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Factors Influencing Behavioral Intention Towards MOOC Platform of Jingdezhen Vocational University of Art Students Majoring in Art and Design in Jiangxi Province, China

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Abstract

The objective of this investigation was to analyze the behavioral intention of students at the Jingdezhen Vocational University of Art who majoring in art and design majors to use the MOOC platform. It was carried out by the researchers using quantitative research techniques. Based on the Theory of Reason and Action (TRA), the Technology Acceptance Model (TAM), and the Unified Theory of Technology Acceptance and Use (UTAUT), this study develops a conceptual framework. Seven potential variables were chosen to assess the validity of the research tool using project-goal consistency and passed the internal consistency test: self-efficacy, perceived ease of use, perceived usefulness, attitude, performance expectancy, subjective norm, and behavioral intention. The reliability was evaluated by Cronbach α coefficient through the pilot test. In addition, the sampling strategy was multi-stage sampling. In the course of the study, a face-to-face questionnaire was distributed to 500 professional undergraduates majoring in art and design with MOOC platform experience at the School of Ceramic Art and Design and the School of Digital Art of Jingdezhen Art Vocational University. As statistical analysis tools, confirmatory factor analysis and structural equation modeling were applied in this research to advance the influence on data, matrix accuracy, basic variables, hypothetical support, and path coefficients. The results revealed that all the hypotheses are suggested, and the subjective norm was the most influential factor that affected art and design majors' behavioral intention to use the MOOC platform.

Keywords: MOOC Platform, Self-Efficacy, Perceived Ease of Use, Perceived Usefulness, Attitude, Performance Expectancy, Subjective Norm, Behavioral Intention

Introduction

MOOCs which means massive open online courses are the largest online open course in the world at present. As a very representative online open learning platform, it integrates social network connections, the guidance of famous experts in a certain research field, and free online resources (Luo et al., 2018). The creation of the MOOC platform makes college students' learning ubiquitous, promoting higher education equity and the sharing of top-notch resources. In China's higher education, the massive open online course has experienced more than ten years of development, both in the total number of courses and in the scale of students participating in the study, which has made considerable progress (Quan, 2015). To encourage the thorough integration of information technology and teaching, The Ministry of Education in China has promulgated and implemented many engineering projects and educational informatization plans (Yan &Yang, 2021). Education informatization construction in major regions of China has made huge progress in fund allocation, construction scale, hardware and software platform, and implementation of teaching informatization, which has played a significant part in promoting the digital transformation of China's higher education, enhancing education equity and high-level growth (Chen, 2018).

Nonetheless, vocational undergraduate education in China is still in its infancy, and the utilization rate in the massive open online course needs to be improved. To actively promote the widespread use of information technology in vocational undergraduate education and let more undergraduate students choose to use MOOC platform resources, it is crucial to comprehend the variables influencing undergraduate students' behavior toward massive open online courses platform. Although the academic circle is active in the study of MOOCs, the researches of scholars mainly focus on the status and development of MOOCs, comparison and analysis, construction and operation, teaching and curriculum, and so on. Most of the articles are qualitative research, lacking quantitative research results for vocational universities. Therefore, this study examines the variables that have a major impact on art and design students in the Jingdezhen Vocational University of Art, and based on previous literature, a questionnaire representing the actual situation of Jingdezhen art vocational university students regarding the MOOC platform is compiled. Based on the above considerations, it is very necessary to make a quantitative study on the behavioral intention of art and design majors at the Jingdezhen Vocational University of Art, including six basic latent variables corresponding to behavioral intention.

Literature Review

In this study, the researchers revised the conceptual framework based on the three theories and three major previous research results. Theory of reasoned action (TRA) proposed by Fishbein and Ajzen (1975), the theory of technology acceptance model (TAM) designed by Davis (1989) and the unified theory of acceptance and use of technology （UTAUT） introduced by Venkatesh et al. (2003), they were applied as the most essential theories to develop the conceptual framework to explain user’s behavioral intention. In addition, these are very significant technology acceptance theories in the current education field. Based on these theoretical frameworks, the corresponding variables are selected.

