International Journal of Sociologies and Anthropologies Science Reviews
Volume 5 Issue 1: January-February 2025: ISSN 2985-2730
Website: https://so07.tci-thaijo.org/index.php/IJSASR/index

Influencing Factors of Art Students' Behavioral Intention on XueXitong Usage Among Three Universities, Chengdu, China

Yi Jiang[1] and Satha Phongsatha[2]
[1]Ph.D. Candidate, Graduate School of Business and Advanced Technology Management, Assumption University, Bangkok, Thailand
[2]Program Director of M.Ed. Teaching and Technology, Graduate School of Business and Advanced Technology Management, Assumption University, Bangkok, Thailand
[1]E-mail: 258605294@qq.com, ORCID ID: https://orcid.org/0009-0003-7496-9850
[2]E-mail: sathaphn@au.edu, ORCID ID: https://orcid.org/0000-0002-7035-4678

Received 22/08/2024 Revised 31/08/2024 Accepted 31/09/2024

Abstract

Background and Aim: Facing the increasingly prevalent trend of online education among art students in China, This study aims to investigate the factors influencing the behavioral intentions of art students at three universities in Chengdu toward the use of XueXiTong. Drawing on the Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB), and the extended Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), a conceptual framework was established. Nine variables were selected for this study: Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Attitude (ATT), Habit (H), Performance Expectancy (PE), Effort Expectancy (EE), Behavioral Intention (BI), Subjective Norm (SN), and Actual Usage (AU).

Materials and Methods: The researcher used a quantitative method, distributing questionnaires to 500 respondents through online channels. The data were analyzed using confirmatory factor analysis and structural equation modeling to validate the goodness of fit of the model, determine causal relationships between variables, and perform hypothesis testing.

Results: The data analysis results indicated that all variables had a significant impact on the behavioral intention of art major students to use XueXiTong in Chengdu, China, and all hypotheses were supported. Among the variables, behavioral intention was found to have the greatest effect on actual usage.

Conclusion: The study findings suggest that enhancing students' perceived ease of use and perceived usefulness of XueXiTong, along with improving their attitude, subjective norm, effort expectancy, performance expectancy, and habit, significantly influences their behavioral intention and actual usage of the platform. These findings emphasize the importance of optimizing these factors for effectively promoting the use of XueXiTong among art students at three universities in Chengdu, China.

Keywords: Higher education; Art major; XueXiTong; Behavioral intention; Actual usage

Introduction

The development and widespread adoption of information technology has made educational informatization a prominent trend in university education. Since the 1990s, China has been actively constructing and promoting educational information. Presently, the level of educational informatization in universities indicates a region or institution's comprehensive strength. Despite not initially applying the Internet for higher education until 1999, China's higher education sector has made substantial strides in distance education over the years (Li, 2009). Large-scale remote online teaching is well-established (Zhang, X., 2020).

Since art studies were established as an independent discipline in China in 2011, the enrollment of students in art-related majors has consistently increased year-on-year, highlighting the significant role that art students now play in the country's higher education landscape.

XueXiTong, a professional mobile learning platform compatible with smartphones, tablets, and other mobile terminals, has been selected as an online teaching platform by multiple universities in Chengdu.

In this context, online education has broadened research and learning opportunities in the field of art. However, due to the nature of art majors, which emphasizes the integration of theory and practice in teaching (Xia, W., 2017), art students exhibit distinct learning behaviors compared to students in other majors, demonstrating unique characteristics when engaging in online learning.

Citation
Yi, J., & Phongsatha, S. (2025). Influencing Factors of Art Students' Behavioral Intention on XueXitong Usage Among Three Universities, Chengdu, China. International Journal of Sociologies and Anthropologies Science Reviews, 5 (1), 837-852. DOI: https://doi.org/10.60027/ijsasr.2025.5505

International Journal of Sociologies and Anthropologies Science Reviews
Volume 5 Issue 1: January-February 2025: ISSN 2985-2730
Website: https://so07.tci-thaijo.org/index.php/IJSASR/index

Current research indicates two primary issues: firstly, there is a lack of studies on the relationship between online learning and art majors. Secondly, there is limited research on students' behavioral intentions and use of online learning. Given these factors, this study focuses on art students from universities in Chengdu to conduct an in-depth analysis of the influencing factors that promote online learning.

Objectives

The research aims to reveal the causal relationships among the nine selected variables in terms of the behavioral intention to use XueXiTong among art students at three universities in Chengdu. These variables include perceived ease of use, perceived usefulness, attitude, performance expectations, effort expectations, habit, subjective norms, behavioral intention, and actual usage.

Literature review

The conceptual framework of this study is constructed based on three theoretical frameworks: the Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB), and the Unified Theory of Acceptance and Use of Technology (UTAUT2). Based on this framework, nine variables were identified: perceived ease of use (PEOU), perceived usefulness (PU), performance expectancy (PE), effort expectancy (EE), habit (H), subjective norms (SN), attitude (ATT), behavioral intention (BI), and actual usage (AU).

Perceived Ease of Use

Perceived ease of use refers to the extent to which an individual perceives that using a specific technology will not be complicated (Davis, 1989). In the context of e-learning, perceived ease of use relates to the degree to which a student believes that using an e-learning system will not be demanding and will be straightforward (Salloum et al., 2019). Within the context of MOOCs, perceived ease of use can be defined as the extent to which an individual believes that using MOOCs will be effortless. An example of this concept could be how easily someone can acquire skills using MOOCs (Wu & Chen, 2017). Perceived ease of use plays a crucial role in shaping attitudes and perceived usefulness toward adopting e-learning 2.0 (Wu & Zhang, 2014). Accordingly, this research hypothesizes the following:

H1: Perceived ease of use has a significant influence on attitude.

H2: Perceived ease of use has a significant influence on perceived usefulness.

Perceived Usefulness

Perceived usefulness refers to the extent to which an individual believes that using information technology or a system can improve their work performance. In other words, users tend to hold a positive attitude toward systems that enhance their work (Venkatesh et al., 2003). According to Davis (1989), perceived usefulness is another crucial construct that predicts intention in the Technology Acceptance Model (TAM). When applied to MOOCs, "perceived usefulness" can be described as the extent to which an individual believes that MOOCs can act as a driving force toward achieving their learning goals (Wu & Chen, 2017). Perceived usefulness directly influences attitude, adding value to the existing MOOC learning approach (Yang & Su, 2017). Accordingly, this research hypothesizes the following:

H3: Perceived usefulness has a significant influence on attitude.

