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The Assessment of Attitude and Behavioral Intention of E-Learning Among Art and Design Students of Chengdu Textile College in China

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Abstract

Purpose: With the pandemic outbreak worldwide, electronic learning has been increasing in higher education. It is critical to survey students' willingness to utilize e-learning. Thus, the purpose of the research is to study the factors significantly impacting on perceived usefulness, attitude, and behavioral intention of e-learning in college education among art and design significant students at Chengdu Textile College (CTC) of Sichuan Province in China. **Research design, data, and methodology:** A quantitative approach was applied with 500 samples and distributed questionnaires to target art school students at Chengdu Textile College. The sampling methods for data collection involve judgmental, quota and convenience sampling. The Confirmatory Factor Analysis (CFA) and Structural Equation Model (SEM) were applied in statistical analysis, including model fits, validity and reliability of constructs, and hypothesis testing. **Results:** The results of the study confirm that the causal relationships among self-efficacy, perceived ease of use, social influence, and performance expectancy on perceived usefulness, attitude, and behavioral intention toward e-learning utilization. **Conclusion:** This study contributes to educators to put forward suggestions for college education management, curriculum designers, and researchers to get better acquainted with e-learning and make active implementation due to students' higher perceived usefulness and active attitude and willingness of electronic learning utilization.

Keywords: E-Learning, Technology Acceptance Model, The Unified Theory of Acceptance and Use of Technology, Attitude, Behavioral Intention

JEL Classification Code: E44, F31, F37, G15

1. Introduction

Essentially, e-learning is an approach that uses the technology of computers and networks to help organizations offer learning materials to learners through electronic media (Welsh et al., 2003). Mikhaylov and Fierro (2015) stated that in many western countries, e-learning currently has been considered a powerful and revolutionary method to expand traditional learning ways and build education and training abilities. The history of e-learning can be traced back to the

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United States around the 1990s. Based on the development of digital network technology, multimedia technology, and artificial intelligence technology, the concept of e-learning emerged when society entered the digital era. Currently, e-learning is nearly at the heart of American technology used in education. In light of the Educational Technology White Paper of the U.S. in 2000, e-learning is a kind of education mode that mainly refers to the communication mechanism and interaction between people within the context of new technology. E-learning consists of different stages, from the multimedia and internet Era to the artificial intelligence Era (Zhao, 2021). There is more literature on e-learning in developed nations than underdeveloped countries (Tarhini et al., 2014). Generally speaking, e-learning contains network-based learning, computer-based learning, virtual classroom, and digital cooperation. Therefore, the online learning data can also be used as part of the reference of e-learning research to some extent.

In 2020, global education encountered an unprecedented crisis. Nearly 200 million students in higher institutes from 188 countries around the world were closed due to the epidemic's impact. The government, colleges, and universities have taken resolute and effective measures to cope with the situation, including implementing digital courses. The coronavirus pandemic outbreak has had a tremendous intermediate effect on human adoption of digital devices, online materials, mass media technology, and online learning events (Mulenga & Marbán, 2020). In 2022, 36,623 students participated in the unified art examination in the Sichuan province of China, maintaining a 16% growth from the previous year. As the capital city of Sichuan Province, Chengdu was the most important economic and cultural city in the mid-west area of China, and its higher education had certain advantages and prospects. Chengdu Textile College is a college with a long history of more than 80 years and featured textiles and clothing. So how to create the reform and innovation of art education ideas became the critical content of the future development of the college.

The digital art museum gradually became a popular resource for art lovers and academic learners in the late years. These specialized digital museums might inject vitality into studying art and design education in college. The online museum was carefully designed based on the physical museum. Russo et al. (2009) reckoned that people understand the value of digital museum displays and how they could significantly advance education, cultural evolution, the content of their physical holdings, and entire museum marketing. According to Limongelli et al. (2009), the main idea of the research was that learning environments could be deemed the correct tool for displaying cultural sites and artifacts. These descriptions were made in different orders and depths depending on the attitudes and interests of end-users or tourists. The e-learning experience in the open and rich art museum is bound to be a new teaching environment different from the traditional art teaching classroom, giving learners and broader art-depth experience. Based on previous studies and the factors mentioned above, it is imperative to apply a quantitative survey to probe the crucial impacts that had a considerable effect on the e-learning behavior intention of students at Chengdu Textile College.

