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Analysis of Factors Affecting Art Major Students' Behavioral Intention of Online Education in Public Universities in Chengdu

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Abstract

Purpose: This research emphasizes factors affecting behavioral intentions of online education among art major undergraduate students from three universities in the Chengdu region of China. Perceived ease of use, perceived usefulness, social influence, effort expectancy, self-efficacy, perceived satisfaction and behavioral intention were examined in the research framework. Research design, **data and methodology:** The researchers employed a quantitative study with 500 samples and administered the statistically survey distributing to undergraduates at three universities. The nonprobability sampling techniques were applied, including judgmental, quota and convenience samplings. Before the data collection, the Item Objective Congruence (IOC) Index is used for screening the items' quality, and Cronbach's alpha coefficient values were approved from the pilot testing of 50 participants. Confirmatory Factor Analysis (CFA) and Structural Equation Model (SEM) were utilized for the statistical analysis, which include validity and reliability test, and goodness of model fits. **Results:** Factors affecting behavioral intentions of online education are perceived ease of use, perceived usefulness, social influence, effort expectancy and self-efficacy, except perceived satisfaction. **Conclusions:** Education department administrators at public institutions are recommended to identify the primary contributors for the implementation of contemporary online learning in order to enhance student engagement and learning behavioral intention.

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

JEL Classification Code: E44, F31, F37, G15

1. Introduction

At the beginning of 2020, the COVID-19 pandemic has had a significant impact on the global social economy, encouraging the rise of system and a large-scale practice of online education in China. Online education is a way of learning through the application of information and fast internet technology to disseminate content. Online education during the pandemic has enabled more than 200 million Chinese students to study in closed classrooms with the help of online platforms and digital learning resources. This practice has a significant impact on future education reform, making educators and students realize that online education is not only a way to solve current education problems, but also a trend to promote the reform of education, teaching and educational

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organization in the new era. After more than 30 years of development, China's online education has undergone an unprecedented expansion and modernization (Jiang, 2021). Especially, after COVID-19, online education in Chinese universities has been fully implemented, which also shows the obvious advantages of online education in the new era (Gong & You, 2021).

The study emphasizes to fill the gap of online education adoption, reviewing and collating the latest research papers, data and other academic results in China. Art students in Chinese universities have been studied through modern educational technology online platforms during the period. In the COVID - 19 outbreak, teaching and learning have been continued via online digital content to widespread the access to information and knowledge, breaking the limit of physical space and the art of traditional education mode. Online education achieves the quality of the integration of resources and transfer, and overturns the traditional line art professional learning mode. The art major is a multi-disciplinary and cross-cultural study. Its goal is to encourage the interaction and influence of different arts and cultures through communication and dialogue, while online education has broadened the research and learning space in the professional field of art (Wang, 2013).

The study of Chinese college art professional online education can help teachers under the environment of COVID - 19 outbreak. Accordingly, online education is widely used today, combing the advantages and disadvantages of education model. Online format emphasizes the internal differences, resources tilt, result oriented, adjustment, improvement of teachers' teaching and students' learning. It further achieves the purpose of enabling the quality of education and promotes the sustainable development of education.

1.1 Objectives of this Research

a) To investigate the factors affecting behavioral intention of online education among art major undergraduates from three public colleges in 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.

1.2 Conceptual Framework

The conceptual framework was developed by reviewing previous academic research. The model is adapted from four theoretical frameworks, using TAM, UTAUT and 3-TUM theories. Shin and Kang (2015) provide a theoretical framework for the interplay of three key variables: perceived ease of use (PEOU), perceived usefulness (PU), and behavioral intention (BI). By examining the influence of self-efficacy (SE) and effort expectation (EE) on behavioral intention (BI), Venkatesh et al. (2003) verified the second theoretical framework based on UTAUT model. Cheung and Vogel (2013) developed a theoretical framework to illustrate three variables: social effect (SE), expected effort (EE), and behavioral intention (BI). By looking at the effects of perceived ease of use, perceived usefulness, and perceived satisfaction (PS) on behavioral intentions (BI), Cigdem and Ozturk (2016) confirmed the relationships among them.

