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Behavioral Intention to Use E-learning: A Case Study of Apparel School Students at Chengdu Textile College in China

Hongxia Fu*, Deping Feng

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Abstract

Purpose: To create a student-centered art teaching model, e-learning is considered a new possibility to enhance the curriculum learning approach. Therefore, this research aimed to study significant factors of school of apparel students' behavioral intention to utilize e-learning at Chengdu Textile College. The conceptual framework consists perceived ease of use, perceived usefulness, attitude, self-efficacy, performance expectancy, social influence and behavioral intention. **Research design, data, and methodology:** The researcher used a quantitative approach (n=488). Questionnaires were distributed to apparel school students in Chengdu Textile College. The research data was gathered through judgmental, quota and convenience sampling. The following statistical analysis was implemented through the Confirmatory Factor Analysis (CFA) and Structural Equation Model (SEM), including model fit, validity, and reliability of each construct. **Results:** Perceived ease of use has a significant effect on perceived usefulness and attitude. Perceived usefulness has a significant effect on attitude and behavioral intention. Furthermore, attitude, self-efficacy, performance expectancy and social influence significantly affect behavioral intention. **Conclusion:** The research makes recommendations for college education policymakers, college teaching quality supervision, and teacher to encourage the integration of e-learning into the fundamental teaching process and establish a modern digital and intelligent education environment in college education.

Keywords: E-learning, Percived Ease of Use, Perceived Usefulness, Attitude, Behavioral Intention

JEL Classification Code: E44, F31, F37, G15

1. Introduction

In recent years, along with the development of network technology, e-learning has become a new and convenient educational method and means. Kelly and Bauer (2003) proposed that e-learning assists users in actively learning via web-based communication. E-learning pertains to learning based on learning resources. It supports learners to realize in-depth learning through digital resources with the characteristics of diversity, interactivity, and humanization to accelerate the realization of high-level thinking and learning objectives. E-learning provides students with the flexibility of time and place; also, it is an educational tool that integrates self-motivation, communication, efficiency, and technology (Janda, 2016). E-learning is acquiring and applying knowledge mainly diffused and promoted by electronic means. From the aspect of teaching form, with e-learning

1 *Hongxia Fu, Art and Design Office,School of Art ,Chengdu Textile College,China. Email: 497128884@qq.com
2 Deping Feng, Dean of the Department of Marxism and Foundmental Education, Chongqing Vocational College of Intelligent Engineering, China. Email: ping0239@vip.sina.com

teaching mode, learners can actively learn through multimedia means within a stand-alone circumstance, and on the other hand, they also can scan or download curriculum and relevant materials from the Internet for learning by LAN; Relying on the Internet, global distance education and virtual teaching can be realized. From the intention, it is stressed the combination of digital content and network resources tightly by e-learning. According to Wang et al. (2007), education activities (teaching and learning) are no longer limited to traditional classrooms. However, merely providing learners with a Web-based learning system does not ensure that e-learning will be effective. The top priority for education and training operators, specialists, investigators, and providers are the assurance of quality and advance of e-learning (Ozkan & Koseler, 2009). Graphics, music, video, and a variety of other technologies can be combined into systems of e-learning (Liu et al., 2009). Ngai et al. (2007) stated that e-learning systems could offer e-learning platforms that employ the Internet, intranets, extranets, or a variety of other electronic media as means of delivery to enable learners from all over the globe to receive a variety of learning resources for their e-learning curriculum.

In the mid-1990s, with global information, China opened the “China Education and research computer network” in 1996. Subsequently, the construction of campus networks and online schools has become a universal concern in education. Statistics from China’s Ministry of Education show that by May 8, 2020, 1,454 colleges and universities have implemented online teaching, and in the process, 17.75 million college students have attended online learning. In light of a survey by the industry Research Institute on China, Chinese online education users have increased to 324.93 million. As the statistic of China’s Ministry of Education showed, Chengdu ranked eighth in the country regarding the number of universities in 2022, including 58 higher institutions. Hence, the development level of higher education in Chengdu plays a reference role for China’s central and western regions. Therefore, the research on Chengdu Textile College is of particular practical significance. Nowadays, digital museum learning within the scope of e-learning is worthy of the attention of college education. Museum education is a unique education mode in art. Museums are crucial for social communication instruction and active cultural interpretation (Talboys, 2018). Visitors to museums particularly are given a high level of experiential participation, becoming the objects of exploration, experience, and interaction, actively obtaining a variety of intellectual cognition and experience from the exhibition, and even evoking self-identifying emotional responses, which can occasionally have more creative possibilities with non-formal l education models (Ansbacher, 2013). Furthermore, the learning activity of museums has created many educational opportunities and access points to meet multiple instructional demands of learners and often fosters high-level abilities for the twenty-first century, such as critical thinking (Kratz & Merritt, 2011). As a new typical example of modern museums, digital museums benefit from significant market demand and reasonably established technology. It uses digital technology’s capabilities to give online virtual displays, rapid information dissemination, and personalized search features, which will change the time and space of exhibits and the interaction with the audience (Dong et al., 2006). Mohd Nizar et al. (2019) explicated that digital museums would enhance the delivery of information and knowledge, resulting in a more meaningful experience for visitors. In sum, viewing an art museum is a unique experience. Further, the interaction with digital art museums is an innovative exploration of the art knowledge on the foundation of technology. Therefore, exploring the behavioral of electronic learning of school of apparel’s students at Chengdu Textile College is imperative.