2. Literature Review

2.1 Technology Acceptance Model (TAM)

TAM is deemed as the current concept that can have a good explanation for how to employ technology for the Internet. The effect of external factors (belief, attitude, and intention, for instance) is the primary content of TAM Research (Davis et al., 1989). Venkatesh and Davis (2000) stated that TAM demonstrated the adoption of this technology with its rough, robust, compact structure and well-developed theory. According to Davis et al. (1989), it settled a foundation for further exploring the external to internal elements of technology goods and services, including beliefs, attitudes, and intentions. Acceptance model theory is an affected concept explaining the action and organizational adoption. The theory is mainly related to the application of technology. Nonetheless, its theoretical framework is pervasive (Davis, 1989; Doll et al., 1998). Taylor and Todd (1995) mentioned that TAM was applied in the Internet technology area to provide usefulness to proficient and unskilled consumers from various specialized knowledge criteria.

2.2 Theory of Social Cognitive (SCT)

It is proposed that Social Cognitive Theory (SCT) comes from social learning theory, in which learners can learn lessons from being aware of others and following others (Bandura, 1978). Bandura (1986) proposed that SCT originated from social psychology and was regarded as a theoretical framework for investigating the interaction between psychological factors, internal motivation, and external factors of the environment on individual behavior. Social cognitive theory (SCT) has universal and mighty peculiarities in explaining individual behavior (Bandura, 1986; Compeau et al. (1999). According to Bandura (2009), SCT plays a crucial role in perception, substitution, self-regulation, and self-examination. Self-regulation of intentions, emotions, and actions is achieved by building internal standards and assessing responses to individual behaviors.

2.3 The Unified Theory of Acceptance and use of Technology (UTAUT)

Ngampornchai and Adams (2016) mentioned that antecedent research has shown that the Unified Theory of Acceptance and Use of Technology (UTAUT) was a powerful model for making complex decisions on technology adoption. It was addressed that this model was shaped for integration and originated from eight well-matched technology models (Venkatesh et al., 2008). The purpose of the UTAUT theory is to discuss the acceptance and use of technology by employees in the organization. UTAUT comprises four vital aspects: performance expectation, effort expectation, social influence, and facilitating conditions. The four constructs are the preceding causes of the purpose for applying technology. It is essential to link UTAUT with diversified culture, technical features, and surroundings because the use of technology would alter with the change of culture, objective individuals, and technical features (Venkatesh et al., 2012).

2.4 Perceived Ease of Use

Rogers (1993) posited that perceived ease of use (PEOU) reflected how simple they believed it was to understand and utilize a new approach. Subsequently, the extent to which people considered that innovative technology was simple was then highlighted by Davis (1989). PEOU is also mentioned how it connects to one's assessment of the spiritual efforts made when the system is implemented (Didyasarin et al., 2017). The psychological burden and ease of learning brought on by technology were, to some extent, about PEOU. Moreover, users believed using the Google application would be simple. Ultimately, Lin et al. (2011) argued that PEOU was deemed a measure of how easy it would be to utilize an e-learning system in the case of electronic learning.

Based on the TAM framework, Davis et al. (1989) found that end-users who judged a technique's simplicity of use were aware of the technique's efficacy. Additionally, they encouraged the employment of novel techniques since the PEOU was vital. TAM assumed that the influence of PU and PEOU on system acquisition was significant. Likewise, Poon (2007) found that PEOU actively impacted new system acceptance. Based on Davis's (1989) research, PEOU also indirectly affected ATT and PU. In such cases, ATT might influence behavioral intention. According to Shin (2012), PU was significantly influenced by PEOU. Moreover, experience had a direct effect on how simple people viewed using e-learning to be. Similar to this, Masrom (2007) argued that PEOU impacted e-learning adoption via attitude, which was mediation, but not directly. While using e-learning, PEOU substantially predicted ATT (Fokides, 2017). Thereby, below hypotheses are indicated:

H1: Perceived ease of use has a significant impact on perceived usefulness.

H3: Perceived ease of use has a significant impact on attitude.

2.5 Perceived Usefulness

Perceived usefulness (PU) pertains to how much special group adoption would improve an individual's work execution (Davis, 1989). Similarly, Davis (1993) described it as the realization that innovative approach deployment can enhance task achievement. Likewise, users believe that system adoption would benefit one's behavior abilities in the PU explanation (Davis et al., 1989). Moreover, it is defined as the subjective likelihood that a potential user would sense usefulness when using a specific application and that it would improve organizational work performance.