Subjective Norm

Subjective norm is defined as an individual's perception of the consensus among significant individuals in their social circle regarding whether they should or should not engage in a specific behavior within a particular context (Khoa et al., 2020). Subjective norms are influenced by normative beliefs and motivations to conform to social expectations (Dong et al., 2023). In the context of online learning, subjective norms represent students' perceptions of others' views, especially those significant to them, such as their lecturers and peers, regarding the performance of the same behavior (Cheon et al., 2012). Lin et al. (2013), DiGuiseppi et al. (2018), and Taylor and Todd (1995) found that when students are

Citation
Yi, J., & Phongsatha, S. (2025). Influencing Factors of Art Students' Behavioral Intention on XueXitong Usage Among Three Universities, Chengdu, China. International Journal of Sociologies and Anthropologies Science Reviews, 5 (1), 837-852. DOI: https://doi.org/10.60027/ijsasr.2025.5505

influenced by important social connections such as peers, friends, and educators, their behavioral intention toward MOOC learning can be significantly affected. Accordingly, this research hypothesizes the following:

H4: Subjective norm has a significant influence on behavioral intention.

Attitude

Attitude is defined as an individual's inclination or desire to use a system (Karjaluoto et al., 2002). Regarding MOOCs, the attitude toward using them can be seen as the degree to which an individual perceives positive or negative emotions related to MOOCs (Wu & Chen, 2017). Numerous researchers (Davis, 1989; Lee et al., 2005; Liu et al., 2009) have consistently demonstrated that attitude serves as a direct determinant of behavioral intention. As Rabaa'i (2016) pointed out, a student's behavioral intention can be influenced by their feelings towards the system. If students have a negative perception of the system or experience discomfort when using it, they are more likely to consider switching to a different one. Accordingly, this research hypothesizes the following:

H5: Attitude has a significant influence on behavioral intention.

Habit

Habit is defined as an automated behavioral pattern in a specific context that is relatively independent of an individual's goals and intentions (Venkatesh et al., 2012). Limayem et al. (2007) describe habit as the degree to which people tend to automatically perform a behavior due to prior learning, while Kim, S. S. and Malhotra (2005) equate habit with automaticity. Jameel et al. (2020) found that habit has a positive and significant impact on behavioral intention to use e-learning, meaning that habit increases the acceptance of using e-learning among university students. As a result, the sixth hypothesis suggested in the study is the following:

H6: Habit has a significant influence on behavioral intention.

Performance Expectancy

Performance expectancy is defined as "the extent to which an individual believes that using the system will contribute to improving their job performance" (Davis et al., 1992; Shin, 2009; Venkatesh et al., 2003). In essence, performance expectancy is the anticipation that using technology for a specific activity will enhance the user's performance (Singh & Matsui, 2017). It reflects an individual's assessment of the external benefits derived from the adoption or utilization of technology (Sharif et al., 2019). In several online contexts, including the acceptance of blended learning (Azizi et al., 2020), use of e-learning (Tarhini et al., 2017; Thongsri et al., 2020), adoption of mobile learning in the context of higher education (Arain et al., 2019), use of learning management systems (Ain et al., 2015), and factors influencing the adoption of online teaching by school teachers (Tandon, 2020), performance expectancy has been shown to influence behavioral intention to use a system. As a result, the seventh hypothesis suggested in the study is the following:

H7: Performance expectancy has a significant influence on behavioral intention.

Effort Expectancy

Effort expectancy is defined as "the degree of ease associated with the use of a system" (Raman & Don, 2013; Venkatesh et al., 2003). Effort expectancy pertains to the extent to which a user anticipates that using a technology (e.g., online learning) will be straightforward and uncomplicated (Goto & Munyai, 2022). In the context of effort expectancy, when the use of e-learning applications is perceived as easy, clear, and user-friendly, and students can become proficient in using them without much difficulty, they are more likely to use these applications (Venkatesh et al., 2003). In several studies, including the acceptance of blended learning (Azizi et al., 2020), the use of e-learning (Handoko, 2019), and the use of learning management systems (Widjaja et al., 2019), effort expectancy has been shown to influence behavioral intention. As a result, the eighth hypothesis suggested in the study is the following:

Citation
Yi, J., & Phongsatha, S. (2025). Influencing Factors of Art Students' Behavioral Intention on XueXitong Usage Among Three Universities, Chengdu, China. International Journal of Sociologies and Anthropologies Science Reviews, 5 (1), 837-852. DOI: https://doi.org/10.60027/ijsasr.2025.5505

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

Behavioral Intention

Behavioral intention refers to the motivational factor driving a user to use a particular system or technology in the future (Venkatesh et al., 2003). Ajzen (1991) states that behavioral intention is the most immediate predictor of actual behavior. In the context of e-learning, behavioral intention (BI) refers to learners' intent to use e-learning systems and involves sustained use from the present into the future (Liao & Lu, 2008). In several studies, including the use of e-learning (Salloum et al., 2019) and the use of learning management systems (Ikhsan & Prabowo, 2021), behavioral intention has been shown to influence actual use. Alwahaishi (2021) found that students who had a higher level of intention to use the technology were positively influenced toward the actual use of e-learning. As a result, the ninth hypothesis suggested in the study is the following:

H9: Behavioral intention has a significant influence on actual usage.

Actual Usage

Actual usage is defined as the frequency and extent of technology usage, including usage frequency and times ((Kim, B. G. et al., 2007)). It refers to the level of system use by the user (Chen et al., 2018). Actual usage is further defined as the degree and manner in which users employ the capabilities of an information system. This includes the amount of use, frequency of use, nature of use, appropriateness of use, extent of use, and purpose of use (DeLone & McLean, 2016). Among these, Venkatesh and Davis (2000), Heijden (2003), and Dishaw and Strong (1999) all found that intention significantly influenced the actual use of an online portal, website, and information technology, respectively. In the context of mobile use, both Kim, B. (2012) and Cheong and Park (2005) reported positive relationships between users' intention to use and their actual use of mobile services.

Conceptual Framework

The conceptual framework of this study is based on three theories: TAM, TPB, and UTAUT2. The Technology Acceptance Model (TAM) was initially proposed by Davis (1989) to explain and predict computer technology adoption. Mason's (2007) results of the study show that TAM can be used to explain the students' acceptance of e-learning technology. The Theory of Planned Behavior (TPB) aims to explain the behavior of individuals based on the belief–altitude relationship and intention behavior. Gómez-Ramirez et al. (2019) study results suggest that all of the constructs of TPB and TAM have a moderate impact on the intention to adopt m-learning. The extended unified theory of acceptance and use of technology (UTAUT2) is an extension of the unified theory of acceptance and use of technology (UTAUT). It has been mainly used for explaining the reasons behind technology adoption by organizations. Terblanche et al. (2023) research results show that UTAUT2 can be used to examine the relevance of its constructs in understanding students' intent to use e-learning applications.