Self-efficacy

Self-efficacy is a person's capacity to evaluate, convince or grasp whether he can finish off an activity at a certain level (Bandura, 1977). To derive the unambiguous influence of self-efficacy on perceived usefulness and ease of use, Hasan (2007) added self-efficacy as an external variable to the Technology Acceptance Model. Tarhini et al. (2017) proposed that for online learning, much prior research on information systems found a link between SE and PEOU. According to Fokides (2017), self-efficacy has a remarkable impact on a person's apprehensive or anxious state and can shape people's selection of behavioral tasks as well as their persistence and effort in the task. Concurrently, it also influences people's thinking patterns and emotional response patterns in the process of performing assignments on the MOOC platform. According to Shao's (2018) research, people with a high sense of self-efficacy believe that they can use the systems effectively. On the other hand, people who lack self-confidence would give up the chance to adopt technology.

H1: Self-efficacy has a significant effect on perceived ease of use.

Perceived Ease of Use

Davis (1989) contended that perceived ease of use is the extent to of a person who kept faith that applying technology will be unproblematic. Moreover, it is the degree to which someone assumes that manipulating the system is simple and effective (Rui-Hsin & Lin, 2018). Yip et al. (2020) had been demonstrated that PEOU performs a driving role in influencing behavior intention. Elkaseh et al. (2016) also exhibited the student's motivation as well as the result of a critical direction for adopting the technology. The chance of applying a new technology would be higher if users thought it was easy to combine the technology with their activities (Shao, 2018). This evidences that the more easily students can achieve their goals with this method, the more probable it is that they will come to rely on it and use it.

H2: Perceived Ease of Use has a significant effect on perceived usefulness.

Perceived usefulness

Davis (1989) corroborated the degree to which a person considers that adopting a particular system will upgrade their fulfillment was defined as perceived usefulness. For the technology acceptance model, the adoption of that system is determined by behavioral intention and behavioral intention is firmly established by attitude and perceived usefulness. That means both PU and PEOU were indispensable factors in information system acceptance. Moreover, it is also used to clarify users' acceptance of technology (Huang et al., 2007). Furthermore, the literature that is now available also backed up the huge influence of perceived usefulness on users' attitudes (Qin et al., 2019). For instance, Yan and Su (2017) conducted a specific interaction between perceived usefulness and attitude through the analysis of technology adoption intention. Wu and Chen (2016) conceived that students' attitude toward using MOOC platforms is precisely impressed by its usefulness to help students acquire. To be specific, if an individual thought it helps raise expectations for results and made it more accessible to achieve the goals, he or she would feasible to use it with a clear attitude (Cheung & Vogel, 2013).

H3: Perceived Ease of Use has a significant effect on attitude.

H4: Perceived usefulness has a significant effect on attitude.

Attitude

Ajzen (1991) proved that the degree to which users approve or disapprove of new technology is called their attitude toward it. Hu and Zhang (2016) noted that attitude is how you feel after using an application to accomplish a target task and how much you support or oppose it. According to the theory of TAM, an individual's feeling toward applying the system under examination as well as the perception of its utility would impact their cognitive and behavioral purpose (Davis, 1989). In addition, the TPB theory assumed that a person's intention to engage in an appropriate behavior is regulated by their psychological reaction (Ajzen, 1991). In other words, it indicates the attitude as the degree of influence on some objects. Specifically, it was the feeling of using some kind of application to accomplish the target task. Park and Kim (2014) noted that it also interpreted that attitude determines a person's intention to engage in certain actions. When Chinese students perceived mobile library applications as useful, the researcher found that this helped them develop a good attitude toward them, which in turn had a remarkable impact on their behavioral intentions to use them. In other words, they would have a stronger intention to use it (Hu & Zhang, 2016).

H5: Attitude has a significant effect on behavioral intention.

Performance expectancy

The extent to which someone thought that operating the system would enable them to improve their academic performance is known as performance expectancy (Salloum & Shaalan, 2019). Additionally, it reflects how strongly students think that technology will improve their academic performance and grades. In the UTAUT model, the most reliable indicator of behavioral intention to use a variety of technologies in both voluntary and involuntary circumstances is performance expectancy (Venkatesh et al., 2003). Several kinds of literature had generated that performance expectancy had a dramatically shaped query on the intention to adopt cultural and behavioral changes (Batara et al., 2017). Students' behavior intention to embrace online learning systems will rise when they thought that it will improve their academic performance and help them get better grades (Mtebe & Raisamo, 2014). Tarhini et al. (2017) proposed that the research results indicate that students are more willing to embrace the learning system into their academic routines when they believe it can enhance performance.

H6: Performance expectancy has a significant effect on behavioral intention.