The conceptual framework of this study consists of seven factors that can be classed as independent variables or dependent variables. The conceptual framework was a model that was constructed in the study to present all variables and their relationships (Hair et al., 2013). The conceptual framework was developed based on the previous literatures (Clark & Ivankova, 2016). In this study, the independent variables include perceived ease of use (PEOU), perceived usefulness (PU), social influence (SI), effort expectancy (EE), self-efficacy (SE), and perceived satisfaction (PS), and dependent variable is behavioral intention (BI), which is the key component of this investigation as shown in Figure 1.

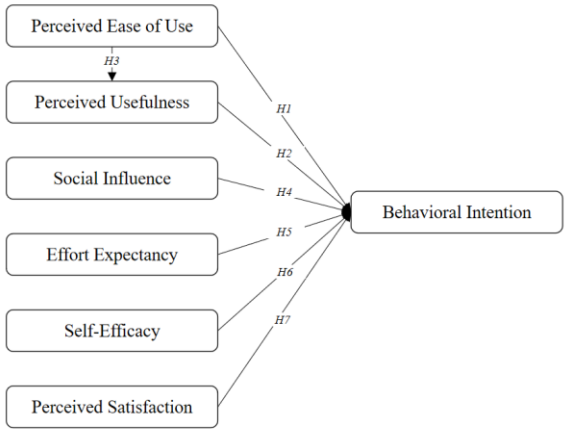

Figure 1: Conceptual Framework

1.3 Significance of the Study

Behavioral intention (BI) is an important factor in assessing whether students adopt an assigned learning pattern in a psychological level. Furthermore, the students' behavior impacts their learning potential and career opportunity. As a result, it is clear that quantitative research is required to examine the mechanism for behavior intention

(BI) associated with six crucial latent variables that affecting behavioral to use online education among art design undergraduate students in China's Chengdu region.

The findings will be beneficial to front-line instructors. In terms of teaching, corresponding professors may select impactful teaching mode for art major students to build a more logical teaching content, which can help the learning efficiency of students. Furthermore, teaching administration of public universities may develop a management system for the better alignment with the online features, and reduce the excessive investment in software, hardware, and other online teaching resources.

2. Literature Review

2.1 Perceived Ease of Use

The perceived ease of use is a significant factor in the technology adoption model. Students' motivation is originated from their assessment of an important aspect of using technology, such as the interfaces and processes involved in its use. Perceived ease of use refers to a person's knowledge of whether or not a certain system is simple to use (Davis, 1989). Users expect that the usage of the target system's services will be more effective, and PEOU refers to users' belief in the future of technology was not difficult to use (Bashir & Madhavaiah, 2015). Perceptions of how easy it is to use technology serve as an intrinsic motivation and behavioral intention. The degree to which customers believe that using technology would be easy can also be perceived that such system is useful (Zeithaml et al., 2002). Based on the discussion above, hypotheses are proposed:

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

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

2.2 Perceived Usefulness

Perceived usefulness refers to people's trust in a system when it comes to executing their duties, and it can help them perform better (Saade & Bahli, 2005). Some scholars described perceived usefulness as the extent to which people believe that adopting a given system will help them succeed in performing a task and will increase output as expected (Davis, 1989). Users believe that using a service would improve their outcomes (Benjangjaru & Vongurai, 2018). Perceived usefulness generalizes the extent to which individuals believe that technology will be useful and they tend to have willingness to use it (Venkatesh et al., 2003). Many studies have been conducted to investigate the impact of perceived usefulness on behavioral intention (Venkatesh & Bala, 2008). Accordingly, a following hypothesis is derived:

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

2.3 Social Influence

Social influence is defined as a change in one's mind, feelings, attitude, or behavior are influenced by another person (Liestiawati & Agustina, 2018). Individuals' behavior is influenced by how other expect them to use a technology, and how possible an individual will consider other beliefs and expectation that he or she should use the new system technology. Social influence can be simply referred as a person's ability to persuade others (Venkatesh et al., 2003). This study emphasizes on social influence in connection with the number of students who claimed their e-learning usage was influenced by other influencers such as peers or instructors (Vululleh, 2018). People can be influenced by what others believe and may perform an 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). Thereby, a hypothesis is developed.