Citation
Yi, J., & Phongsatha, S. (2025). Influencing Factors of Art Students' Behavioral Intention on XueXitong Usage Among Three Universities, Chengdu, China. International Journal of Sociologies and Anthropologies Science Reviews, 5 (1), 837-852. DOI: https://doi.org/10.60027/ijsasr.2025.5505

International Journal of Sociologies and Anthropologies Science Reviews
Volume 5 Issue 1: January-February 2025: ISSN 2985-2730
Website: https://so07.tci-thaijo.org/index.php/IJSASR/index

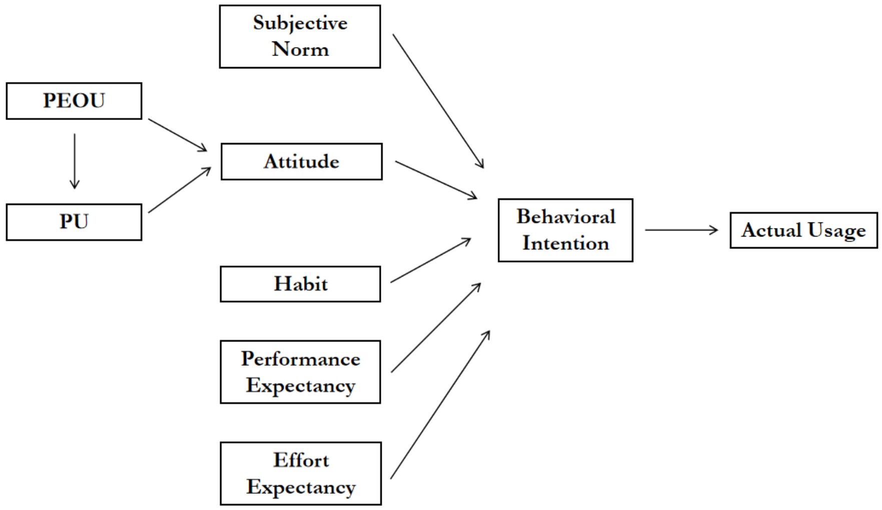

Figure 1 Conceptual Framework

Methodology

Research Methodology

Data were collected using an online questionnaire that was structured into three main sections: screening questions to ensure that participants met the inclusion criteria (at least one year of XueXiTong usage experience and sophomore or above); demographic information, including gender, grade, and university; and scaling questions designed to measure the nine variables of interest. Before distribution, three experts evaluated the questionnaire for Project Objective Consistency (IOC), and a pilot test involving 30 students was conducted to assess the internal consistency reliability of each questionnaire section, ensuring the reliability and consistency of the research tool.

The questionnaire was distributed online to the target population of art major students at three universities in Chengdu. To maximize the diversity of the sample and encourage participation, the questionnaire was shared with different teachers, who then forwarded it to their students. Additionally, students were encouraged to share the questionnaire with their classmates. Ultimately, 500 valid responses were obtained.

The collected data were analyzed using SPSS and AMOS software. Confirmatory Factor Analysis (CFA) was employed to validate the structural validity and model fit, while Structural Equation Modeling (SEM) was used to demonstrate the significant impact between variables and to test the research hypotheses.

Population and Sample Size

The target population for this study was art students from three universities in Chengdu. To determine the minimum sample size required for the study, the researchers used a statistical calculator, which indicated a minimum of 460 participants (Soper, 2022). To better conduct the study, the sample size was set at 500.

Sampling Techniques

This study is based on the non-probability sampling method, primarily completed through two steps: judgment sampling and quota sampling. First, a judgment sampling technique was used to select 3076 art students with experience in using XueXiTong from three universities in Chengdu. Then, quota sampling was applied to calculate the individual sample size for each university within a total of 500 samples. The specific sampling information is shown in Table 1.

Citation
Yi, J., & Phongsatha, S. (2025). Influencing Factors of Art Students' Behavioral Intention on XueXitong Usage Among Three Universities, Chengdu, China. International Journal of Sociologies and Anthropologies Science Reviews, 5 (1), 837-852. DOI: https://doi.org/10.60027/ijsasr.2025.5505

Table 1 Sample units and sample size of 3 universities

Universities	Grade	First Stage Sample Size Total= 3076	Proportional Sample Size Total = 500
Sichuan Tourism University College of Art	Sophomore	238	39 (238*500/3076)
	Junior	240	39 (240*500/3076)
	Senior	245	40 (245*500/3076)
College of Chinese & Asian Arts	Sophomore	137	22 (137*500/3076)
	Junior	163	26 (163*500/3076)
	Senior	199	32 (199*500/3076)
College of Art Design and Animation of Sichuan University of Media and Communications	Sophomore	485	79 (485*500/3076)
	Junior	681	111 (681*500/3076)
	Senior	688	112 (688*500/3076)

Results

Demographic Information

Table 2 provides a detailed descriptive statistical summary of the demographic characteristics of the 500 respondents. According to the statistics, there were 199 male respondents, accounting for 39.8% of the total, and 301 female respondents, accounting for 60.2%. In terms of the academic year, there were 104 second-year students, representing 20.8% of the total; 171 third-year students, representing 34.2%; and 95 fourth-year students, representing 19%. Regarding the duration of using the Chaoxing Learning platform, 89 respondents had been using it for less than one year, accounting for 17.8%; 243 respondents had been using it for 1-2 years, accounting for 48.6%; and 168 respondents had been using it for more than two years, accounting for 33.6%.