According to Shin (2012), previous events might impact how beneficial electronic learning was. Meanwhile, behavior intention to utilize e-learning was greatly affected by PU. Similarly, PU affected the willingness to use e-learning (Al-Gahtani, 2016). When system adopters thought a technique was proper, they were more likely to put it to use. Additionally, it would be supported and viewed favorably if the equipment significantly improved performance. Subsequently, it was said that during COVID-19, PU and PEOU had a positive and vital effect on learners' utilization of e-learning (Alokaily et al., 2020). In contrast, the effect of PU on BI was not substantial, indicating that the influence of creative technology might not be as significant as previously thought (Wang et al., 2019). According to Lee and Lehto (2013), PU did not significantly predict whether or not people would utilize YouTube to learn a process. Hence, two hypotheses are set:

H2: Perceived usefulness has a significant impact on attitude.

H4: Perceived usefulness has a significant impact on behavioral intention.

2.6 Attitude

It is considered an inclination to react negatively or positively to an item was defined as attitude (ATT). (Kaplan, 1972). As Davis (1989) stated, an adopter's attitude might be measured by how passionate they are about adopting a system. It is a critical component that determines important behavior aims and produces practical applications. ATT refers to the user's interest in a specific system, which immediately affects the user's readiness to utilize the system (Bajaj & Nidumolu, 1998). Also, it is a fundamental component of adoption in various studies (Alharbi & Drew, 2014). Furthermore, based on Gilbert (2015), ATT includes active and passive emotions in behavioral expression. ATT directly affects an individual's behavior intention (Farah, 2014). Previous studies have enormously influenced ATT intention.

It was discovered that ATT had been a notion in research for more than a century. It is crucial in forecasting the action (Taylor & Todd, 1995). In Cruz-Cárdenas et al. (2019), ATT plays a crucial role in accounting for technology use. According to Schierz et al. (2010) and Wu et al. (2011), an enthusiastic attitude is a foundation for encouraging creative techniques in TAM settings. According to Maio and Haddock (2009), an enthusiastic attitude can guide action, and a good learning attitude is conducive to the effective utilization of learning programs. However, regardless matter how advanced and sophisticated technology is, if users do not have a positive attitude toward using it, learning will be neglected (Liaw, 2008). Additionally, past studies on e-learning implementation (Cheung & Vogel, 2013) revealed that ATT was the critical factor in determining e-learning usage intention. Additionally, Hartshorne and Ajjan (2009) studied about Web 2.0 collaboration technology and it was predicted that learners' intentions would be influenced by their attitudes due to the compatibility of the online tool with their needs per a proposed hypothesis:

H5: Attitude has a significant impact on behavioral intention.

2.7 Self-efficacy

Bandura (1982) elaborated that self-efficacy (SE) is supposed to be a people's trust in one's capacity to realize, representing an individual's confidence in controlling one's ambiance. Also, SE is a person's faith in one's ability. This is a critical element in satisfaction. Similarly, as a capability assessment, it could realize the activities required to achieve a specific type of implementation. In the study of Venkatesh et al. (2008), SE indicated a personal estimation of the capacity to fulfill particular tasks using technology. Moreover, it is a person's confidence in their capacity to finish work by employing computers (Compeau & Higgins, 1995). In particular, Chu and Mastel-Smith (2010) hypothesized that computer and network self-efficacy was one of the critical characteristics for learners to complete electronic learning in developing countries.

SE impacts three dimensions which are behavior, struggle, and motivation (Bandura, 1997). Similarly, with more commitment, effort, and perseverance, trust in SE could also make people excellent (Pintrich, 2003). Moreover, SE of online learning is a personal element of psychology that influenced in-depth learning (Bandura, 1982). Bandura (1978) proposed that the current IT usage model enabled SE as a precondition of intention. Based on previous research, it was one of the variables related to e-learning. Concerning e-learning, it was developed to represent the construction of computer SE in TAM. Computer-related SE affected PEOU and willingness to utilize technology, which was conducive to learning (Gong et al., 2004). More specifically, supposing that students considered they could not achieve their goal successfully, they would not endeavor to do it (Alqurashi, 2019). Thus, this study hypothesizes per following:

H6: Self-efficacy has a significant impact on behavioral intention.

2.8 Performance Expectancy

Performance expectancy(PE) is supposed as the degree to which an individual believed that adopting a set of structures is conducive to improving working efficiency and is considered to be the level at which people believe that adopting a set of structures is helpful to enhance work execution or achieving the common objectives of work performance or benefits. Additionally, it is defined as the degree of expected success as a result of the use of technology in the implementation of some activity (Venkatesh et al., 2008), as well as the level of faith in the utilization of the conventional information system.