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

2.4 Effort Expectancy

Another component of UTAUT model is effort expectancy, which deals with how much work an individual expects to exert in order to finish a task (Joo et al., 2014). The amount of effort that is expected by users can be described as effort expectancy. Individuals put an effort to use a system technology. Hence, the level of comfort and ease associated with the use of a technology is important to predict the behavioral intention. The ease of use of a technology can be employed greatly impacts the technology adoption (Venkatesh et al., 2003). Effort expectancy reflects students' belief in adopting online education would be simple and free of effort (Mtebe & Raisamo, 2014). Effort expectation conceptualizes the degree on how users are more likely to use a technology which can motivate them to express a behavioral intention (Hosizah et al., 2016). Thus, a proposed hypothesis is obtained:

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

2.5 Self-Efficacy

Self-efficacy was identified as a critical aspect in human behavior, and was characterized as how people motivate themselves and their activities (Kim et al., 2010). Self-efficacy was defined as a person's assessment of their own ability to plan and carry out the procedures necessary to achieve a certain objective. When a person believes they can finish activities on their own, they approach and solve difficulties with a willing, efficient, and cheerful attitude (Jaradat & Al-Mashaqba, 2014) In some technological contexts, self-efficacy was also characterized as an exceptional knowledge of one's ability to use information technology to fulfill tasks (Compeau & Higgins, 1995). The researchers discovered that self-efficacy can contribute to a behavioral intention (Johnson et al., 2008). Many literatures confirmed the relationship between users' self-efficacy and behavioral intention to use a system technology (Eom, 2012). Hence, H6 is set:

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

2.6 Perceived Satisfaction

Perceived satisfaction is a measure of pleasant sentiments when the services meet or exceed the customers' expectations. The purchase of a commodity and the consistent application of a product/service by a consumer are similar. Users' satisfaction is one of the most critical factors in assessing the effectiveness of information technologies (Shin & Kang, 2015). Perceived satisfaction describes the feeling of having a complete and successful task (Belanche et al., 2012). Therefore, perceived satisfaction influences the behavioral intention of the students of using the learning system. The learning satisfaction relates to the personal sense that students have positive feeling or pleasure about their learning experience, including the content, tactics, process, and consequences of learning activities (Liestiawati & Agustina, 2018). Therefore, we hypothesize that:

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

2.7 Behavioral Intention

Behavioral intention can be described as intent to undertake a specific act (Davis, 1989). Students potentially adopt an e-learning system as they believe it can help them to achieving their education's goals. Distant learning can be influenced by social, technological, and organizational aspects (Salloum & Shaalan, 2018). Behavioral intention refers to the extent to which a person makes conscious plans to carry out or refrain from carrying out specific performance (Bashir & Madhavaiah, 2015). Behavioral intention is described as a person's willingness to engage in a given behavior (Cheung & Vogel, 2013). It is also referred to a person's inclination to engage some behavior (Vululleh, 2018). Individual's desire to carry out the intended task is similar to the use of system technology (Cigdem & Ozturk, 2016). In addition, the behavioral intention is a significant predictor to the use behavior (Bardakcı, 2019; Kitcharoen, & Vongurai, 2021).