2. Literature Review

2.1 Technology Acceptance Model (TAM)

According to Davis et al. (1989), Technology Acceptance Model or TAM is a well-known prediction framework due to its simplicity, high interpretation, and ability to be applied in various circumstances or contexts of research. Davis (1989) described the TAM matrix to examine the effect of persons’ behavior on the actual application of technology, which integrated several cognitive psychology concepts. TAM is first developed as a predictor of consumers’ adoption or usage of new information technology (IT) at work since it is difficult to assess actual technology utilization (Davis, 1989).TAM is a popular and commonly utilized model for determining user acceptance behavior (Ma & Liu, 2004). TAM is widely recognized as the main theoretical framework above other theoretical models, which was a framework for behavioral intention (Mathieson, 1991).In pedagogical research, TAM is commonly utilized to predict participants' perceived usefulness, attitudes, or behavioral intentions regarding a specific instructional strategy (Fan et al., 2021). The conceptual framework was constructed with the use of three constructs from TAM; these were perceived ease of use (PEOU), perceived usefulness (PU), and attitude (ATT).

2.2 Theory of Social Cognitive (SCT)

As one of the most extensive human behavior theories, SCT (social cognitive theory) provides a comprehensive approach to understanding human behavior and sophisticated learning abilities (Bandura, 1986). A study from Jonassen (1991) highlights what learners know and how they acquire information by considering the relationship between the individual, their behavior, and their surroundings. Reciprocal determinism, also known as triadic reciprocity, is a central idea in SCT. It describes how environment, personal characteristics, and behavior interact and dynamically affect one another (Bandura, 1977). Furthermore, SCT can be used to explain why students fail. As indicated by the opinion of Conner and Norman (2005), a few critical aspects impact an individual's behavior, including self-efficacy, outcome expectancies, and additional categories, such as objectives and factors with social structure. SCT has a lengthy history that is based on learning theory. Hence, SCT can be beneficial in forecasting e-learning use and acceptance. Moreover, the conceptual framework was completed by selecting self-efficacy (SE) and behavioral intention (BI) from SCT.

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

The UTAUT is an integrative model that incorporates components from eight different models. Due to the integration of the eight additional research models, it is more sophisticated than the prior theory. Davis et al. (1989) explained that prior behavioral models, for instance, the TRA, TPB, TAM, and others, have attempted to clarify the use of information technology. The theory identifies four key variables as recommendations: performance expectancy, effort expectancy, social influence, and enabling environments. Venkatesh et al. (2003) mentioned that the UTAUT was intended to include a variety of contexts, such as individual and entertainment use of technology. UTAUT's objective is to create a cohesive theoretical model by fusing many ideas and researching people's adoption of information technology. By the complex and advanced characteristics of UTAUT, it is reasonable to explore e-learning adoption with this theory. The survey used performance expectancy (PE) and social influence (SI) for analysis.

2.4 Perceived Ease of Use

Perceived ease of use (PEOU) is related to the degree to which the operator thought using a particular specific approach was not tough (Davis et al., 1989). Equally, Lee et al. (2009) illustrated that PEOU measures how easily learners believe something for use. Additionally, Dishaw and Strong (1999) explained that PEOU is crucial in system acceptance. Similarly, Zhang et al. (2008) mentioned that PEOU shows that implementing novel technology may be simple and straightforward.