Table 2 Demographic Information of Samples

Demographic Information (N=500)		Frequency	Percentage
Gender	Male	199	39.8%
	Female	301	60.2%
Education level	Sophomore	104	20.8%
	Junior	171	34.2%
	Senior	95	19%
experience in using XueXiTong	Less than 1 year	89	17.8%
	1-2 years	243	48.6%
	More than 2 years	168	33.6%

Citation
Yi, J., & Phongsatha, S. (2025). Influencing Factors of Art Students' Behavioral Intention on XueXitong Usage Among Three Universities, Chengdu, China. International Journal of Sociologies and Anthropologies Science Reviews, 5 (1), 837-852. DOI: https://doi.org/10.60027/ijsasr.2025.5505

Confirmatory Factor Analysis (CFA)

The confirmatory factor analysis (CFA) model encompasses both observed and latent variables, facilitating an assessment of internal consistency, reliability, and construct validity (Muhamad Safiih & Azreen, 2016). Using AMOS software, the study analyzed a dataset consisting of 500 observations to evaluate the model fit indices, which are presented in Table 3. CMIN/df was 1.750, GFI was 0.905, AGFI was 0.886, NFI was 0.910, CFI was 0.959, TLI was 0.954, and RMSEA was 0.039. When compared to the Acceptable Criteria, these results indicate that the model exhibits a good fit to the data.

Table 3 Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/df	< 5.00 (Awang, 2012; Al-Mamary & Shamsuddin, 2015)	1.750
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.905
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.886
NFI	≥ 0.80 (Wu & Wang, 2006)	0.910
CFI ≥	≥ 0.80 (Bentler, 1990)	0.959
TLI	≥ 0.80 (Sharma et al., 2005)	0.954
RMSEA	< 0.08 (Pedroso et al., 2016)	0.039
Model Summary		Acceptable Model Fit

Remark: CMIN/DF = The ratio of the chi-square value to the degree of freedom, GFI = Goodness-of-fit index, AGFI = Adjusted goodness-of-fit index, NFI = Normed fit index, CFI = Comparative fit index, TLI = Tucker-Lewis index, and RMSEA = Root mean square error of approximation

Based on the data provided in Table 4, all measurement item factor loadings were greater than 0.5 and statistically significant ($p < 0.05$). All variables had composite reliability (CR) values exceeding 0.7. The results also indicated that all variables had average variance extracted (AVE) values greater than 0.4. According to Hair et al. (2006), factor loadings should be higher than 0.50, and p-values should be less than 0.05. Additionally, following the recommendations by Fornell and Larcker (1981), the CR exceeded the threshold of 0.7, and the AVE was above the cutoff point of 0.4. These findings suggest that the model has acceptable convergent validity.

Table 4 Confirmatory Factor Analysis Result, Composite Reliability (CR) and Average Variance Extracted (AVE)

Variable	Factors Loading	t-value	CR	AVE
Perceived ease of use (PEOU)			**0.903**	**0.700**
PEOU1	0.824	21.315*		
PEOU2	0.904	24.110*		
PEOU3	0.794	20.235*		
PEOU4	0.821	-		
Perceived usefulness (PU)			**0.890**	**0.622**

Citation
Yi, J., & Phongsatha, S. (2025). Influencing Factors of Art Students' Behavioral Intention on XueXitong Usage Among Three Universities, Chengdu, China. International Journal of Sociologies and Anthropologies Science Reviews, 5 (1), 837-852. DOI: https://doi.org/10.60027/ijsasr.2025.5505

International Journal of Sociologies and Anthropologies Science Reviews
Volume 5 Issue 1: January-February 2025: ISSN 2985-2730
Website: https://so07.tci-thaijo.org/index.php/IJSASR/index

Variable	Factors Loading	t-value	CR	AVE
PU1	0.828	20.000*		
PU2	0.805	14.329*		
PU3	0.885	21.683*		
PU4	0.625	19.310*		
PU5	0.775	-		
Attitude (ATT)			**0.912**	**0.723**
ATT1	0.877	-		
ATT2	0.779	21.948*		
ATT3	0.819	23.953*		
ATT4	0.920	29.953*		
Effort expectancy (EE)			**0.782**	**0.474**
EE1	0.664	13.306*		
EE2	0.695	13.870*		
EE3	0.632	12.704*		
EE4	0.757	-		
Subjective Norm (SN)			**0.734**	**0.480**
SN1	0.708	11.956*		
SN2	0.711	11.985*		
SN3	0.658	-		
Behavioral Intention (BI)			**0.918**	**0.739**
BI1	0.863	-		
BI2	0.896	27.268*		
BI3	0.755	20.353*		
BI4	0.915	28.310*		
Actual Usage (AU)			**0.799**	**0.499**
AU1	0.693	-		
AU2	0.713	13.226*		
AU3	0.731	13.474*		
AU4	0.687	12.862*		
Performance Expectancy (PE)			**0.746**	**0.423**
PE1	0.661	11.127*		
PE2	0.653	11.036*		
PE3	0.661	11.133*		
PE4	0.627	-		
Habit (H)			**0.754**	**0.506**
H1	0.737	12.951*		
H2	0.670	12.272*		

Citation
Yi, J., & Phongsatha, S. (2025). Influencing Factors of Art Students' Behavioral Intention on XueXitong Usage Among Three Universities, Chengdu, China. International Journal of Sociologies and Anthropologies Science Reviews, 5 (1), 837-852. DOI: https://doi.org/10.60027/ijsasr.2025.5505

Variable	Factors Loading	t-value	CR	AVE
H3	0.725	-		

Note: CA = Cronbach's Alpha, CR = Composite Reliability, AVE = Average Variance Extracted, *=p-value<0.05.

Based on the data in Table 5, the discriminant validity of all variables is reasonable because the square root of the average variance extracted (AVE) for each variable is greater than its correlation with any other variable.

Table 5 Discriminant Validity

	PEOU	PU	ATT	EE	SN	BI	AU	PE	H
PEOU	**0.836**								
PU	0.486	**0.788**							
ATT	0.568	0.774	**0.850**						
EE	0.320	0.238	0.266	**0.688**					
SN	0.164	0.243	0.248	0.452	**0.692**				
BI	0.302	0.288	0.327	0.472	0.469	**0.859**			
AU	0.314	0.332	0.336	0.397	0.324	0.391	**0.706**		
PE	0.249	0.179	0.185	0.396	0.403	0.424	0.271	**0.650**	
H	0.114	0.252	0.253	0.285	0.365	0.386	0.269	0.443	**0.711**

Note: The diagonally listed value is the AVE square roots of the variables

Structural Equation Model (SEM)

Structural equation modeling (SEM) is a widely utilized method in the social sciences, as noted by Cheung and Rensvold (2002). For the structural equation model analysis, the recommended fit indices to be used are CMIN/df, RMSEA, as well as NFI, TLI, and CFI (Yaşlıoğlu, M., & Yaşlıoğlu, D. T., 2020). Therefore, in this research, the CMIN/df, RMSEA, NFI, TLI, and CFI were utilized to estimate the model fit, as presented in Table 6. The calculated statistical values indicated a CMIN/DF of 2.652, an NFI of 0.857, a CFI of 0.905, a TLI of 0.898, and an RMSEA of 0.058. These values confirm the fitness of the structural model.