Subjective Norm

By Ajzen (1991), the person's belief that the majority of individuals who are significant to him or she should or not undertake the action is how the term "subjective norm" is defined. It refers to students' perceptions of other people's attitudes toward performing the same behavior as them, particularly those who are important to them, including professors and peers (Kumar et al., 2020). In the TRA model, one of the factors in judging behavioral intention is SN. In addition, TRA and TPB both include a component called subjective norm that demonstrates how behavioral intentions can be impacted by subjective norm to affect behavior (Punniyamoorthy & Asumptha, 2019). As a result of the widespread use, numerous researches have determined the power of subjective norms. Yau and Ho (2015) believed that SB was a curial component influencing learners' behavioral intention to use the online platform. While some studies suggested SN and BI for mobile learning had a substantial association (Alasmari & Zhang, 2019; Park et al., 2012).

H7: Subjective norm has a significant effect on behavioral intention.

Behavioral Intention

According to the Technology Acceptance Model, a behavioral model that reflected the acceptance of information technology in the past, it was used to gauge how quickly people adopted new technology (Davis, 1989). Moreover, technology acceptance behavioral intention had been discussed and reported to a large extent as the most powerful factor in determining an individual's behavior toward new technologies (Wut & Lee, 2021). In other words, a user's behavioral intent to apply the system also reflects the system's acceptance. The more users who accept the new system, the more likely it is that they will start using it (Hu & Zhang, 2016). Furthermore, Slatten (2012) believed that for Internet-based applications, behavior is based on the attitude of users toward using the system under review and perceived usefulness. Tarhini et al. (2017) indicated that attitude acted as a mediator between PU and PEOU's impacts on behavioral intention.

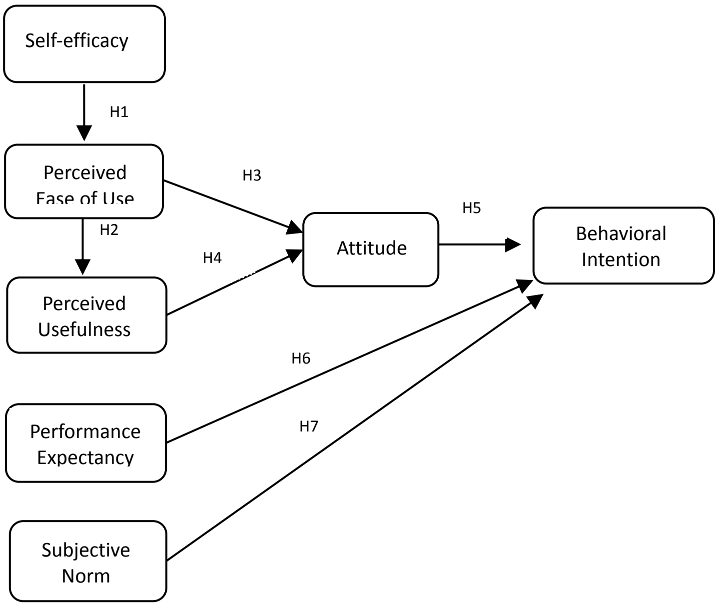
Research Methods and Materials

Conceptual Framework

Concerning building the conceptual structure, previous academic research methodologies were examined. It was based on the four primary research frameworks as well as the theory of reason action (TRA), the technology acceptance model theory (TAM), and the unified theory of technology acceptance and use (UTAUT). Initially, Shao (2018) identified a link between perceived usefulness, perceived ease of use, and self-efficacy. Moreover, Cheung and Vogel (2013) established a link between attitude, perceived usefulness, perceived ease of use, and behavioral intention. Additionally, Tarhini et al. (2017) showed a connection between behavioral intention and performance expectancy. Lastly, Punniyamoorthy and Asumptha (2019) indicated the interconnection between subjective norms and behavioral intention. The conceptual framework will enable MOOC researchers, practitioners, and university teachers delivering courses on MOOCs to better understand the reasons and motivations behind student behavior. Figure 1 claclarifiese the investigation's conceptual framework.

Figure 1

Conceptual Framework



Note: Created by the Author

This survey sought to check over the critical factors for the behavioral intention on the MOOC platform based on a variety of latent variables which were self-efficacy, perceived ease of use, perceived usefulness, performance expectancy, subjective norm, and attitude of art and design majors of Jingdezhen Art Vocational University. Additionally, the causative association pathway between each latent construct was investigated after analyzing the elements that influence behavioral intention.