PE plays a role in predicting behavioral intentions (Sharma et al., 2016). Based on Brown et al. (2010) related to the idea that users would benefit significantly from technological adoption. The individual had hope for new adoption in contrast to prior ability or equipment; this hope might also be seen as an external willingness aspect (Venkatesh et al., 2008). Specifically, PE could signal the adoption of innovative systems in many ways, such as e-learning (Ali et al., 2018) and social media or electronic learning. Previous studies (Alalwan et al., 2018) found that in the e-learning case, PE had a direct and critical impact on BI. Consequently, a hypothesis is proposed:

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

2.9 Social Influence

Social influence (SI) refers to a person's attention and understanding ability to be controlled and influenced by others. The degree to which one considered it necessary to accept others' suggestions on new system learning (Venkatesh et al., 2008). It was correlated with the extent to which others approved of the new system. It was based on closely related features, including firm principles, societal aspects, and impressions (Zhou et al., 2010). According to Bagozzi and Lee (2002), individuals tended to use standard technologies if someone they cared about advised it. Adopting family members or close friends might encourage greater engagement (Shankar et al., 2016). Also, Alalwan et al. (2018) also specified that it referred to the importance of one's belief that others believed they should adopt innovative systems.

Social influence (SI) positively affects the behavioral tendency to accept high-tech creation (Tsu Wei et al., 2009). Chang et al. (2015) regarded the tendency of individuals to use systems based on networks, which would be affected by people associated with their careers and lives. Moreover, individuals were vulnerable to the influence of people around them and adopted new technologies. Specifically, SI performs a vital and positive function in the successive acceptance of electronic learning systems (Bakar et al., 2013). Besides, social influence was an early determining factor for behavior intention regarding electronic learning (Tsu Wei et al., 2009). Therefore, a hypothesis is developed:
H8: Social influence has a significant impact on behavioral intention.

2.10 Behavioral Intention

Behavioral intention (BI) is a personal view of or predisposition toward particular conduct. With greater willingness, a person is more inclined to participate in behavior (Ajzen, 1991). Behavioral intention pertains to whether to conduct behavior through one's own decision (Ajzen, 2005). In the same way, behavioral intention is considered a personal willingness to fulfill a specific behavior (Sripalawat et al., 2011). Yueh et al. (2015) proposed that it refers to a specific conduction likelihood. Moreover, for Alotaibi and Wald (2013), it is related to the determination of specific action implementation. If a person has a solid incentive to realize the behavior and personal motivation to realize the adoption of technology, he or she is more likely to take action.

Ajzen and Fishbein (1980) stated that BI is an assessment for determining how likely a person is to utilize the application. Moreover, Davis (1989) said that in the original TAM framework, BI is influenced by ATT, PU, and PEOU. What users are willing to do is closely related to what he or she does, which has been proved by some research theories and empirical methods (Lucas & Spitler, 1999). Taylor and Todd (1995) stated that because the BI might harmonize the change with the execution of the action, it could accurately indicate the behavior to be performed. Fogg (2009) pointed out that behavior ability is necessary for planning behavior. Past research (Venkatesh et al., 2008) indicated that intention has an effect on the actual deployment of an electronic learning system. Nevertheless, regarding the limitations, BI does not fully hold the external factors that might hinder or promote behavior performance (Cao & Jittawiriyanukoon, 2022). From the formation of BI to implementing behavior, BI is not mighty in predicting and explaining uncertainty and unexpected events. In addition, BI could not predict behaviors that are eventually not administrated by personal intention (Venkatesh et al., 2008).

3. Research Methods and Materials

3.1 Research Framework

The conceptual framework was constructed from prior relevant studies. It was established with three theoretical frameworks. Cheung and Vogel (2013) explored the willingness of collaborative technology of e-learning. Next is Zulherman et al. (2021), which studied google classroom acceptance of Indonesian students during the COVID-19 period. The final study, by Mailizar et al. (2021), demonstrated university students' behavioral intention to utilize e-learning during the COVID-19 pandemic. The conceptual framework for this study is proposed in Figure 1.