Table 6 Goodness of Fit for Structural Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/df	< 5.00 (Awang, 2012; Al-Mamary & Shamsuddin, 2015)	2.652
NFI	≥ 0.80 (Wu & Wang, 2006)	0.857
CFI ≥	≥ 0.80 (Bentler, 1990)	0.905
TLI	≥ 0.80 (Sharma et al., 2005)	0.898
RMSEA	< 0.08 (Pedroso et al., 2016)	0.058
Model Summary		**Acceptable Model Fit**

Remark: CMIN/DF = The ratio of the chi-square value to the degree of freedom, NFI = Normed fit index, CFI = Comparative fit index, TLI = Tucker-Lewis index, and RMSEA = Root mean square error of approximation

Citation
Yi, J., & Phongsatha, S. (2025). Influencing Factors of Art Students' Behavioral Intention on XueXitong Usage Among Three Universities, Chengdu, China. International Journal of Sociologies and Anthropologies Science Reviews, 5 (1), 837-852. DOI: https://doi.org/10.60027/ijsasr.2025.5505

Research Hypothesis Testing Result

Table 7 displays the strength of the influences among the variables. Based on the data results, it can be summarized that perceived usefulness has the strongest positive impact on attitude, with a β value of 0.815 and a t-value of 16.825*. Perceived ease of use has the second strongest positive impact on perceived usefulness, with a β value of 0.544 and a t-value of 10.973*. The behavioral intention has a relatively strong positive influence on actual usage, with a β value of 0.445 and a t-value of 7.919*. Effort expectancy has a positive influence on behavioral intention, with a β value of 0.349 and a t-value of 6.901*. Subjective norm has a positive influence on behavioral intention, with a β value of 0.302 and a t-value of 5.745*. Performance expectancy has a positive influence on behavioral intention, with a β value of 0.218 and a t-value of 4.297*. Attitude has a positive influence on behavioral intention, with a β value of 0.187 and a t-value of 4.274*. Perceived ease of use has a positive influence on attitude, with a standardized coefficient (β) of 0.138 and a t-value of 4.020*. Finally, the habit has a positive influence on behavioral intention, with a β value of 0.182 and a t-value of 3.711*. All t-values were statistically significant ($p < 0.05$), indicating that the relationships between the variables are significant.

Table 7 Hypothesis Testing Result of the Structural Model

Hypothesis	Standardized Coefficients (β)	t-value	Result
H1: Perceived ease of use has a significant influence on Attitude.	0.138	4.020*	Supported
H2: Perceived Usefulness has a significant influence on Attitude.	0.815	16.825*	Supported
H3: Perceived Ease of Use has a significant influence on Perceived Usefulness.	0.544	10.973*	Supported
H4: Subjective Norm has a significant influence on Behavioral Intention.	0.302	5.745*	Supported
H5: Attitude has a significant influence on Behavioral Intention.	0.187	4.274*	Supported
H6: Habit has a significant influence on Behavioral Intention.	0.182	3.711*	Supported
H7: Performance Expectancy has a significant influence on Behavioral Intention.	0.218	4.297*	Supported
H8: Effort Expectancy has a significant influence on Behavioral Intention.	0.349	6.901*	Supported
H9: Behavioral Intention has a significant influence on Actual Usage.	0.445	7.919*	Supported

Note: *=p-value<0.05

Based on Table 7, it can be summarized that all tested hypotheses were supported, Specifically, H1 was confirmed, showing that perceived ease of use significantly influences attitude; H2 was supported, suggesting that perceived ease of use has a significant influence on perceived usefulness; H3 was also confirmed, indicating that perceived usefulness has a significant influence on attitude; H4 was confirmed, indicating that subjective norm has a significant influence on behavioral intention; H5 was supported, showing that attitude has a significant influence on behavioral intention; H6 was confirmed, suggesting that habit has a significant influence on behavioral intention; H7 was supported, indicating that

Citation
Yi, J., & Phongsatha, S. (2025). Influencing Factors of Art Students' Behavioral Intention on XueXitong Usage Among Three Universities, Chengdu, China. International Journal of Sociologies and Anthropologies Science Reviews, 5 (1), 837-852. DOI: https://doi.org/10.60027/ijsasr.2025.5505

performance expectancy has a significant influence on behavioral intention; H8 was confirmed, showing that effort expectancy has a significant influence on behavioral intention; and finally, H9 was supported, indicating that behavioral intention has a significant influence on actual usage.

Discussion

This study integrated the Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB), and the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) to develop a comprehensive conceptual framework aimed at elucidating the multifaceted factors influencing the behavioral intentions of art students at three universities in Chengdu, China, toward the XueXiTong platform. The research underscored the effectiveness of these models in elucidating and predicting online learning behaviors across different cultural and educational contexts. The results not only confirmed significant relationships among key variables but also validated the applicability of the models, revealing the critical factors affecting art students' use of XueXiTong.

Specifically, the study corroborated the direct impact of perceived ease of use and perceived usefulness on attitude, as well as the facilitative effect of perceived ease of use on perceived usefulness, aligning closely with the core tenets of TAM. This finding emphasized the importance of user-friendly interfaces and functional utility in enhancing user acceptance. Moreover, subjective norms, attitudes, habits, performance expectations, and effort expectations were all confirmed as important predictors of behavioral intentions, enriching the application of TPB and UTAUT2 in a specific context. Notably, the UTAUT2 perspective on the tight link between behavioral intentions and actual use was validated, underscoring the decisive role of strong behavioral intentions in driving behavior.

The findings of this study revealed the factors influencing the behavioral intentions of art students at three universities toward XueXiTong. Beyond the behavioral characteristics of art students, these results are also intertwined with the local social and cultural background in China. Currently, although traditional face-to-face teaching remains the norm in Chinese education, the growing prevalence of online learning has influenced students' performance expectations regarding its use. With the rapid development of electronic information technology, younger generations have generally acquired the skills necessary for the use of information technology, providing a foundation for the enhanced perceived ease of use of platforms like XueXiTong. Additionally, the ingrained respect for authority and elders in Chinese culture may subtly influence students' subjective norms, shaping their learning behaviors.