Previous research has provided sufficient evidence to demonstrate the direct or indirect influence of PEOU on appropriate intention (Jahangir & Begum, 2008). Additionally, the PEOU of the information system would increase the learners' desire to adopt (Doll & Torkzadeh, 1988). Nevertheless, in contrast to PU, Lee et al. (2009) noted that PEOU for e-learning has less impact on adoption intention. Subsequently, until recently, learners' perceptions that e-learning is beneficial to them have been frequently used in related research, which has been linked to PU and PEOU (Almaiah et al., 2020). Hence, two hypotheses are developed:

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

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

2.5 Perceived Usefulness

Mathwick et al. (2002) concluded that perceived usefulness (PU) is how much a person considers a given system may improve their task execution. As a result, it has the potential to influence personal inclination to use creative techniques. Zhang et al. (2008) addressed that PU is the degree to which people believe it is favorable for task performance. Furthermore, PU is a significant factor in being appropriate for innovation (Tan & Teo, 2000). It is the primary influencing factor in the newly adopted technique (Deb & Lomo-David, 2014). Meanwhile, it was claimed that the prospective crowd's expectation of a particular application would improve task execution in the context of PU (Amoako-Gyampah & Salam, 2004). In light of this, the adopter believes electronic learning effectively achieves their educational objectives (Lin et al., 2011).

PU may allow information integration into the TAM structure as a crucial factor (Davis, 1989; Davis et al., 1989). Past research (Fathema et al., 2015) argued that system quality considerably affects PU. Furthermore, from the research of Abdullah et al. (2016) and Martinho et al. (2018), PU has the most significant impact on ATT. Moreover, it was found immediate impact between PU and ATT on using regarding the acceptance of e-learning and factors that influence teachers and students to employ technology (Seif et al., 2012). However, it was said that throughout the COVID-19 period, learners' ATT toward electronic learning is not affected by PU (Sukendro et al., 2020). Based on the above assumptions, the followed hypotheses are proposed:

H2: Perceived usefulness has a significant effect on attitude.

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

2.6 Attitude

Morosan (2014) proposed that attitude (ATT) is an individual's response to concepts or goals. In addition, achieving established goals through pleasant and unpleasant ways is the meaning of ATT (Ajzen, 1991). Additionally, it accurately predicts a personal inclination to engage in activities related to their physical state (Conner et al., 2001). A similar finding was made by Pino et al. (2012), who concluded that it is adequate to one's propensity for action. In addition, ATT is based on some psychological intention of judging behavior. It consists of two parts, one is the internal relationship, and the other is the evaluation method (Ajzen, 1991). The ATT of objects and behaviors were separated into two categories in Fishbein and Ajzen's (1975) norm form of ATT. Additionally, it was intended to be created by a beneficial and essential evaluation of an activity (Chan & Fishbein, 1993).

Dabholkar and Bagozzi (2002) clarified that ATT directly and actively impacts the tendency of many inventions to be adopted, including approaches in the area of working independently, holding with convenience, and smartphones. A personal ATT toward utilizing technology, from Akbar (2013), reflects own total emotional response to using technology. Likewise, Toh (2013) stated that the purpose of ATT toward method is related to usefulness and enjoyment experienced during use. Finally, to maintain learners' reservations and positive ATT towards education through the internet, the fast growth of mixed learning in university education has become an important motivating undertaking (Dumford & Miller, 2018). Nassuora (2012) posited that learners' favorable ATT about electronic learning is caused by the active effect on their motivation and respect for themselves. Thus, a hypothesis is framed:

H5: Attitude has a significant effect on behavioral intention.

2.7 Self-efficacy

Bandura (1977) stated that self-efficacy (SE) is an independent-administrated trust that could maximize the utilization of learning resources within or outside the institution. It was indicated that one and conduction motivation depends on the belief in SE (Bandura, 1977). In addition, as supported by Wang and Newlin (2002), SE is the faith in one's capacity to accomplish a specific task at a specified level. It has been demonstrated that SE is a predictor of successful learning outcomes. Furthermore, SE pertains to the ability to interact with technical methods (Liaw, 2008). SE is supposed to impact technology adoption and use (Padumadasa, 2012).

The research from Yeo and Neal (2013) showed that, particularly in the principle of social cognition, it is easier for people with high SE to set concrete goals than those who are short of SE and work harder to achieve goals consistent with setbacks. Regarding SE, there are four preconditions: the first is the knowledge or skills acquired previously. The second is to present or substitute learning by observing other successful practices. The third is the influence of society or belief, including the courage or assertiveness of others. The fourth is the nutritional status, involving sadness. Additionally, Chien (2012) noted that due to the nature of online learning, educational research generally focuses on examining learners' SE concerning various technological modes of usage (for instance, internet applications, computer, and learning management systems). Moreover, Chiu and Wang (2008) determined that functional relationships existed among self-efficacy, satisfaction toward behavioral intention to use e-learning. Based on previous studies, researchers hypothesize that:

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

2.8 Performance Expectancy

Performance expectancy (PE) belongs to the components of action expectation, accomplishing a goal through creative skill means (Chen & Chang, 2013). Similarly, Venkatesh et al. (2003) pointed out that as a theoretical structure derived from UTAUT, the PE implies to what extent the technology application would improve the efficiency of routine activities.

