis	Paths	Standardized Path Coefficient (β)	t-Value	Tests Result
H1	PEOU→BI	0.128	2.518	Supported
H2	PU→BI	0.141	2.766	Supported
H3	PEOU→PU	0.373	7.203	Supported
H4	SI→BI	0.138	2.891	Supported
H5	EE→BI	0.087	1.814	Not Supported
H6	SE→BI	0.144	2.947	Supported
H7	PS→BI	0.151	3.190	Supported

Source: Created by the author

According to the information in Figure 2 and Table 6, it may be able to obtain the following extensions.

H1 confirmed that perceived ease of use is an important component in perceived usefulness, with the standardized route coefficient value in the structural pathway of 0.128. The perceived of ease of use is one of the most critical factors in predicting a student's behavior intention to use online education (Davis, 1989).

The correlational statistics result for H2 validated the hypothesis for the strong impact of perceived usefulness on behavioral intention, which was described by the standard coefficient value of 0.141. Many academics have investigated the impact of perceived usefulness on behavioral intention, which explains that students would have an intention to use online education if they feel it is useful (Venkatesh & Bala, 2008).

H3 supported that perceived ease of use is an important component of perceived usefulness, with the standardized route coefficient value of 0.373. Students' perceptions engage the level of ease to use online education (Vululleh, 2018).

Furthermore, the H4 revealed that social influence is a determinant of behavioral intention in this study, with the standard coefficient value of 0.138. Social influence plays a significant role to behavioral intention that peers and lecturers could convince students to have an intention to use online education (Salloum & Shaalan, 2019).

The statistical results of this study do not support the notion of effort expectancy and behavioral intentions as standard coefficient value of H5 is 0.087. Among all other variables, effort expectancy had no impact on students' behavioral intention to use online education as opposed with many scholars (Honarpisheh & Zualkernan, 2013; Salloum & Shaalan, 2019).

H6 discovered that self-efficacy impacted behavioral intention, with a standard coefficient value of 0.144. This study studied confirmed that self-control in using online education can enhance behavioral intention to use online education among Master of Arts students (Coskuncay & Ozkan, 2013).

For H7, perceived satisfaction reinforced behavioral intention, as evidenced by the statistic value of 0.151 on the standard coefficient value. According to previous studies, many scholars reported that student satisfaction greatly affected behavioral intention to use online education (Damnjanovic et al., 2013).

5. Conclusions and Recommendation

5.1 Conclusion

The purpose of this study was to confirm the considerable factors influencing behavioral intention among Master of Arts students in public universities of Chengdu, China. In the conceptual framework was construct to developing hypotheses. The questionnaires were distributed to 501 graduate students who had at least one month experience of online education. Confirmatory Factor Analysis (CFA) was used to perform statistical analyses on validity and reliability. Furthermore, Structural Equation Modeling (SEM) was used to confirm the primary influencers of behavioral intention.

The findings showed that perceived ease of use had the strongest impact on perceived usefulness towards online education behavioral intention, which is consistent with previous studies. Perceived ease of use, perceived usefulness, social impact, self-efficacy and perceived satisfaction have significant influence on graduate students' behavioral intention in online education. Effort expectancy was not a significant determinant of behavioral intention in this study. This suggests that the convenience of using online education is not the most important factor influencing the adoption of online education by graduate students. This result can be attributed to the lack of easy access to learning resources in online education. According to the query and analysis of the target population, online education has become an important learning format in the context of the epidemic, and the target audience cannot easily find the detailed learning resources they need. As a result, the effort expectations of the target population are unclear. Students majoring in art have a strong ability to accept new things, and professional courses have always been made with new media technology, which is also the direction of the current development of the discipline.

5.2 Recommendation

The researchers investigated the basic determinants of behavioral intention among Master of Arts students in Chengdu. In order to maximize learning efficiency, the design of college painting teaching program should consider students' behavioral intention. It is suggested to reduce the difficulty of obtaining learning resources via online education. Universities should improve the enrichment of specific professional learning resources of online education, and incorporate these factors into the design and reform of online education courses for art majors in the future, so as to achieve more ideal teaching quality via online education.

The TAM and UTAUT models introduced in this study is generally aimed at the general exploration and investigation. However, the effect of effort expectation on behavioral intention in this study was not verified in this unique sample population, because graduate students in the arts major may have less abundant learning resources due to the specific major. Therefore, academic practitioners are suggested to deep dive effort expectancy in some other context or other situation e.g., post-covid.

Online education has been competitive in the education market industry. It is not only the offer during the pandemic for students to continue their learning, but also the opportunity for the extended programs which higher institutions should expand it market to offer online programs internationally. Big players in the developed country have penetrated to provide online programs for international students which incur less cost, less manpower and more convenient to increasing their sales revenue. Accordingly, universities should be very keen on significant factors for the successful adoption of online education both to existing and prospective students.

5.3 Limitation and Further Study

The study's drawback is that the demographic and sample were limited to graduate students majoring in fine arts from three public universities in Chengdu, China. Future research could look into two approaches. One option is to broaden the scope of the research to other parts of China. Secondly, the research framework can be extended to more factors such as attitude towards use, trust, performance expectancy, and facilitation conditions. Additionally, the qualitative approaches should be added in order to provide a deeper understanding of the findings.

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