However, despite integrating three major theoretical models and examining nine key variables, this study has limitations. It did not fully cover all potential external factors that might influence the use of XueXiTong, such as regional cultural differences, the adequacy of technological infrastructure, and individual learning styles. Furthermore, the study primarily relied on quantitative data from online questionnaires, which, while capturing broad trends, limited the depth and breadth of understanding students' perceptions and experiences.

More importantly, due to restrictions on data access, the study could not include objective data sources such as actual usage logs from the XueXiTong platform, nor conduct longitudinal analysis across time points to capture the dynamic impact of time on students' behavioral intentions.

Given these limitations, future research will aim to broaden the sample range, incorporate qualitative research methods to gather richer data, and utilize more comprehensive data sources for in-depth studies over periods. This approach will provide a more complete understanding of the complex mechanisms underlying online learning behavioral intentions and offer more scientific and precise guidance for educational practices.

Conclusion

The study has found that perceived usefulness (PU), perceived ease of use (PEOU), performance expectancy (PE), effort expectancy (EE), habit (H), subjective norms (SN), and attitude (ATT) have a positive and significant impact on the behavioral intention and actual use of XueXiTong among art major university students in Chengdu. Behavioral intention (BI) plays a critical role in predicting the actual use

Citation
Yi, J., & Phongsatha, S. (2025). Influencing Factors of Art Students' Behavioral Intention on XueXitong Usage Among Three Universities, Chengdu, China. International Journal of Sociologies and Anthropologies Science Reviews, 5 (1), 837-852. DOI: https://doi.org/10.60027/ijsasr.2025.5505

(AU) of XueXiTong among these students. Among the identified factors, performance expectancy (PE), effort expectancy (EE), and subjective norms (SN) have the most significant effects. Therefore, in teaching, consideration of multiple factors and adoption of comprehensive strategies are important to promote students' behavioral intention and actual use of XueXiTong.

Recommendation

This study delved into the multifaceted factors influencing the behavioral intentions and actual usage behaviors of art students at three universities in Chengdu on the XueXiTong online learning platform. Based on extensive questionnaire survey data, researchers put forward a series of recommendations aimed at optimizing the interplay between key factors (including perceived ease of use, perceived usefulness, attitudes, habits, performance expectations, effort expectations, subjective norm, behavioral intentions, and actual usage) through carefully designed strategies. The goal is to promote the active adoption and effective utilization of online learning platforms by art students.

Firstly, considering the emphasis on personalization among art students, the XueXiTong platform should strive to offer diverse course content. Teachers should proactively expand learning resources, avoiding mere duplication of offline teaching materials, and instead incorporate novel and in-depth online courses that align with the characteristics of art programs. Additionally, the integration of theory and practice should be emphasized through the introduction of real-world cases and project schemes, thereby enhancing students' perception of the usefulness of XueXiTong.

Regarding the enhancement of perceived ease of use, teachers should take into account the aesthetic preferences and intuitive thinking patterns of art students when designing simple, visually appealing course interfaces and operation flows. Through intuitive icons and instructions, students can easily grasp the use of XueXiTong, thereby improving their user experience and satisfaction.

Secondly, cultivating a positive attitude towards online learning is crucial. Schools should provide explicit encouragement and support for platforms like XueXiTong at the policy level, creating a positive learning atmosphere. Teachers should act as active promoters of this transition by showcasing students' outstanding works on XueXiTong, encouraging students to share their learning experiences, and recognizing outstanding performances, thus fostering students' positive feelings and identification with online learning.

In terms of habit formation, teachers should deeply integrate XueXiTong into daily teaching routines, such as assigning homework, taking attendance, and facilitating classroom interactions, to foster regular use of the platform among students.

Furthermore, to further enhance the effectiveness of the XueXiTong platform, researchers recommend considering factors such as performance expectations and effort expectations. Given that online learning transcends temporal and spatial constraints, school management must ensure stable network environments and adequate hardware to support the smooth operation of XueXiTong. In addition, educational administration should prioritize the dissemination and training of software applications, offering foundational information technology courses to enhance students' technical proficiency and reduce their effort expectations when using XueXiTong.

During the teaching process, teachers can employ gamification and reward mechanisms to stimulate students' motivation. For instance, setting up instant feedback quizzes where students receive evaluations immediately after answering questions can help them promptly identify learning gaps and effectively enhance their performance expectations regarding the XueXiTong platform.

Lastly, given the significant impact of subjective norms on behavioral intentions, schools and teachers should focus on shaping positive peer effects and social influences. Through online group discussions and other forms of interaction, students can be encouraged to communicate and collaborate, fostering a conducive learning environment that reinforces students' subjective norms regarding the use of XueXiTong.

Citation
Yi, J., & Phongsatha, S. (2025). Influencing Factors of Art Students' Behavioral Intention on XueXitong Usage Among Three Universities, Chengdu, China. International Journal of Sociologies and Anthropologies Science Reviews, 5 (1), 837-852. DOI: https://doi.org/10.60027/ijsasr.2025.5505

In conclusion, implementing the aforementioned comprehensive strategies can not only help students better adapt to online learning environments but also encourage teachers and educational administrators to continuously improve and refine the use of online learning platforms.

References

Ain, N., Kaur, K., & Waheed, M. (2015). The influence of learning value on learning management system use: An extension of UTAUT2. *Information Development*, 1, 16.

Ajzen, I. (1991). The theory of planned behavior. *Organizational behavior and human decision processes*, 50(2), 179-211.

Al-Mamary, Y. H., & Shamsuddin, A. (2015). Testing of the technology acceptance model in the context of Yemen. *Mediterranean Journal of Social Sciences*, 6(4),1-10.

Alwahaishi, S. (2021). Student use of E-Learning during the coronavirus pandemic: an extension of UTAUT to trust and perceived risk. *International Journal of Distance Education Technologies (IJDET)*, 19(4), 72-90.

Arain, A. A., Hussain, Z., Rizvi, W. H., & Vighio, M. S. (2019). Extending UTAUT2 toward acceptance of mobile learning in the context of higher education. *Universal Access in the Information Society*, *18*, 659-673.

Awang, Z. (2012). *Structural equation modeling using AMOS graphic*. Penerbit Universiti Teknologi MARA

Azizi, S. M., Roozbahani, N., & Khatony, A. (2020). Factors affecting the acceptance of blended learning in medical education: application of UTAUT2 model. *BMC Medical Education*, *20*, 1-9.

