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Factors Influencing the Undergraduate Students of Music Education Use Behavior to Mooc In Guangxi, China

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Abstract

Purpose: The purpose of this study aims to explore undergraduate students' use behavioral to online platform in Guangxi, China. Base on UTAUT2 model to distribute the conceptual framework. **Research design, data and methodology:** This is a quantitative study, using judgment sampling and quota sampling method to choose 500 participants from five universities who have experience for education online platform to collected data. 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:** The results show that model is partially supported by data verification. Behavioral Intention had the strongest influence on use behavioral. Furthermore, Performance Expectancy, Effort Expectancy, Facilitating Condition, Learning Value and Work Life Quality, significantly impacted behavioral intention. Self-Efficacy and Hedonic Motivation had no significant impact on Behavioral Intention. **Conclusions:** This study describes the relationship between all variables, the result and provides data information resources assistance to other educators and technology developers in the future.

Keywords: Music Education, Use Behavior, Behavioral Intention, online plarform, UTAUT2

JEL Classification Code: E44, F31, F37, G15

1. Introduction

The education system is one of the biggest victims of the impact of COVID-19 (Ghosh et al., 2020; Mittal et al., 2021). In order to keep education activities in order, the world is facing an unprepared transition from offline to online education (Kuhfeld et al., 2020). It is precisely because of this change that the further development and promotion of teaching technology are promoted. In addition, substantial research efforts have been undertaken to assess and analyze the impact of the pandemic on higher education outcomes (Aristovnik et al., 2020). In the 21st century, most universities offer not only online courses, but also full online degree programs (Wallace, 2003).

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MOOCs is an online course platform for the masses where people can learn online. It is the latest development of distance education (Kaplan & Haenlein, 2016). MOOCs have brought a lot of convenience to Chinese students during the epidemic, but there are also some problems.

Undergraduate is the foundation of higher education, the results of this study have certain reference value for entrepreneurs, developers, managers, and teachers of online education platforms in universities.

1.1 Objectives of this Research

To explore the factors influencing the use behavior of online education among undergraduate music education students in five public universities in Guangxi Province

1.2 Conceptual Framework

During the development of the conceptual framework of this study, previous literature and models were reviewed, as shown in Figure 1. Based on UTAUT2 model. Zwain (2019) investigated the significant relationship between learning value (LV) and behavioral intention (BI) and use behavior (UB). Tarhini et al. (2017) studied the significant effects of performance expectation (PE), effort expectation (EE), facilitation condition (FC), hedonic motivation (HM), and self-efficacy (SE) on behavioral intention (BI). Samsudeen and Mohamed (2019) found a supportive relationship between quality of work life (WLQ) and behavioral intention (BI).

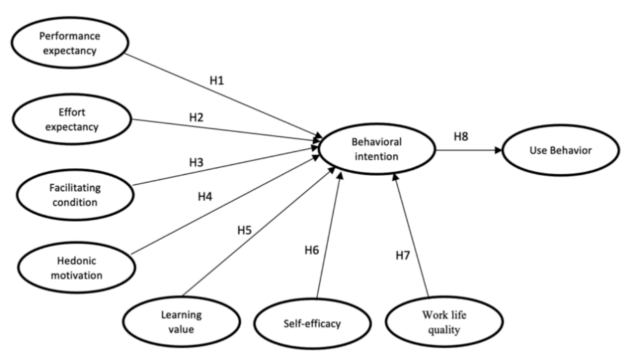

Figure 1: Conceptual Framework
Source: Created by the author

1.3. Significance of the Study

The results of this study have certain reference value for entrepreneurs, developers, managers, and teachers of online education platforms in universities.

These results are valuable to entrepreneurs or developers looking for online education platforms or other online learning courses that offer opportunities to learn, evaluate, report, and analyze technology. This study can fully explain the behavioral intentions and predictors of online education platform use behavior.