3. Research Methods and Materials

3.1 Research Methodology

The researchers employed a quantitative study, using nonprobability sampling strategy to distributing on-site and online questionnaires to art undergraduates of three colleges which are Chengdu University (CDU), Sichuan University (SCU), and Sichuan Normal University (SNU). The questionnaire is designed into three parts. Firstly, screening questions are generally used to verify qualified respondents and avoid unqualified respondents (Hair et al., 2013). Secondly, demographic data includes respondents' gender, and year of study, which is an important type of data in providing respondents' characteristics (Salkind, 2017). Finally, the 5-point Likert scale is given for respondents to select a magnitude representation between agreement and disagreement (Lavrakas, 2008).

Before the data collection, the Item Objective Congruence (IOC) Index was used for screening the items' quality with three qualified experts and professionals e.g., PhD. IOC results were passed at a scored 0.6 and above. (Turner & Carlson, 2003). Prior to a large-scale distribution of survey, pilot testing was used to examining a small sample of people (Cooper & Schindler, 2014). The number of participants in the pilot test could be between 10 to 30. (Hill, 1998). In this study, the Cronbach's Alpha coefficient value was used to measuring internal consistency reliability in the pilot test of 30 undergraduate students, resulting all constructs were accepted at a score 0.7 and over (Sarmento & Costa, 2016).

In the process of data collection, 500 undergraduate students from three universities are selected as a population of interest. The researchers used IBM SPSS and AMOS to analyze the data. Confirmatory Factor Analysis (CFA) was accounted to assessed factor loadings, t-value, composite reliability (CR), average variance extraction (AVE), and discriminant validity. The implications of the assumptions, as well as the direct, indirect, and total effect of the relationships in the test of hypotheses are inspected by structural equation modeling (SEM).

3.2 Population and Sample Size

The target population are art major's students at Chengdu University (CDU), Sichuan University (SCU), and Sichuan Normal University (SNU) in Chengdu, China. The researchers chose these three universities for several reasons. Firstly, these three higher education institutions are representatives of different regions located in Chengdu. Secondly, these universities have been established more than 40 years old. Thirdly, these universities have more than 20,000 students. Lastly, all three institutes offer online education programs. According to Israel (1992), the minimum sample size for the complex assessment framework in the structural equation model should be between 200 and 500 samples. Following judgmental sampling and quota samplings, 500 students were selected as the final sample for this study.

3.3 Sampling Techniques

The researchers employed three sampling techniques. The researchers used judgmental sampling to identify 4,987 art major undergraduates with at least one month experience of online education from the three public colleges in the Chengdu region of China. In addition, 500 participants were selected as the final sample for three distinct subgroups based on quota samplings as indicated in Table 1. Afterwards, the questionnaire was distributed via both on-site and online format including administration offices and WeChat application as convenience sampling.

Table 1: Sample Units and Sample Size

Target Universities	Sampling Units	First Stage Sample Size Total = 4,987	Proportional Final Stage Sample Size Total = 500
Chengdu University	Freshman	352	35
	Sophomore	108	11
	Junior	118	12
	Senior	120	12
Sichuan University	Freshman	256	26
	Sophomore	240	24
	Junior	261	26
	Senior	227	23
Sichuan Normal University	Freshman	839	84
	Sophomore	803	81
	Junior	839	84
	Senior	824	83

Source: Created by the author.

4. Results and Discussion

4.1 Demographic Information

The demographic profile for 500 participants has been completed. Male respondents constitute 31.60%, and female respondents account 68.40%. According to Table 2, 26.60% of students are freshmen, 24.80% are juniors, 24.60% are sophomores, and 24.00 % are seniors.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	158	31.6%
	Female	342	68.4%
Year of Study	Freshman	133	26.6%
	Sophomore	123	24.6%
	Junior	124	24.8%
	Senior	120	24.0%

Source: Created by the author

4.2 Confirmatory Factor Analysis (CFA)

In this study, Confirmatory Factor Analysis (CFA) was performed. According to Arbuckle (2008), CFA is a statistical research method used to assess the variables of the study. The measurement models add to a greater comprehension of the degree to investigating the data reliabilities, validities and fit model (Khan & Qudrat-Ullah, 2021). The factor loadings are more than 0.30 and the p-value is less than 0.05. The construct reliability exceeds the threshold of 0.70, and the average variance extracted exceeded the threshold of 0.50 (Fornell & Larcker, 1981). CFA determines if the structural and load quantities of each observed variable are consistent with the null hypothesis (Malhotra et al., 2004).