Bentler, P. M. (1990). Comparative fit indexes in structural models. *Psychological Bulletin*, 107(2), 238–246. https://doi.org/10.1037/0033-2909.107.2.238

Chen, Y., Teng, F., & Yu, Z. (2018). A Study on the User'Actual Use and the Behaviors Influencing Factors in Online Learning Platform of Coursera. *Adv. Educ*, 8, 254-268.

Cheon, J., Lee, S., Crooks, S. M., & Song, J. (2012). An investigation of mobile learning readiness in higher education based on the theory of planned behavior. *Computers & Education*, 59(3), 1054-1064.

Cheong, J. H., & Park, M. (2005). Mobile Internet acceptance in Korea. *Internet Research*, 15, 125-140. Retrieved from http://www.emeraldinsight.com/loi/intr

Cheung, G. W., & Rensvold, R. B. (2002). Evaluating goodness-of-fit indexes for testing measurement invariance. *Structural equation modeling*, 9(2), 233-255.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and users' acceptance of information technology. *MIS Quarterly*, 13(3), 319-340.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1992). Extrinsic and intrinsic motivation to use computers in the workplace. *Journal of Applied Social Psychology*, 22(14), 1111 - 1132.

DeLone, W. H., & McLean, E. R. (2016). Information systems success measurement. *Foundations and Trends® in Information Systems*, 2(1), 1-116.

DiGuiseppi, G. T., Meisel, M. K., Balestrieri, S. G., Ott, M. Q., Cox, M. J., Clark, M. A., & Barnett, N. P. (2018). Resistance to peer influence moderates the relationship between perceived (but not actual) peer norms and binge drinking in a college student social network. Addictive behaviors, 80, 47-52.

Dishaw, M. T., & Strong, D. M. (1999). Extending the technology acceptance model with the task–technology fit constructs. *Information & Management*, 36(1), 9-21.

Dong, L., Ji, T., & Zhang, J. (2023). Motivational Understanding of MOOC Learning: The Impacts of Technology Fit and Subjective Norms. Behavioral Sciences, 13(2), 98.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of marketing research*, 18(1), 39-50.

Gómez-Ramirez, I., Valencia-Arias, A., & Duque, L. (2019). Approach to M-learning acceptance among university students: An integrated model of TPB and TAM. *International Review of research in open and distributed learning*, 20(3), 141-164. https://doi.org/10.19173/irrodl.v20i4.4061

Citation
Yi, J., & Phongsatha, S. (2025). Influencing Factors of Art Students' Behavioral Intention on XueXitong Usage Among Three Universities, Chengdu, China. International Journal of Sociologies and Anthropologies Science Reviews, 5 (1), 837-852. DOI: https://doi.org/10.60027/ijsasr.2025.5505

Goto, J., & Munyai, A. (2022). The acceptance and use of online learning by law students in a South African University: An Application of the UTAUT2 Model. *The African Journal of Information Systems*, 14(1), https://digitalcommons. kennesaw.edu/ajis/vol14/iss1/3

Hair, J., Black, W., Babin, B., Anderson, R., & Tatham, R. (2006). *Multivariate Data Analysis.* 6th edition. Harlow, England: Pearson Education.

Handoko, B. L. (2019, July). Application of UTAUT theory in higher education online learning. *In Proceedings of the 2019 10th International Conference on E-business, Management and Economics (pp. 259-264).*

Heijden, H. (2003). Factors influencing the usage of website: the case of a generic portal in The Netherlands. *Information & Management,* 40, 541-549.

Ikhsan, R. B., & Prabowo, H. A. R. T. I. W. I. (2021). Drivers of the mobile-learning management system's actual usage: Applying the output model. ICIC express letters. *Part B, Applications: an international journal of research and surveys,* 12(11), 1067-1074.

Jameel, A. S., Abdalla, S. N., & Karem, M. A. (2020, November). Behavioral Intention to Use E-Learning from student's perspective during the COVID-19 Pandemic. *In 2020 2nd Annual International Conference on Information and Sciences (AiCIS) (pp. 165-171).* IEEE.

Karjaluoto, H., Mattila, M., & Pento, T. (2002). Factors underlying attitude formation towards online banking in Finland. *International journal of bank marketing*, 20(6), 261-272.

Khoa, B. T., Ha, N. M., Nguyen, T. V. H., & Bich, N. H. (2020). Lecturers' adoption to use the online Learning Management System (LMS): Empirical evidence from TAM2 model for Vietnam. *Ho Chi Minh City Open University Journal of Science-Economics and Business Administration,* 10(1), 3-17.

Kim, B. (2012). The diffusion of mobile data services and applications: Exploring the role of habit and its antecedents. *Telecommunications Policy,* 36, 69–81. doi: 10.1016/j.telpol.2011.11.011

Kim, B. G., Park, S. C., & Lee, K. J. (2007). A structural equation modeling of the Internet acceptance in Korea. *Electronic Commerce Research and Applications,* 6(4), 425-432.

Kim, S. S., & Malhotra, N. K. (2005). A longitudinal model of continued IS use: An integrative view of four mechanisms underlying postadoption phenomena. *Management Science,* 51(5), 741-755.

Lee, M. K. O., Cheung, C. M. K., & Chen, Z. (2005). Acceptance of Internet-based learning medium: The role of extrinsic and intrinsic motivation. *Information & Management,* 42, 1095–1104.

Li, X. (2009). Review of distance education used in higher education in China. *Asian Journal of Distance Education,* 7(2), 30-41. https://www.asianjde.com/ojs/index.php/AsianJDE/article/view/146

Liao, H. L., & Lu, H. P. (2008). The role of experience and innovation characteristics in the adoption and continued use of e-learning websites. *Computers & Education,* 51(4), 1405-1416.

Limayem, M., Hirt, S. G., & Cheung, C. M. K. (2007). How Habit Limits the Predictive Power of Intention: The Case of Information Systems Continuance. *MIS Quarterly*, 31, 705-737. https://doi.org/10.2307/25148817

Lin, S., Zimmer, J. C., & Lee, V. (2013). Podcasting acceptance on campus: The differing perspectives of teachers and students. *Computers & Education,* 68, 416-428.

Liu, S. H., Liao, H. L., & Pratt, J. A. (2009). Impact of media richness and flow on e-learning technology acceptance. *Computers & Education,* 52(3), 599-607.

Masrom, M. (2007) Technology Acceptance Model and E-Learning. *12th International Conference on Education, 21-24 May 2007, Brunei Darussalam: Universiti Brunei Darussalam,* 1-10.