2. Literature Review

2.1. Performance Expectancy

Performance Expectancy (PE) represents the level of usefulness associated with using the system (Ali, 2019). Performance Expectancy as the primary prediction structure using learning technology intentions has been widely used in various studies (Gunasinghe et al., 2020; Lwoga & Komba, 2015; Šumak et al., 2010). In addition, Performance Expectancy has a significant impact on scholars' adoption of online learning, and Performance Expectancy is an important predictor of students' willingness to use e-learning (Gunasinghe et al., 2020; Kim & Park, 2018; Samsudeen & Mohamed, 2019). Previous studies on online learning have pointed out the significant impact of PE on behavioral intention or use behavior (El-Masri & Tarhini, 2017; Mosunmola et al., 2018; Pynoo et al., 2011). In addition, other studies have highlighted the significant impact of PE on willingness to adopt online learning tools or platforms (Tarhini et al., 2016; Tseng et al., 2019). Therefore, a hypothesis is proposed:

H1: Performance Expectancy has significant influence on Behavioral Intention

2.2 Effort Expectancy

Effort Expectancy (EE) can be defined as the user's assessment of the Effort required to complete a job by using a specific information system and it is also can defined as the user's observation on system ease-of-use after using the system, and its role is similar to the perceived ease-of-use in TAM (Venkatesh et al., 2003). This variable covers a wide range of fields. UTAUT2 is used in different environments to reveal whether there is a relationship between Effort Expectancy and users' intention of using technology and the application. As for the tourism industry, a study on the positive impact of Effort Expectancy on tourists' willingness to use travel mobile apps was conducted (Gupta et al., 2018). There are studies on the positive correlation between restaurant consumers' intention to use mobile food apps (Okumus et al., 2018). Therefore, a hypothesis is proposed:

H2: Effort Expectancy has significant influence on Behavioral Intention

2.3 Facilitating Condition

Facilitating conditions (FC) is defined as the extent to which the user believes the technology or platform infrastructure supports or facilitates the system in use (Venkatesh et al., 2003). The study of El-Masri and Tarhini (2017) showed that FC was found to have a significant positive correlation effect on college students' willingness to use e-learning systems. FC was also found to be an important independent variable of the behavioral intention of the elderly to use ICT (Macedo, 2017). At the same time, FC indicates the degree of control users have over the use of a technology, or the extent to which a resource is available to facilitate individuals to accomplish a particular task through the use of technology (Ajzen, 1991; Venkatesh et al., 2012). Therefore, a hypothesis is proposed:

H3: Facilitating Condition has significant influence on Behavioral Intention

2.4 Hedonic Motivation

Hedonic Motivation (HM) is defined as the joy, fun and enjoyment obtained by users in the use of platform or technology (Venkatesh et al., 2012). The study of Okumus et al. (2018) shows that HM is an important predictor of the acceptance of e-learning technology, and enjoyment will stimulate the willingness of users to adopt the technology. Lin et al. (2017) found that HM significantly influenced consumers' willingness to use online travel service platforms. HM has been found to influence behavioral intention in many studies (Ali, 2019; Venkatesh et al., 2012). HM also influences use behavior (Hoi, 2020; Šumak & Sorgo, 2016). Therefore, a hypothesis is proposed:

H4: Hedonic Motivation has significant influence on Behavioral Intention

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2.5 Learning Value

Learning Value (LV) can be defined as the degree of perceived value of users' time and effort spent on the system, platform, or technology (Ain et al., 2015). In the study of Ain et al. (2015), the Learning Value structure was added to consider the influence on LMS. The extended variable was verified in the LMS system, showing a good measurement model fitting, and LV showed a strong influence on the behavior intention of the LMS system. The research of Heijden and Spurk (2019) shows that the learning value of work is significantly positively correlated with expectation and optimization, enterprise consciousness and balance. Therefore, a hypothesis is proposed:

H5: Learning Value has significant influence on Behavioral Intention

2.6 Self-Efficacy

Self-efficacy is defined as users' judgment or perception of their own abilities during use, or users' perception of their ability to use computers when completing tasks (Bandura, 1997; Compeau & Higgins, 1995; Tarhini et al., 2017). Many studies show that self-efficacy is an important predictor that can directly affect users' behavioral intentions (Downey, 2006; Guo & Barnes, 2007; Hernandez et al., 2009). Bandura (1997) believes that there is no universal self-efficacy. Due to the differences in different fields of activities, the required abilities and skills also vary greatly, which all refer to self-efficacy associated with a specific field. Therefore, a hypothesis is proposed:

H6: Self-Efficacy has significant influence on Behavioral Intention

2.7 Work Life Quality

Work life quality (WLQ) refers to people's perception t hat the use of certain technology in Work or life will impro ve their efficiency (Samsudeen & Mohamed, 2019). Althou gh many studies (Kripanont, 2007; Tarhini et al., 2014) inv estigated the importance of Work life quality, and few studi es focused on the field of online learning platform (Tarhini et al., 2014). The study of Samsudeen and Mohamed (2019) replaces price values and habits with Work life quality an d Internet experience. Therefore, a hypothesis is proposed:

H 7 : Work Life Quality has significant influence on Behavioral Intention

2.8 Behavioral Intention

Behavioral intention (BI) represents the user's intention to use the system or platform, the possibility of an individual participating in a specific activity, or the strong commitment of the user to participate in a specific behavior (Venkatesh et al., 2003; Yakubu & Dasuki, 2018; Zhang et al., 2020). In addition, the strength of an individual's commitment to engage in a particular behavior can be assessed by behavioral intention (Ngai et al., 2007). Many studies have reported that behavioral intention to use significantly affects actual system use (Davis, 1989; Motaghian et al., 2013; Raman & Don, 2013). Therefore, a hypothesis is proposed:

H8: Behavioral Intention has significant influence on Use Behavior

2.9 Use Behavior

Use behavior (UB) refers to the user's continuous commitment to a product or service, which is the most important variable in UTAUT2 architecture (Black, 1983; Venkatesh et al., 2003). Hart and Sutcliffe (2019) argue that

UB is a default rather than an explicit measurement or evaluation. Most of these studies evaluate the use or adoption of m-learning only. To test whether students and teachers are prepared to properly manage the educational process with social distancing, the focus is on the actual use of m-learning rather than unproven intentions (Sitar-Taut & Mican, 2021).

3. Research Methods and Materials

3.1 Research Methodology

In this quantitative study, a mixed sampling method was used to sample the undergraduate students majoring in music education from five public universities in Guangxi Province. The questionnaire design is divided into three parts, Screening questions to determine the qualifications of survey respondents. Demographic information, including gender and age. Using five-point Likert scale to measure items, 5 point indicates strongly agree and 1 point indicates strongly disagree.

Three experts and professionals were invited to complete the item-objective congruence (IOC) content validity index. Results: The scale items score above 0.67 was accepted. In terms of pilot test validity assessment, 30 respondents were invited. The Cronbach's Alpha scale came from 30 college students, and the results showed that all scale items score above 0.70. For the data collection of this study, 500 undergraduates from five universities were invited to finished questionnaire. JAMOVI and AMOS were used as statistical tools to test confirmatory factor analysis (CFA) and structural equation models (SEM).

3.2 Population and Sample Size

This study takes the undergraduate music education students of five public universities in Guangxi as the research object. According to Soper (n.d.) algorithm, the minimum sample size for a complex framework in SEM should be at least 460 respondents. Through judgment sampling and quota sampling, 500 students were selected from 3620 students as the final sample.

3.3 Sampling Techniques

The sampling process involves several steps. First, the researchers used judgment sampling to select 3,620 music education students from five public universities in Guangxi Province, China, who had at least one month's prior experience with an online learning platform. The quota sampling method was used to allocate 500 students to each university. In order to facilitate sampling, the questionnaire was distributed online through the Jinshan form platform.

Table 1: Sample Units and Sample Size

Target Public Universities	Population Size Total = 3620	Proportional Sample Unit Size Total = 500
University A	1300	180
University B	1000	138
University C	320	44
University D	200	28
University E	800	110
Total	3620	500

Source: Created by the author.

4. Results and Discussion

4.1 Demographic Information

The data are distributed among students majoring in music education in five colleges and universities in Guangxi. Among them, there were 113 males and 387 females, accounting for 22.6% and 77.4% respectively. There are 161 freshmen, 173 sophomores and 166 juniors, accounting for 32.2%, 34.6% and 33.2% respectively.

4.2 Confirmatory Factor Analysis (CFA)

Confirmatory factor analysis (CFA) was used to evaluate the measurement model. CFA can also be used to analyze reliability and validity and determine whether the structure and load of each observed variable are consistent with the hypothesis (Byrne, 2010; Malhotra et al., 2017). In this study, the average variance extracted (AVE) measure is used to investigate the convergence validity, and the minimum acceptable value of AVE is 0.50(Hair et al., 2013).

CFA was used to verify the structure number and the factor load of the 36 observed variables. The measurement model was adjusted to 2.350 degrees of freedom (CMIN/DF), the goodness of Fit index (GFI) was 0.873, the adjusted Goodness of Fit index (AGFI) was 0.848, the normalized fitting index (NFI) was 0.953, and the comparative fitting index (CFI) was 0.973. The Tuck-Lewis index (TLI) is 0.969 and the approximate root mean square error (RMSEA) is 0.052. Therefore, the results present an acceptable model fit in the CFA. According to the CFA statistical results summarized in Table 2, when Cronbach's Alpha value is greater than 0.70, factor load is greater than 0.30, p value is less than 0.05, compound reliability (CR) is greater than 0.70, and mean variance extraction (AVE) is greater than 0.50, All values are accepted (Fornell & Larcker, 1981).