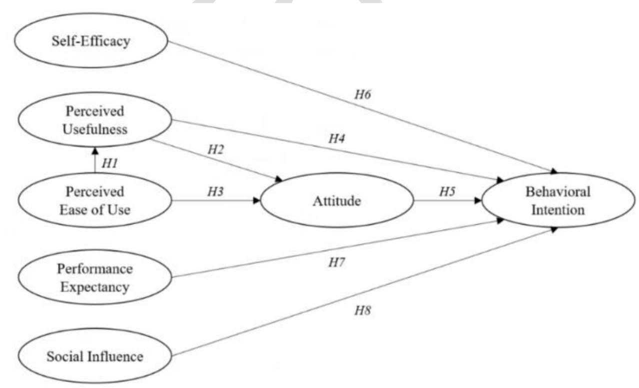

Figure 1: Conceptual Framework

H1: Perceived ease of use has a significant impact on perceived usefulness.
H2: Perceived usefulness has a significant impact on attitude.
H3: Perceived ease of use has a significant impact on attitude.
H4: Perceived usefulness has a significant impact on behavioral intention.
H5: Attitude has a significant impact on behavioral intention.
H6: Self-efficacy has a significant impact on behavioral intention.
H7: Performance expectancy has a significant impact on behavioral intention.
H8: Social influence has a significant impact on behavioral intention.

3.2 Research Methodology

This research applied a non-probability sampling technique. A questionnaire was taken for each participant who had experienced e-learning in art school at Chengdu Textile College (CTC), and the learning orientation was relevant to art and design. Research data was collected and analyzed to determine the features of participants' behavioral intention toward e-learning. The questionnaire was designed in three sections involving screening questions, demographic information, and observed variables. Firstly, for the aim of specific characteristics distinction and examination, a standardized screening question was primarily designed (Cooper & Schindler, 2011). Secondly, demographic surveys were used to obtain background information about respondents, such as gender, major, and relevant university information. Thirdly, the five-point Likert scale was applied for assessment.

Before the questionnaire was distributed to the target population, item-objective congruence (IOC) was evaluated by three experts with more than ten years of education experience with a Ph.D. for content validity. The IOC results showed that all items were passed at a score of 0.6. Afterward, internal consistency reliability was tested through the pilot test with 30 art and design students. Cronbach's Alpha score of 0.7 or over was applied to evaluate the reliability of each variable and confirmed the consistency reliability.

The questionnaire was distributed to 498 qualified students, and data gathering and analysis were executed by employing SPSS and Amos. Afterward, Confirmatory Factor Analysis (CFA) was employed to test and verify the model fit, including construct and discriminant validity. Lastly, the Structural Equation Model (SEM) was applied to demonstrate the causal relationship of variables.

3.3 Population and Sample Size

The art and design students in the art school at Chengdu Textile College (CTC) in the Sichuan Province of China were the target population in this study. The calculator for structural equation models suggested 425 respondents. Research samples with several variables might range from 30 to 500 eligible samples (Roscoe, 1975). A more significant population made it simpler to realize the interchange of professional information and new diverse programs. The greater the sample size, the lesser the sampling error (Boddy, 2012). Therefore, the survey selected 500 for the target population. Eventually, there was only 498 valid respondents for future investigation after the screening test.

3.4 Sampling Technique

The researcher executed sampling methods, including judgmental, quota and convenience sampling. In the first stage, judgmental sampling was applied to select 1,519 art and design college students from the art School of Chengdu Textile College in Sichuan Province, China, who have ever had e-learning education experience. Afterward, 500 students were chosen as the quota sampling. Consequently, 498 questionnaires were eligible for practical research, and two questionnaires were ineligible and removed. Lastly, convenience sampling was conducted by distributing online survey to the target students via WeChat and emails.

Table 1: Sample Units and Sample Size

School of Chengdu Textile College (CTC)	Grade	Sample Size (Total =1519)	Proportional Sample Unit Size Total = 500
School of Art	Freshman	554	182
	Sophomore	521	172
	Junior	444	146

Source: Created by the author

4. Results and Discussion

4.1 Demographic Information

Relevant demographic characteristics were gathered in Table 2. Among the 498 respondents, it was described that the majority of e-learning adopters were female, 62.45% (311 respondents), and male was accounted for 37.55% (187 respondents). Regarding central direction, the digital media design major was 19.28% (96 respondents), product art design was 30.32% (151 respondents), visual communication design was 24.90% (124 respondents), and another design major was 25.50% (127 respondents).