Research Methodology

The researchers adopted the method of probability sampling and conducted a questionnaire survey among the students majoring in art design in two schools of the Jingdezhen Vocational University of Art. The target schools are the School of Ceramic and Art Design and the School of Digital Arts. Observational data were pooled and analyzed to identify fundamental characteristics that had a substantial impact on MOOC platform participants' behavioral intentions. There are three sections to the questionnaire. To begin, screening questions for ensuring that the researcher selects respondents with the necessary expertise or experience to complete the questionnaire (Cooper & Schindler, 2011).

Next, the researcher designed a set of demographic questions for undergraduates to gather basic information about gender, grade, major direction, and school information. Eventually, the Likert scale of five points was used for rating the answer to the question. It stated that remarks on a Likert scale might indicate a positive or negative attitude toward a certain object (Cooper & Schindler, 2011). Each response on the Likert scale has a numerical score, and they reflect a positive or negative attitude, 5 is strongly agreed, and 1 strongly disagrees.

For analyzing the accuracy of the objectives postulated by the instrument developers for this study, three experts with a Ph.D. education background and expertise in online education were invited to conduct the item-objective congruence for content validity. Additionally,30 students took part in the pilot test to ensure the instrument's reliability. The paper-based questionnaires were given to 500 undergraduate students from the target colleges after determining the questionnaires' accuracy and reliability. The statistics of the research were evaluated by using jamovi. Besides that, the researcher utilized confirmatory factor analysis (CFA) to prove the discriminant validity, average variance extracted (AVE), composite reliability (CR), factor loading, and t-value. Consequently, a structural equation model (SEM)was applied to test the effects of the direct and indirect relationships between the latent constructs.

Population and Sample Size

This survey's population consists of art and design majors from Jingdezhen Vocational University of Art's School of Ceramic Art (SCAD) and Design and School of Digital Art (SDA). The research employed a multistage sampling methodology which could be divided into two components. A total of 1,149 students with at least one month of experience on the MOOC platform were chosen from two target schools in the Jingdezhen Vocational University of Art. There are 7 latent variables and 29 observed variables in the framework of this paper, and at least 425 people are calculated by professional statistical calculators. The final sample was chosen using quota selection from 500 respondents from the two schools in order to ensure the validity of its data.

Sampling Strategy

The research employed a multistage sampling methodology which could be divided into two components. A total of 1,149 students with at least one month of experience on the MOOC platform were chosen from two target schools in the Jingdezhen Vocational University of Art. The researchers selected the appropriate number of students according to the quota sampling design and the proportional sample size. In the School of Ceramic Art and Design (SCAD), proportional sample size of freshman is 175, proportional sample size of sophomore is 98; In the School of Digital Arts (SDA), proportional sample size of freshman is 176, proportional sample size of sophomore is 51. The total size is 500 respondents.

Table 1

Sample units and sample size

Target Schools in Jingdezhen Art Vocational University.	Grade	Population Size Total = 1149	Proportional Sample Size Total= 500
School of Ceramic Art and Design (SCAD)	Freshman	403	175(403*500/1149)
	Sophomore	224	98(224*500/1149)
School of Digital Arts (SDA)	Freshman	405	176(405*500/1149)
	Sophomore	117	51(117*500/1149)

Note: Created by the Author

Results and Discussion

Demographic Information

The detailed demographic profile information for the 477 respondents is summarized in Table 2. The questionnaire distributed 500 samples, 23 of which were invalid, resulting in 477 samples. Male respondents composed 48.01 percent of the total, while female respondents composed 51.99 percent. According to the School's affiliation, 54.93 percent of students attended the School of Ceramic Art and Design (SCAD), and 45.07 percent attended the School of Digital Arts (SDA). For the grade classification, 71.07% of respondents were freshmen, and 28.93 percent were sophomores. For the distribution of majors, 28.30 percent of students were ceramic art design majors, 3.56 percent were sculpture majors, 18.24 percent were environmental art design Major, 4.19 percent were product design majors, 32.70 percent were visual communication design majors, and13.01percent were animation majors.