Table 2:Confirmatory Factor Analysis Result, Composite Reliability (CR) and Average Variance Extracted (AVE)

Laten Variable	Source of Questionnaire	No. of Items	Cronbach's Alpha	Factor Loadings	CR	AVE
Performance Expectancy	Tarhini et al. (2017)	5	0.989	0.821~0.896	0.942	0.764
Effort Expectancy	Tarhini et al. (2017)	4	0.982	0.887~0.899	0.940	0.769
Facilitating Condition	Tarhini et al. (2017)	4	0.990	0.889~0.902	0.941	0.800
Hedonic Motivation	Tarhini et al. (2017)	4	0.985	0.826~0.885	0.925	0.755
Learning Value	Zwain (2019)	3	0.980	0.886~0.905	0.926	0.806
Self-Efficacy	Tarhini et al. (2017)	4	0.981	0.875~0.894	0.937	0.787
Work Life Quality	Samsudeen and Mohamed (2019)	4	0.983	0.890~0.899	0.940	0.797
Behavioral Intention	Zwain (2019)	5	0.989	0.884~0.901	0.952	0.797
Use Behavior	Samsudeen and Mohamed (2019)	3	0.955	0.891~0.900	0.923	0.800

Convergent validity is determined when CR value is higher than AVE, and convergent validity is determined when AVE value is higher than 0.50 (Hair et al., 2006). The value of discriminant validity is tested and demonstrated and exceeds the critical value. Subsequently, the convergence validity and discriminative validity of this study were sufficient (Fornell & Larcker, 1981). (In Table 3)

Table 3: Discriminant Validity

	PE	EE	FC	HM	LV	SE	WL	BI	UB
PE	**.874**								
EE	.126	**.892**							
FC	.165	.243	**.894**						
HM	.056	.075	.202	**.868**					
LV	.016	.220	.234	.205	**.897**				
SE	.034	.134	.143	.181	.315	**.887**			
WL	.021	.045	.086	.170	.188	.172	**.892**		
BI	.115	.223	.313	.168	.364	.194	.220	**.892**	
UB	.135	.239	.191	.134	.296	.084	.095	.454	**.894**

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

4.3 Structural Equation Model (SEM)

In this study, two methods were used to verify the degree of fit between variables. First, CFA method was used to verify the degree of fit between variables, and then structural equation model (SEM) was used to estimate and verify the fit of the model. Table 4 shows the results adjusted by the IBM AMOS statistical program, including all CMIN/DF, GFI, AGFI, CFI, TLI, and RMSEA values. In conclusion, after SEM verification, every goodness-of-fit index in this study is satisfactory.

Table4: Goodness of Fit for Structural Model

Index	Criterion	Source	After Adjustment Values
CMIN/DF	< 5.0	Hair et al. (2010)	1.237
GFI	≥0.85	Sica and Ghisi (2007)	0.926
AGFI	≥0.80	Sica and Ghisi (2007)	0.916
NFI	≥0.80	Arbuckle (1995)	0.805
TLI	≥0.80	Hair et al. (2006)	0.946
CFI	≥0.80	Hair et al. (2006)	0.950
RMSEA	< 0.08	Pedroso et al. (2016)	0.025

Source: Created by the author.

4.4 Research Hypothesis Testing Result

Regression weights and R2 variance were used to calculate the significance of each variable. Table 5 shows the calculation results of each structure path.

Behavioral Intention had the strongest impact on Use Behavior, with the standardized path coefficient (β) result of 0.936 (t-value = 5.25***).

Learning Value significantly impacted Behavioral Intention, with β as 0.648 (t-value = 5.195**).

Facilitating Condition significantly impacted Behavioral Intention, with β as 0.251 (t-value = 3.200**).

Work Life Quality significantly impacted Behavioral Intention, with β as 0.230 (t-value = 2.045**).

Performance Expectancy significantly impacted Behavioral Intention, with β as 0.177 (t-value = 2.537**).

Effort Expectancy significantly impacted Behavioral Intention, with β as 0.145 (t-value = 2.965**).

Self-Efficacy had no significant impact on Behavioral Intention, with β as 0.170 (t-value = 1.112).

Hedonic Motivation had no significant impact on Behavioral Intention, with β as 0.095 (t-value = 0.999).