Table 2: Demographic Profile

Demographic and General Data (N=498)		Frequency	Percentage
Gender	Male	187	37.55%
	Female	311	62.45%
Major Direction	Digital Media Design	96	19.28%
	Product Art Design	151	30.32%
	Visual Communication Design	124	24.90%
	Other design direction	127	25.50%

4.2 Confirmatory Factor Analysis (CFA)

Within this study, confirmatory factor analysis (CFA) was utilized. According to Malhotra et al. (2004), following the completion of data collection, CFA is performed to assess whether the structure and loadings of each observed variable are as predicted in the hypothesis. One benefit of confirmatory factor analysis (CFA) is the ability to assess the reliability and validity of variables (Byrne, 2010). Table 3 shows that the absolute value of average extracted variance (AVE) was more than 0.50, and composite reliability (CR) was above 0.70. Besides, the factor loading exceeded 0.50 (Hair et al., 2010)

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

Variables	Source of Questionnaire	No. of Items	Factors Loading	CR	AVE
Self-Efficacy	Bailey et al. (2022)	5	0.700-0.903	0.900	0.645
Perceived Ease of Use	Sahin et al. (2022)	4	0.626-0.906	0.870	0.632
Perceived Usefulness	Sahin et al. (2022)	4	0.777-0.907	0.900	0.693
Attitude	Bailey et al. (2022)	5	0.786-0.883	0.917	0.689
Performance Expectancy	Tarhini et al. (2017)	5	0.713-0.897	0.890	0.619
Social Influence	Tarhini et al. (2017)	4	0.622-0.891	0.863	0.616
Behavioral Intention	Tarhini et al. (2017)	5	0.721-0.839	0.888	0.615

From Table 4, absolute fit indices (CMIN/DF, GFI, AGFI, and RMSEA) and incremental fit indices (CFI, NFI, and TLI) exceeded the threshold and met the qualification. Accordingly, the convergent validity and discriminant validity were confirmed. Lastly, the goodness of fit of total measurements used in the CFA examination for this scientific investigation was acceptable. In addition, these model measurements validated the discriminant validity and accuracy of the subsequent structural model estimations.

Table 4: Goodness of Fit for Measurement Model

Index	Acceptable Values	Statistical Values
CMIN/DF	< 3.00 (Hair et al., 2010)	1.895
GFI	> 0.90 (Bagozzi & Yi, 1988)	0.904
AGFI	> 0.80 (Sica & Ghisi, 2007)	0.884
RMSEA	< 0.05 (Browne & Cudeck, 1992)	0.042
CFI	> 0.90 (Hair et al., 2006)	0.962
NFI	> 0.90 (Bentler & Bonett, 1980)	0.922
TLI	> 0.90 (Bentler & Bonett, 1980)	0.956
Model Summary		**Acceptable Model Fit**

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

According to Fornell and Larcker (1981), the testing for discriminant validity was assessed by calculating the square root of each AVE. The testing results of the discriminant are presented in Table 5. Further, the diagonal values were the AVE square roots of the latent variables, which should be greater than all inter-construct associations. Thus, discriminant validity was regarded to be acceptable.

Table 5: Discriminant Validity

	SE	PEOU	PU	ATT	PE	SI	BI
SE	**0.803**						
PEOU	0.151	**0.795**					
PU	0.214	0.386	**0.832**				
ATT	0.276	0.341	0.434	**0.830**			
PE	0.216	0.101	0.254	0.212	**0.787**		
SI	0.082	0.014	0.167	0.066	0.219	**0.785**	
BI	0.339	0.143	0.329	0.397	0.317	0.336	**0.784**

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

4.3 Structural Equation Model (SEM)

The following process is to test the structural model for the research model. SEM is a multivariate statistical methodology that assesses the structure and tested hypotheses using an empirical data verification procedure. Structural equation modeling (SEM) verifies the causality between the proposed model's variables and includes measurement errors in the structural coefficients (Hair et al., 2010). After modification of AMOS version 26, the values of CMIN/DF, GFI, AGFI, CFI, NFI, TLI, and RMSEA exceeded the reasonable parameters. Therefore, the goodness of fit of SEM was verified. The structural model's overall fit indexes are as follows:

Table 6: Goodness of Fit for Structural Model

Index	Acceptable Criterion	Statistical Values
CMIN/DF	< 3.00 (Hair et al., 2010)	1.897
GFI	> 0.90 (Bagozzi & Yi, 1988)	0.901
AGFI	> 0.80 (Sica & Ghisi, 2007)	0.884
RMSEA	< 0.05 (Browne & Cudeck, 1992)	0.042
CFI	> 0.90 (Hair et al., 2006)	0.960
NFI	> 0.90 (Bentler & Bonett, 1980)	0.920
TLI	> 0.90 (Bentler & Bonett, 1980)	0.944