Table 2

Demographic Profile

Demographic Information(n=477)		Frequency	percentage
Gender	Male	229	48.01%
	Female	248	51.99%
School Belong	SCAD	262	54.93%
	SDA	215	45.07%
Grade	Freshman	339	71.07%
	Sophomore	138	28.93%
Major Direction	Ceramic Art Design	135	28.30%
	Sculpture	17	3.56%
	Environmental Art Design	87	18.24%
	Product Design	20	4.19%
	Visual Communication Design	156	32.70%
	Animation	62	13.01%

Note: Created by the Author

Confirmatory Factor Analysis (CFA)

In social science research, CFA is a category of specialized advanced factor analysis techniques that makes it easier to identify the factor structure that the researchers are confident the phenomenon follows (Huang & Yuan, 2020). Additionally, as shown in Table 3, the entire threshold of the chi-square value to the degree of freedom (CMIN/DF), goodness-of-fit index (GFI), adjusted goodness-of-fit index (AGFI), comparative fit index (CFI), normalized fit index (NFI), and Tucker Lewis index (TLI) all compared the characteristic. As a result, all of these metrics for the goodness of fit used in the CFA testing for this scientific study were adequate.

Table 3

Goodness of Fit for Confirmatory Factor Analysis

Index	Criterion	Source	Practical Values
CMIN/DF	<3	Hair et al. (2010)	1.979
GFI	>0.90	Hair et al. (2010)	0.905
AGFI	>0.80	Sica and Ghisi (2007)	0.883
RMSEA	<0.05	Hu and Bentler (1999)	0.045
CFI	>0.90	Hair et al. (2010)	0.959
NFI	>0.90	Hair et al. (2010)	0.920
TLI	>0.90	Hair et al. (2010)	0.953

Note: Created by the Author

Table 4

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

Latent Variables	Source of Questionnaire (Measurement Indicator)	Items Amount	Cronbach's Alpha	Factors Loading	CR	AVE
PU	Ibrahim et al. (2017)	5	0.890	0.581-0.846	0.842	0.520
PE	Tarhini et al. (2017)	5	0.887	0.718-0.826	0.879	0.593
BI	Tarhini et al. (2017)	5	0.915	0.777-0.908	0.932	0.735
PEOU	Ibrahim et al. (2017)	4	0.825	0.678-0.928	0.883	0.658
SN	Punniyamoorthy and Asumptha (2019)	4	0.866	0.716-0.917	0.895	0.682
SE	Shao (2018)	3	0.874	0.702-0.891	0.857	0.669
ATT	Hu and Zhang (2016)	3	0.911	0.686-0.827	0.786	0.552

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As illustrated in Table 4, Cronbach's Alpha coefficients for five latent variables were over 0.80, two were over 0.90, the total factor loadings exceeded 0.50, composite reliability (CR) was above 0.70, and average variance extracted (AVE) was above 0.50. According to the discriminant validity results investigated and presented in Table 5, the diagonally specified quantity is the AVE square root of the variables, and all of the coefficients connecting any two latent variables were less than 0.80. Consequently, the discriminant validity was determined by using these quantitative metrics.

Table 5

Discriminant Validity

	PU	PE	BI	PEOU	SN	SE	ATT
PU	0.721						
PE	0.220	0.770					
BI	0.164	0.282	0.857				
PEOU	0.313	0.106	0.205	0.811			
SN	0.197	0.136	0.496	0.186	0.826		
SE	0.065	0.102	0.181	0.235	0.203	0.818	
ATT	0.374	0.118	0.221	0.227	0.190	0.147	0.743

Note: Created by the Author

Structural Equation Model (SEM)

The research objectives and framework of this paper are suitable for factor analysis, so following the CFA evaluation, the structural equation model (SEM) was validated by this research's objectives. Both CFA and SEM are excellent factor analysis methods.SEM was a reliable tool for evaluating complicated models statistically and may be used to examine mediation and moderation effects (Kline, 2016; Schumacker & Lomax, 2010). As demonstrated in Table 6, the aggregate value of CMIN/DF, GFI, AGFI, CFI, NFI, as well as TLI was all above reasonable parameters when corrected by AMOS. As a result, the SEM's goodness of fit was confirmed.