Experts have determined that the Average Variance Extracted (AVE) should fall between 0 and 1, with a value greater than 0.50 suggesting a sufficient degree of convergence validity (Bagozzi & Yi, 1988). According to the statistical results summarized in Table 3, all Cronbach's Alpha coefficient values were greater than 0.80, factor loadings of greater than 0.30, t-value of greater than 1.98, p-value less than 0.50, composite reliability (CR) of greater than 0.70, and average variance extracted (AVE) of greater than 0.50 (Sarmento & Costa, 2016).

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	0.570-0.899	0.863	0.872	0.584
Perceived Usefulness (PU)	Cigdem and Ozturk (2016)	6	0.674-0.924	0.897	0.904	0.615
Social Influence (SI)	Mtebe and Raisamo (2014)	4	0.619-0.924	0.860	0.869	0.630

Effort Expectancy (EE)	Mtebe and Raisamo (2014)	4	0.629-0.860	0.869	0.874	0.637
Self-Efficacy (SE)	Fokides (2017)	4	0.686-0.880	0.877	0.880	0.650
Perceived Satisfaction (PS)	Shin and Kang (2015)	4	0.657-0.883	0.864	0.868	0.625
Behavioral Intention (BI)	Venkatesh et al. (2003)	4	0.696-0.849	0.874	0.876	0.640

Source: Created by the author

When the value of CR is greater than AVE and the AVE is greater than 0.50, the validity is said to be convergent (Hair et al., 2009). The discriminant validity values that were examined and demonstrated in Table 4 also exceeded the critical point values. As a result, the research's convergent validity and discriminant validity were guaranteed.

Table 4: Discriminant Validity

	PEOU	PU	SI	EE	SE	PS	BI
PEOU	**0.764**						
PU	0.435	**0.784**					
SI	0.341	0.309	**0.794**				
EE	0.363	0.375	0.268	**0.798**			
SE	0.369	0.357	0.307	0.245	**0.806**		
PS	0.343	0.307	0.254	0.312	0.337	**0.791**	
BI	0.356	0.316	0.238	0.260	0.267	0.218	**0.800**

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, a structural equation model (SEM) was used to estimate a specific system of linear equations and confirm the model's fit. SEM can be used to measure the relationship between variables (Wanichbancha, 2014). Table 5 shows the results, which were adjusted by SPSS AMOS including CMIN/DF, GFI, AGFI, CFI, TLI, and RMSEA. As a result, each indicator of the goodness of fits in SEM verification was acceptable.

Table 5: Goodness of Fit for Structural Model

Index	Criterion	Source	After Adjustment Values
CMIN/DF	< 5.00	Hair et al. (2010)	2.872
GFI	≥ 0.85	Sica & Ghisi, (2007)	0.856
AGFI	≥ 0.80	Sica & Ghisi, (2007)	0.828
NFI	≥ 0.80	Arbuckle (1995)	0.881
CFI	≥ 0.80	Hair et al. (2006)	0.919
TLI	≥ 0.80	Hair et al. (2006)	0.910
RMSEA	< 0.08	Pedroso et al., (2016)	0.061

Source: Created by the author.