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

4.4 Research Hypothesis Testing Result

As demonstrated measure conclusion in Table 7, perceived usefulness had the most significant direct impact on attitude in a direct manner, with a standardized path coefficient (β) of 0.426 (t-value = 8.491***). Moreover, perceived ease of use had the second most significant influence on perceived usefulness, with β at 0.393 (t-value of 8.019***). Moreover, perceived ease of use impacted attitude with β at 0.340 (t-value of 3.632***). Further, social influence significantly influences behavioral intention with β at 0.310 (t-value of 6.275***). Additionally, attitude impacted behavioral intention significantly with β at 0.308

(t-value of 5.814***). Moreover, self-efficacy markedly influenced behavioral intention with β at 0.254 (t-value of 5.460***). Subsequently, perceived usefulness positively impacted behavioral intention with β at 0.235 (t-value of 1.997*). Finally, performance expectancy had a minor influence on the behavioral intention with β at 0.171 (t-value of 3.839***).

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-Value	Result
H1: PEOU → PU	0.393	8.019***	Supported
H2: PU → ATT	0.426	8.491 ***	Supported
H3: PEOU → ATT	0.340	3.632 ***	Supported
H4: PU → BI	0.235	1.997 *	Supported
H5: ATT → BI	0.308	5.814 ***	Supported
H6: SE → BI	0.254	5.460 ***	Supported
H7: PE → BI	0.171	3.839 ***	Supported
H8: SI → BI	0.310	6.275 ***	Supported

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

Based on the SEM test, the hypothesis result extensions were described as follows:

H1 indicates that PEOU was one of the vital driver factors on PU, representing the standardized coefficient value of 0.393. Many TAM studies demonstrated that technology adopters are more inclined to consider perceived ease of practical use and were disposed to it favorably after they learned a type of representative technology is the ease of use (Cheung & Vogel, 2013; Lee, 2010).

H2 proves the significant influence of PU on ATT, revealing the standardized coefficient value of 0.426. The perceived usefulness of assessments often has a considerable impact on students' perceptions of specific teaching methods (Nagy, 2018).

H3 supports the hypothesis that PEOU substantially impacted ATT with a standardized coefficient value of 0.340. Davis (1989) proposed that perceived ease of use is one of the main factors affecting attitude in the construction of TAM. It is an internal perception related to the individual's judgment of mental effort.

Regarding **H4,** the analysis results of the research-validates PU's premise on BI, indicating the standardized coefficient value at 0.235. According to Bakar et al. (2013), the utilization of electronic devices is greatly influenced by PU.

Due to the standardized path coefficient is 0.308, **H5** validates the hypothesis for the significant influence of ATT on BI. Based on a study by Bajaj and Nidumolu (1998), personal attitude will directly affect one's plans.

For **H6,** the correlation results support the hypothesis that SE significantly affects BI, with a standardized coefficient value of 0.254. Self-efficacy is considered an internal perception, and personal motivation, attitude, and behavior intention are intensely affected by self-efficacy (Hsiao & Tang, 2015).

H7 determines that PE affects BI, resulting in a standardized coefficient value of 0.171. Learned to Venkatesh et al. (2012), performance expectancy is the most effective predictor of future events. It is also considered a correlative aspect that may affect technology implementation.

Finally, **H8** postulated SI significantly influences BI, as evidenced by the statistical value of 0.310 on the standardized coefficient. Social influence can be good for building judgment and self-confidence, and it can instantly affect utilizing wireless internet depending on techniques (Lu et al., 2005).

5. Conclusions and Recommendation

5.1 Conclusion and Discussion

Overall, this research contributes to the factors influencing art and design college students' perceived usefulness, attitude, and behavioral intention for e-learning utilization in Chengdu Textile College in the Sichuan province of China. The hypotheses were presented in a conceptual framework including seven factors (such as self-efficacy, perceived usefulness, perceived ease of use, performance expectancy, social influence, attitude, and behavioral intention). During the survey, a total of 498 respondents with e-learning experience were valid, and from whom the data collection was completed. Statistical analysis was implemented by Confirmation Factor Analysis (CFA) to examine the validity and reliability of the conceptual framework. Similarly, the Structural Equation Model (SEM) was conducted to evaluate the critical factors which controlled perceived usefulness, attitude, and behavioral intention. Ultimately, the complete hypotheses were determined to be supported.