Table 6

Goodness of Fit for Structural Equation Modeling

Index	Criterion	Source	After Adjust Values
CMIN/DF	<3	Hair et al. (2010)	1.826
GFI	>0.90	Hair et al. (2010)	0.911
AGFI	>0.80	Sica and Ghisi (2007)	0.895
RMSEA	<0.05	Hu and Bentler (1999)	0.042
CFI	>0.90	Hair et al. (2010)	0.964
NFI	>0.90	Hair et al. (2010)	0.924
TLI	>0.90	Hair et al. (2010)	0.960

Note: Created by the Author

Hypothesis Testing Results

Considering the calculated findings in Table 7, the subjective norm had the highest direct influence on behavioral intention, culminating in a standardized path coefficient (β) of 0.435 (t-value of 9.296***). Moreover, performance expectancy has the second greatest significant influence on behavioral intention with β at 0.252 (t-value at 5.481***), followed by the attitude with β at 0.153 (t-value at 3.267**). Furthermore, perceived usefulness has the highest impact effect on attitude with aβ at 0.418 (t-value at 7.012***), which has a significant influence effect in this quantifiable investigation, and perceived ease of use has the second-highest impact with β at 0.275 (t-value at 2.740**).In addition, perceived ease of use has a significant influence on perceived usefulness, it had proven that the β at 0.313 (t-value at 5.762***). The results also reveal that self-efficacy has clout on perceived ease of use with β at 0.273 (t-value at 5.191***).

Table 7

Hypothesis Result of the Structural Equation Modeling·

Hypotheses	Path	Standardized Path Coefficient (β)	T-Value	Tests Result
H1	PEOU ← SE	0.273	5.191***	Supported
H2	PU ← PEOU	0.313	5.762***	Supported
H3	ATT ← PEOU	0.275	2.740**	Supported
H4	ATT ← PU	0.418	7.012***	Supported
H5	BI ← ATT	0.153	3.267**	Supported
H6	BI ← PE	0.252	5.481***	Supported
H7	BI ← SN	0.435	9.296***	Supported

Note: *** p<0.001,**p<0.01,* p<0.05

Note: Created by the Author

Based on the research findings in Table 7, researchers would recommend the following extensions: H1 has asserted that self-efficacy is a major variable for perceived ease of use, with the standardized path coefficient threshold in this structural technique being 0.273. Shao (2018) proposed the hypothesis that participants' activity assessments of the target learning system's perceived ease of use are a highly crucial component of self-efficacy. In other words, whether students believe they can use the MOOC platform well. Individuals with high self-efficacy believed that they could perform well when using the systems. Individuals with low self-efficacy, On the contrary side, people with low self-efficacy will be more easily frustrated by arduous challenges and simply abandon the opportunity to use it.

With a standardized path coefficient value of 0.313, the analysis results for H2 revealed that perceived ease of use is one of the key elements of perceived usefulness. Wang et al. (2017) implied that perceived ease of use has the forefront of the investigation of perceived usefulness. Hence, this implies that students will only consider the MOOC platform useful if they assumed it is convenient and simple to use. For the MOOC platform, the easier a platform is to use, the more value the user perceives.

The statistical outcome for H3 approved the hypothesis for the significant clout of perceived ease of use on attitude, representing the standard coefficient value of 0.275. Yang and Su (2017) found that attitudes toward adopting new technology have a dramatic impact on perceived ease of use. Users were likely to accept this technology when they found it was easy to use innovative technology. That is, when students find the MOOC platform easy to use, they will embrace it.

Furthermore, in terms of H4, the investigation result proffered that perceived usefulness has a critical influence on academic dialogue on learners' attitudes, with the standard coefficient value at 0.418. Qin et al. (2019) verified that perceived ease of use in information systems has significant shape queries on persons' psychological reactions. If users were willing to incorporate new technology into their daily activities, they were more likely to embrace it. Hence, if the MOOC platform is convenient for students to use in their daily lives, they are more likely to accept it.

Additionally, H5 validated that attitude contributes to behavioral intention in this study, indicating the standard coefficient value at 0.153. Park and Kim (2014) interpreted that attitude is an essential indicator of a person's intention to engage in certain actions. This demonstrates that students who have a favorable attitude toward the MOOC platform will more likely to use it.

For H6, Table 2 implements a summary of the 477 respondents' detailed demographic profile information confirming that performance expectancy had a powerful appeal to behavioral intention, culminating in a standard coefficient value of 0.252. According to Batara et al. (2017), performance expectancy was widely accepted as the antecedent variable of the intention to accept cultural and behavioral changes. That is, students' expectations about whether they will be able to obtain academic achievement from the MOOC platform will have a huge impact on their use of the platform.