4.4 Research Hypothesis Testing Result

The research matrix was computed using the regression weights and R2 variances to determine the significance of each variable. According to the results illustrated in Table 6, perceived ease of use has the strongest impact on perceived usefulness with the standardized path coefficient (β) result as 0.382 (t-value = 7.384). Secondly, perceived usefulness had a significant impact on behavioral intention with β as 0.201 (t-value = 3.916). Thirdly, perceived ease of use significantly impacted behavioral intention with β as 0.178 (t-value = 3.409). Fourthly, self-efficacy had a significant influence on behavioral intention with β as 0.140 (t-value = 2.895). Next, effort expectancy significantly impacted behavioral intention with β as 0.117 (t-value =2.487). Lastly, social influence had a significant influence on behavioral intention with β as 0.104 (t-value = 2.154). Consequently, six hypotheses were significantly supported with p values less than 0.05. On the other hand, the relationship between perceived satisfaction and behavioral intention was not supported, with β at -0.058 (t-value = -1.415).

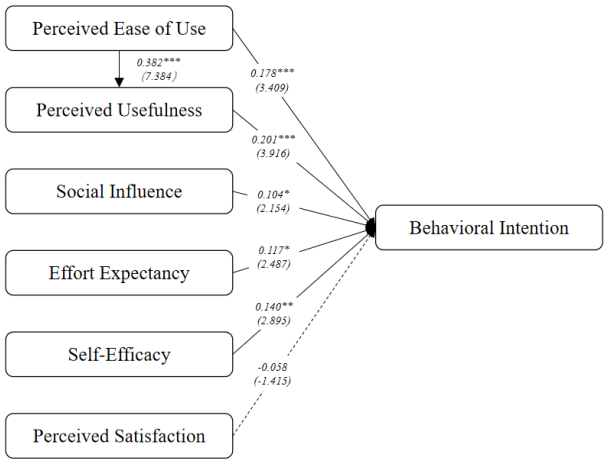

Figure 2: Structural Equation Model (SEM)
Note: *** p<0.001, ** p<0.01, * p<0.05

Table 6: Hypothesis Result of the Structural Equation Model

Hypothesis	Paths	Standardized Path Coefficient (β)	T-Value	Tests Result
H1	PEOU→BI	0.178	3.409	Supported
H2	PU→BI	0.201	3.916	Supported
H3	PEOU→PU	0.382	7.384	Supported
H4	SI→BI	0.104	2.154	Supported
H5	EE→BI	0.117	2.487	Supported
H6	SE→BI	0.140	2.895	Supported
H7	PS→BI	-0.058	-1.415	Not Supported

Source: Created by the author

According to the data in Figure 2 and Table 6, the findings are explained as follows:

With a standardized path coefficient value of 0.178, H1 was confirmed that perceived ease of use is one of the most important determinants of behavioral intention. According to the study, perceived ease of use had a significant impact on students' behavioral intent to use online education (Neo, et al., 2015).

The result of H2 supported the hypothesis of a significant relationship between perceived usefulness and behavioral intention, as described by the standard coefficient value of 0.201. The perceived usefulness of a system was arguably the most important factor to consider when deciding whether or not to employ it, and the subjective likelihood that employing a particular example technology will enhance job performance was measured by perceived usefulness (Davis, 1989).

H3 confirmed that perceived ease of use is one of the essential factors for perceived usefulness, with the structural approach yielding the highest standardized path coefficient value of 0.382. Previous research demonstrated that perceived ease of use determines perceived usefulness of an online education among students (Agrebi & Jallais, 2015).

H4 demonstrated that social influence was the influencer of behavioral intention in this study, resulting the standard coefficient value of 0.104. According to previous research on the relationship between social influence and value perception, marketing professionals have defined value perception as an individual's comprehensive evaluation and view of the benefits of a product or service (Zeithaml et al., 2002).

H5 showed that effort expectancy had a significant influence on behavioral intention, as indicated by the standard coefficient value of 0.117. Effort expectancy was also crucial in determining behavioral intention to use online education among students (Teo & Noyes, 2014).