Muhamad Safiih, L., & Azreen, N. (2016). *Confirmatory Factor Analysis Approach.* Malaysian Journal of Mathematical Sciences

Pedroso, R., Zanetello, L., Guimaraes, L., Pettenon, M., Goncalves, V., Scherer, J., Kessler, F., & Pechansky, F. (2016). Confirmatory factor analysis (CFA) of the crack use relapse scale (CURS). *Archives of Clinical Psychiatry,* 43 (3), 37-40.

Rabaa'i, A. A. (2016). Extending the technology acceptance model (TAM) to assess students' behavioral intentions to adopt an e-learning system: The case of Moodle as a learning tool. *Journal of emerging trends in engineering and applied sciences,* 7(1), 13-30.

Citation
Yi, J., & Phongsatha, S. (2025). Influencing Factors of Art Students' Behavioral Intention on XueXitong Usage Among Three Universities, Chengdu, China. International Journal of Sociologies and Anthropologies Science Reviews, 5 (1), 837-852. DOI: https://doi.org/10.60027/ijsasr.2025.5505

Raman, A., & Don, Y. (2013). Preservice teachers' acceptance of learning management software: An application of the UTAUT2 model. *International Education Studies*, 6(7), 157-164.

Salloum, S. A., Alhamad, A. Q. M., Al-Emran, M., Monem, A. A., & Shaalan, K. (2019). Exploring students' acceptance of e-learning through the development of a comprehensive technology acceptance model. *IEEE Access,* 7, 128445-128462.

Sharif, A., Afshan, S., & Qureshi, M. A. (2019). Acceptance of learning management system in university students: an integrating framework of modified UTAUT2 and TTF theories. *International Journal of Technology Enhanced Learning*, 11(2), 201-229.

Sharma, G. P., Verma, R. C., & Pathare, P. (2005). Mathematical modeling of infrared radiation thin layer drying of onion slices. *Journal of Food Engineering*, 71(3), 282–286.

Shin, D. H. (2009). Towards an understanding of the consumer acceptance of mobile wallet Original Research Article. *Computers in Human Behavior*, 25, 1343-1354. doi: 10.1016/j.chb.2009.06.001

Sica, C., & Ghisi, M. (2007). The Italian versions of the Beck Anxiety Inventory and the Beck Depression Inventory-II: Psychometric properties and discriminant power. In M. A. Lange (Ed.), *Leading-edge psychological tests and testing research* (pp. 27–50). Nova Science Publishers.

Singh, M., & Matsui, Y. (2017). How long tail and trust affect online shopping behavior: An extension to UTAUT2 framework. Pacific Asia Journal of the Association for Information Systems, 9(4), 2. DOI: 10.17705/1pais.09401.

Soper, D.S. (2020) A-Priori Sample Size Calculator for Structural Equation Models [Software]. http://wwwdanielsopercom/statcalc

Tandon, U. (2020). Factors influencing adoption of online teaching by school teachers: A study during COVID-19 pandemic. *Journal of Public Affairs*, 21(4), e2503-e2503.

Tarhini, A., Masa'deh, R. E., Al-Busaidi, K. A., Mohammed, A. B., & Maqableh, M. (2017). Factors influencing students' adoption of e-learning: A structural equation modeling approach. *Journal of International Education in Business*, 10(2), 164-182.

Taylor, S., & Todd, P. A. (1995). Understanding information technology usage: A test of competing models. *Information Systems Research*, 6(2), 144-176.

Terblanche, W., Lubbe, I., Papageorgiou, E., & van der Merwe, N. (2023). Acceptance of e-learning applications by accounting students in an online learning environment at residential universities. *South African Journal of Accounting Research*, 37(1), 35-61.

Thongsri, N., Shen, L., & Bao, Y. (2020). Investigating academic major differences in perception of computer self-efficacy and intention toward e-learning adoption in China. *Innovations in Education and Teaching International*, 57(5), 577-589.

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, 46(2), 186-204.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: toward a unified view. *MIS Quarterly*, 27(3), 425-478.

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *Management Information Systems Quarterly*, 36(1), 157–178.

Widjaja, H. A. E., Santoso, S. W., & Petrus, S. (2019, August). The enhancement of the learning management system in teaching teaching-learning process with the UTAUT2 and trust model. *In 2019 International Conference on Information Management and Technology (ICIMTech) (Vol. 1, pp. 309-313*). IEEE.

Wu, B., & Chen, X. (2017). Continuance intention to use MOOCs: Integrating the technology acceptance model (TAM) and task technology fit (TTF) model. *Computers in human behavior*, 67, 221-232.

Wu, B., & Zhang, C. Y. (2014). Empirical study on continuance intentions towards E-Learning 2.0 systems. *Behaviour & Information Technology*, 33(10), 1027e1038.

Wu, J. H., & Wang, Y. M. (2006). Measuring KMS success: A respecification of the DeLone and McLean's model. *Information and Management*, 43(6), 728–739.

Citation
Yi, J., & Phongsatha, S. (2025). Influencing Factors of Art Students' Behavioral Intention on XueXitong Usage Among Three Universities, Chengdu, China. International Journal of Sociologies and Anthropologies Science Reviews, 5 (1), 837-852. DOI: https://doi.org/10.60027/ijsasr.2025.5505

Xia, W. (2017, July). Analysis of Industry University Research Institute Talents Training Mode in College Art Major. *In 2017 7th International Conference on Social Network, Communication and Education (SNCE 2017) (pp. 923-927).* Atlantis Press.

Yang, H. H., & Su, C. H. (2017). Learner behavior in a MOOC practice-oriented course: In empirical study integrating TAM and TPB. *International Review of Research in Open and Distributed Learning*, 18(5), 35-63.

Yaşlıoğlu, M., & Yaşlıoğlu, D. T. (2020). How and when to use which fit indices? A practical and critical review of the methodology. *Istanbul Management Journal*, (88), 1-20.

Zhang, X. (2020, March). Thoughts on large-scale long-distance web-based teaching in colleges and universities under novel coronavirus pneumonia epidemic: a case of Chengdu University. *In 4th International Conference on Culture, Education and Economic Development of Modern Society (ICCESE 2020) (pp. 1222-1225).* Atlantis Press.

Citation
Yi, J., & Phongsatha, S. (2025). Influencing Factors of Art Students' Behavioral Intention on XueXitong Usage Among Three Universities, Chengdu, China. International Journal of Sociologies and Anthropologies Science Reviews, 5 (1), 837-852. DOI: https://doi.org/10.60027/ijsasr.2025.5505