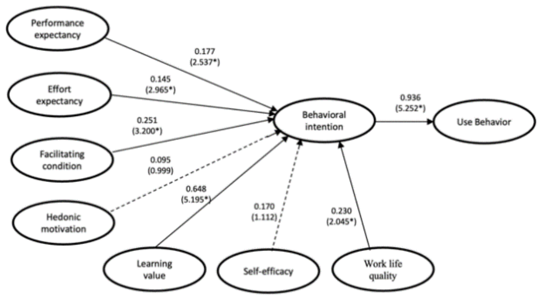

Figure 2: Structural Equation Model (SEM) Note: *** p<0.001, ** p<0.01, * p<0.05
Source: Created by the author

Table 5: Hypothesis Result of the Structural Equation Modeling

Hypothesis	Paths	Standardized Path Coefficient(β)	t-Value	Tests Result
H1	PE→ BI	0.177	2.537*	Supported
H2	EE→ BI	0.145	2.965*	Supported
H3	FC→ BI	0.251	3.200*	Supported
H4	HM→ BI	0.095	0.999	Not Supported
H5	LV→ BI	0.648	5.195*	Supported
H6	SE→ BI	0.170	1.112	Not Supported
H7	WLQ→ BI	0.230	2.045*	Supported
H8	BI→ UB	0.936	5.252*	Supported

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

Based on the information in Figure 2 and Table 5, it might be able to get the following extensions.

Learning value has the greatest influence on behavioral intention. The standardized path coefficient of learning value and behavioral intention is 0.648, and the t value in H5 is 5.195. Facilitating Condition has a significant effect on behavioral intention, and the standardized path coefficient and t value in H3 are 0.251 and 3.200. Effort Expectancy has a significant impact on behavior intention, and the standardized path coefficient and t value in H2 is 0.145 and 2.965. Work Life Quality has a significant effect on behavioral intention, and the standardized path coefficient in H7 is 0.230, and the T-value is 2.045. Performance Expectancy has a significant impact on behavior intention, and the standardized path coefficient and t value in H1 is 0.177 and 2.573. Behavioral intention has a significant effect on Use Behavior, and the standardized path coefficient and t value in H8 are 0.936 and 5.252.

When the standardized path coefficient of H4 was 0.095 and the T-value was 0.999, Hedonic Motivation had no significant influence on behavioral intention. In H6, Self-Efficacy has no significant effect on behavioral intention when standardized path coefficient is 0.170 and T-value is 1.112.

5. Conclusions

5.1 Conclusion

This quantitative science survey identifies the factors influencing the university music education of undergraduate students' use behavior to online education platform in Guangxi, China. A total of 500 valid questionnaires were collected. Base on the UTAUT2 model and literature review. Performance Expectancy, Effort Expectancy, Facilitating Condition, Hedonic Motivation, Learning Value, Self-Efficacy, Work Life Quality and Behavioral Intention is a characteristic of the latent variable. The internal consistency reliability, convergence validity and discriminant validity of JAMOVI 2.2.5 and AMOS 26 were evaluated using data validation methods such as confirmatory factor analysis. In addition, structural equation models were used to evaluate all hypotheses, confirming important determinants of use behavioral in this study. In the measurement model and structural model, a variety of evaluation methods are used. A comparative critical ratio assessment of the parameter prediction was also performed to measure the path variability generated by various latent variables.

The study results show that the degree of impact of Learning Value is most valued by participants, which is of great value to entrepreneurs or developers looking for online education platforms or other e-learning courses that offer technical opportunities to learn, evaluate, report, and analyze.

Secondly, the research results show that Hedonic Motivation and Self-Efficacy have no significant statistical effect on behavioral intention, which also reminds us that the management and teachers of higher education institutions can identify more variables that affect the use of students' learning management system and provide tools for further analysis of investment and optimization of online education platforms.

5.2 Recommendation

The data collection and data analysis obtained only represent Guangxi region of China, it cannot represent other regions. At the same time, with the development of science and technology, the new generation is becoming famous for technology and digital native, so the integration of technology and teaching will be more and more, the choice of technology will be huge of the research. Therefore, as a researcher, would suggest that in future studies, more newer technologies should be considered to integrate into teaching, and more variables can be studied to get more comprehensive conclusions.

5.3 Limitation

Due to the limitation of the research period and the research region, this study only conducted a study on universities in Guangxi region of China with a short period. The limitation of this study is that the number of samples is not large enough, and the sample of the target population through a series of sampling methods may lead to the problem of insufficient representativeness of the study.

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