Ultimately, the subjective norm significantly impacted the behavioral intention, for the standardized path coefficient value at 0.435 in the H7, which was the highest in this study. Yau and Ho (2015) believed that discussions regarding the subjective norm had critically influenced students' behavioral intention in using e-learning. This suggests that undergraduate students will prefer to adopt the MOOC platform if they receive guidance from teachers or professors who are significant to them.

Direct, Indirect, and Total Effects

In this study, 1 dependent variable, 3 mediating variables, and 3 independent variables were investigated. The path diagram results were summarized in Figure 2.

The dependent variable for this investigation was the behavioral intention, with an R^2 of 0.277, indicating that the entire independent factors plus mediator variables could account for 27.7 percent of the variance in behavioral intention. Moreover, three latent variables which were attitude, performance expectancy, and subjective norm had a substantial direct impact on behavioral intention, with the corresponding impact points of 0.153**, 0.252***, and 0.435***.

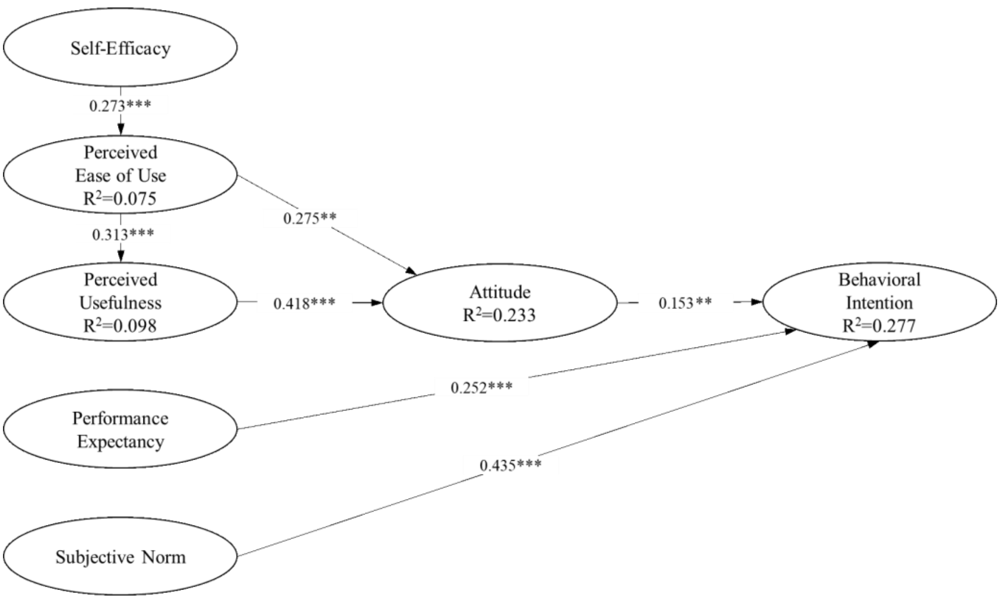
This quantitative approach uses perceived ease of use as the mediator variable, and R^2 of 0.075 shows that self-efficacy explains 7.50 percent of the variance in perceived ease of use. Moreover, a direct correlation of 0.237*** was identified between self-efficacy and perceived ease of use.

Furthermore, perceived usefulness is a mediator variable in this investigation, with R^2 at 0.098, which evidences that perceived ease of user accounts for 9.80 percent of the variance in perceived usefulness. The direct correlation between perceived ease of use and perceived usefulness point was 0.313***.

Besides that, attitude is a meaningful mediator variable in this study, with R^2 equal to 0.233, indicating that perceived ease of use and perceived usefulness account for 23.3 percent of the variance in attitude. The coefficient of determination for the direct relationship between perceived ease of use and attitude point was 0.275**. 0.418*** was the direct link between perceived usefulness and attitude point.

Figure 2

Path Diagram Analysis



Note: *** p<0.001,**p<0.01,* p<0.05
Note: Created by the Author

Conclusions and Recommendations Conclusions

Conclusions

The objective of this research is to explore the main cause of the behavioral intention of students at the Jingdezhen Vocational University of Art who majoring in art and design majors to use the MOOC platform. The conceptual framework was used to construct the seven hypotheses that were used to confirm the link between the perceptions of perceived ease of use, perceived usefulness, self-efficacy, attitude, performance expectancy, subjective norm, and behavioral intention. As a component of the research plan, the scale items were designed and distributed to 500 undergraduate students with experience on the MOOC platform. Confirmatory Factor Analysis (CFA) was used to accomplish scientific calculations to validate the conceptual framework's validity and reliability. Furthermore, the structural equation model (SEM) was applied to strengthen the element influencing behavioral intention, and the data results showed that all hypotheses were well confirmed.