Based on the study's outcomes, the most notable direct impact on behavioral intention is exerted by social influence, and attitude came next. Likewise, Hao et al. (2017) discovered that social impact is the most critical dominant aspect of behavioral intention. Especially, perceived usefulness exerts the most crucial effect on attitude. Meanwhile, the correlation indicating the peak value within this study is consistent with earlier findings (Bhattacherjee, 2000) that perceived usefulness enhances users' attitudes toward using electronic services. Additionally, perceived ease of use actively affects perceived usefulness. In practice, perceived ease of use may be necessary for perceived usefulness (Davis, 1993).

5.2 Recommendation

Based on the research on students' acceptance of e-learning in Chengdu Textile College, combined with the current situation of art design teaching, it could make helpful suggestions for the construction and development of electronic learning in the future:

First, social influence is the most crucial factor in promoting students' behavioral intention to adopt e-learning. Currently, e-learning has not already been prevalent in higher institutions in Chengdu. However, to strengthen the advantages of electronic learning in art and design pedagogy, college educational administrators can increase the extensive publicity and promotion of electronic education and extensively popularize and communicate with classmates, parents, and teachers so that they can understand and trust e-learning methods from the psychological level. For example, professional art forums and lectures, video sharing of interviews with exceptional artists and design work, and network-related art studios may be promoted to create an appropriate campus environment for e-learning.

Secondly, the most potent influence on e-learning attitude is perceived usefulness, which positively impacts attitude, and thus significantly promotes the formation of students' e-learning behavioral intention. Teachers can make greater use of e-learning platforms in the teaching of art and design so that students can access software or data library that provides professional guidance to art and design learning, accumulate art knowledge that is efficient, timely, and contemporary, and realize the transformation from contents to methods. In addition, students can choose what they are interested in for further learning, thus broadening their knowledge and even determining and constructing their art knowledge system, laying a good foundation for art innovation learning. In the future, teachers and educational administrators should increase the application of electronic software in designing and processing art graphics. Moreover, integrate some major global learning platforms in teaching-learning, such as Drawspace, Coursera, and others. At the same time, for example, art apps IMuseum, Art calendar, and digital art websites, for instance art and culture of Google project (https://arts and culture, Google.com), Metropolitan Museum of New York (https://www.metmuseum.org.). The professional and in-depth knowledge learned from the e-learning platform, or the knowledge related to the development of the industry enables students to perceive the usefulness and necessity of this new teaching method. On this basis, they would have a positive and good learning attitude, ultimately affecting the construction of e-learning behavioral intention.

When it comes to perceived ease of use, relevant parts of the school and teachers should make complete preparations for the equipment and network environment conditions of e-learning, including the improvement of network storage, network sharing, and network speed. Secondly, the upgrading and guarantee of hardware equipment for art e-learning. In the teaching process, teachers would introduce and guide the process, learning contents, and learning methods of e-learning in detail. Curriculum design should also consider how to make students master art knowledge quickly and ensure that students can operate and carry out e-learning smoothly and effortlessly.

Regarding self-efficacy, teachers can guide students in art learning from the shallow to the deep in the content rather than arbitrarily increasing the depth and intricacy of e-learning. Using e-learning, a learning platform with good design, simple operation, and pertinence would be adopted. Let students become acquainted with e-learning and effectively acquire and master knowledge step by step. In addition, instructors should enhance real-time control and communication of students' learning status, as well as detailed and complete focus on preview before class, supervision during class, evaluation, and reflection after class, urging students to establish information and courage for e-learning.

Finally, performance expectations had a favorable effect on e-learning behavioral intention. As a new learning method in this era, e-learning has many advantages. It should actively present them in art teaching because students can feel the special significance of e-learning, involving the synchronous acquisition of the global scope of knowledge, the visual impact of current image information, the network communication, and sharing of art knowledge.

5.3 Limitation and Further Study

Some limitations are represented in this research. However, several aspects of limitation would need to be stressed for future study. Initially, this research could extend the sample from one college to higher institutions to improve research meaning for a broader context. Such as other colleges and universities in Chengdu or another region. Alternatively, colleges and universities in other countries might involve together in the research. Besides, in the research, other factors influencing students' utilization of e-learning could be considered to consider the constructs, for instance, perceived enjoyment and culture—moreover, this research aimed at students' acceptance of e-learning. Later, teachers' opinions and perceptions could be examined in a combinational way to survey this innovative learning approach and phenomenon in college comprehensively. Ultimately, from the perspective of research development, longitudinal research methods would be added if long-term and profound observation and research on students' e-learning are needed.

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