H6 determined that self-efficacy influenced behavioral intention, resulting the standard coefficient value at 0.140. The extended TAM includes these external factors such as technology complexity, self-efficacy, compatibility, and subjective norms and examined their influences on academics' behavioral intention to use LMS (Jaradat & Al-Mashaqba, 2014).

Based on the results of H7, the statistical findings of this study do not support the hypothesis that perceived satisfaction influenced behavioral intention with the standard coefficient value is -0.058. Among the related factors of online education for majors in the fine arts in Chengdu, perceived satisfaction has no effect on students' behavioral intention to use online education as contradicted with previous literatures (Belanche et al., 2012; Shin & Kang, 2015).

5. Conclusions and Recommendation

5.1 Conclusion

This research demonstrates the significance of behavioral intention among undergraduate art majors at public universities in Chengdu, China. In the conceptual framework, the hypotheses have been proposed. The questionnaires were distributed to 500 undergraduates with at least one month of online education experience. Confirmatory Factor Analysis (CFA) was utilized to examining the conceptual matrix's validity and reliability. In addition, Structural Equation Model (SEM) was used to confirm the predominant influencers for the factors that influenced behavioral intention.

Consistent with previous research results, perceived ease of use had the strongest direct impact on perceived usefulness, and directly and indirectly impacted online education behavioral intentions. Perceived ease of use, perceived usefulness, social impact, effort expectation and self-efficacy had significant influences on undergraduates' behavioral intention. Nevertheless, perceived satisfaction was not an influential factor of behavioral intention. Based on the findings, the outbreak of the pandemic is the only choice which means the target population has been forced to accept online education. In a short period of time an online education may not be comprehensive and there are still many problems in the process, leading to the subjective perception of the degree of satisfaction. Practical courses for art majors require offline and in-person instruction for the learning efficiency. Nonetheless, due to the exceptional circumstances and the impact of the epidemic, online education remains accessible which is not relevant to the level of student satisfaction. Because of the deficiency of single online education, most colleges and universities are implementing both online and offline education. The

undergraduate students of art major have been affected by the epidemic and the online education background for a considerable amount of time.

5.2 Recommendation

The researchers investigated the fundamental determinants of behavioral intention among art undergraduates in Chengdu. Therefore, it is suggested to popularize the findings to design and reform online courses for art majors to obtain better teaching materials in the future. Perceived ease of use significantly impacted perceived usefulness and had the strongest impact on behavioral intention. Thus, the online education requires a well-designed structure to be easy to use, and universities need to promote the benefits of using such online education by providing other learning features such as recording, breakout room etc. to ensure that students can maximize the use on online learning for the improvement of their learning performance. When students perceive that online education is useful, they are willing to use it more frequently and more effectively as aligned with the result that perceived usefulness significantly impacted behavioral intention.

In order to improve learning efficiency, students' behavioral intention should be fully considered in the design of teaching programs for art higher education majors. Suggestions can be made to improve the functions of online education system, strengthen the real-time interactive experience of online education, and improve student satisfaction in contributing behavioral intention. Social influence is one of the influential factors driving behavioral intention. Online educators can promote the online community, allowing users to exchange knowledge on the use, problems and solutions of using online education. Lectures should design teaching materials to match the online format in order to enhance learning efficiency and behavioral intention of students. Effort expectancy can predict the behavioral inattention of students, so universities could measure the level of effort when using the system and to improve and upgrade the online learning system at all time. In regarding to the significant relationship between self-efficacy and behavioral intention, online educators need to measure the online system to be self-control which the system should be easy to be self-managed.

5.3 Limitation and Further Study

This study has several limitations. Firstly, demographic and sample are restricted to undergraduate students majoring in fine arts at three public universities in Chengdu, China. Future research may investigate in the broaden geographical area of research to include other regions in China. Secondly, future researchers should consider prospective variables such as attitude towards use, trust, performance expectancy, facilitation conditions etc. Finally, qualitative method, such as interview or focus group, should be extended to provide more critical analysis of the findings.

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