The investigation's findings indicated that subjective norm had the highest direct influence on behavioral intention and directly affected the dependent variable. This suggests that students' behavioral intentions to use MOOC platforms will be largely determined by the influence of the outside environment or by teachers' guidance. Moreover, both attitude and performance expectation are variables affecting behavioral intention, and they have the same standardized path coefficient.

In addition, perceived usefulness is a crucial component of attitude in this quantitative survey which indicates that students' belief in the usefulness of MOOC platforms can increase students' feelings toward the recognition of the platform. Self-efficacy and perceived ease of use have the second-rank and third-rank impact on attitude.

Recommendations for Practice

The fundamental determinants for behavioral intention among art and design majors undergraduates in Jingdezhen Vocational University of Art in Jiangxi province of China have been examined. Based on the data from this quantitative investigation, the researcher suggested that the interconnection between self-efficacy, perceived ease of use, perceived usefulness, attitude, performance expectancy, subjective norm, and behavioral intention should be carefully considered. To generate more rational or advanced educational strategies to improve art and design students' behavioral intentions toward MOOC platforms, the following recommendations are outlined.

In terms of self-efficacy, teachers should cultivate students' awareness of independent learning in the teaching process to increase self-efficacy, students will be encouraged to take the online courses on their own time.

For the subjective norm, teachers and relevant teaching departments shall discuss and formulate online and offline teaching models suitable for art and design majors, take courses on the MOOC platform as one of the aspects of the overall course of teaching, and require students to complete corresponding learning content through the MOOC platform. After students complete the courses, the platform will issue a certificate, and the school can give additional credits to students based on the course completion certificate, in order to improve students' behavioral intentions toward the MOOC platform.

As for the attitude, teachers can publicize the MOOC platform through various channels, share the content of MOOC platform courses in class, and improve students' understanding of it.

Regarding perceived ease of use, teachers and teaching institutions of schools must assist more students in gaining experience with MOOCs. Additionally, MOOCs can promote multi-language communication, improve learner interaction, and provide relevant teaching AIDS for art and design courses, making it easier for students to learn on the MOOC platform. MOOC platform teaching modes should not be rigid and one-sided, but rather vivid, interactive, and growable. Students can ask questions using the platform, the MOOC team can respond to students' questions online at any time, and teachers can constantly optimize course resources and course presentation modes based on students' questions.

Regarding perceived usefulness, the MOOC platform must constantly improve the teaching methods and contents of art and design courses. That means MOOCs will move in the direction of precise and personalized course recommendations in the future. The courses can be organized in stages ranging from entry to mastery, it can fully meet students' learning needs at various stages and assist students in selecting appropriate courses of moderate difficulty. At the same time, art and design education is inextricably linked to practice, when teachers are teaching through MOOCs, teachers must use case studies and incorporate practical projects into the classroom. Practical scenarios and project case analysis should be combined so that students can learn alongside work scenarios rather than in isolation.

Last but not least, the curriculum design should make reasonable use of new media technology and gamification thinking in terms of performance expectancy, when combined with the learning characteristics of art majors. MOOCs for art and design majors, for example, have a lot of questions to answer. Only by correctly answering the questions can students' progress to the next stage of learning new knowledge and completing the art and design knowledge they need to master through multiple stages of listening to the class and answering the questions, thereby improving students' learning effect. This type of game approach allows students to focus on the course, master their learning progress, discover learning problems on time, increase the interest and interaction of online course teaching methods, and improve students' learning outcomes.

Limitations and the Further Exploration

For the research, the scope of the study is limited to undergraduate students in Jingdezhen Vocational University of Art in Jiangxi Province, China, and only 7 potential variables were selected in the conceptual framework. For the follow-up exploration, we can explore from three perspectives: extend the research scope to other universities in Jiangxi Province, China. Secondly, more technology acceptance theories, such as TPB can be considered to support the construction of a research framework. Subsequently, platform data can be mined to record learners' learning behavior data at various stages, checked the factors that influence students' behavioral intention on the platform, and provide more explicit guidance for MOOC platform development.

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