Ghalandari (2012) showed that PE significantly affects behavioral tendencies to apply a new skill. Prior studies demonstrated that PE dominates the adoption of skill, whether seen from a voluntary or obligatory standpoint (Dwivedi et al., 2011). Curtis and Payne (2008) pointed out that it would positively influence the adoption of creative technologies during the audit process. PE can effectively affect behavior intention (Thomas et al., 2013). Relevant research has shown that PE is crucial in describing the purpose of adopting networks (Awwad & Al-Majali, 2015).

Similarly, PE has a relevant impact on technology utilization (Akbar, 2013). Al-Gahtani (2016) elaborated that PE significantly impacts teachers' adoption tendencies because digital studying platforms increase work effectiveness to the highest level. In addition, Dwivedi et al. (2011) addressed that PE is related to the number, usefulness, importance, and help of information services to users. In addition, a previous study (Kurfalı et al., 2017) found that network trust impacts performance and behavior intention. Sumak et al. (2010) mentioned that some studies associated with e-learning had verified the critical role of PE.

H7: Performance expectancy has a significantly effect on behavioral intention.

2.9 Social Influence

Social influence (SI) is a vital driving force for technology adoption (Bashir & Madhavaiah, 2015). The continuance of technology adoption is affected by people, relatives, and coworkers (Riquelme & Rios, 2010). A type of outside viewpoint influence that may affect an individual's desire to use information systems (Zhou, 2011). It involves two parts, one relates to social media, and another to interpersonal connection (Tsu wei et al., 2009). In addition, the inclination to act is mainly affected by those who have rights and demand equal responsibilities (San Martín & Herrero, 2012). Furthermore, instead of thinking about themselves, people may utilize new systems to consider other people's viewpoints (Ifinedo, 2016).

Venkatesh et al. (2003) suggested that SI was essential in predicting how people will utilize technology in a persuasive and anticipated context. Moreover, it is considered to be equal to the rule of subjectivity. Additionally, Venkatesh (2000) explained that the influence of SI only appears in the mandatory context, and the influence is weak in the willing context. SI was emphasized as a crucial component in IT adoption (Venkatesh et al., 2012). Moreover, Ali et al. (2018); Tarhini et al. (2017) stated that SI is recognized as a significant factor in the application of innovative technologies, for example, e-learning systems. Sumak et al. (2010) proposed that when it comes to e-learning systems and other users, the adoption of the technology would be impacted by instructors and coworkers.

H8: Social influence has a significant effect on behavioral intention.

2.10 Behavioral Intention

Behavioral intention (BI) indicates a personal willingness to employ a system, the possibility of an individual participating in a specific behavior, or his or her intense devotion to engaging in that conduct (Yakubu & Dasuki, 2019). Abbasi and Hossaina (2011) further elaborated that BI is a cognitive process in which an individual prepares to perform a representative behavior form, which is the direct premise of user behavior. BI is the crucial element in determining the realization of the system (Abdullah et al., 2016).

Moreover, it was also clarified that BI indicates the possible judgment of adopting technology (Venkatesh et al., 2012). In various fields, many studies have demonstrated the association (Alsaif, 2014). Afterward, the adopters' intention is so important to research because it can directly predict the actual adoption of the technology (Yu, 2012). In IT, BI represents the behavioral propensity to accept or recommend the technology to other individuals (Celik, 2016). Regarding electronic learning, the BI determines the expectation of system adoption. (Salloum et al., 2019). However, some discussions held that action could not be carried out if it depended on intention. The theory showed that a proper act incentive might not fully regulate the actual action (Cao & Jittawiriyanukoon, 2022). It was believed that people should handle this phenomenon of action change from now to later correctly (Wiafe et al., 2011).

3. Research Methods and Materials

3.1 Research Framework

Prior academic research was studied and analyzed to create the conceptual framework of this research. The conceptual framework was based on three theoretical frameworks related to TAM, SCT, and UTAUT theories. The study (Cheung & Vogel, 2013) initially verified that forecasting the acceptance of e-learning with the extension of TAM. Then, the study from Farah et al. (2021) addressed Indonesian students' acceptance of google classroom during COVID-19. Ultimately, Mailizar et al. (2021) presented the behavioral intention of university students to use e-learning when COVID-19 was spreading. The conceptual framework for the study is presented in Figure1.

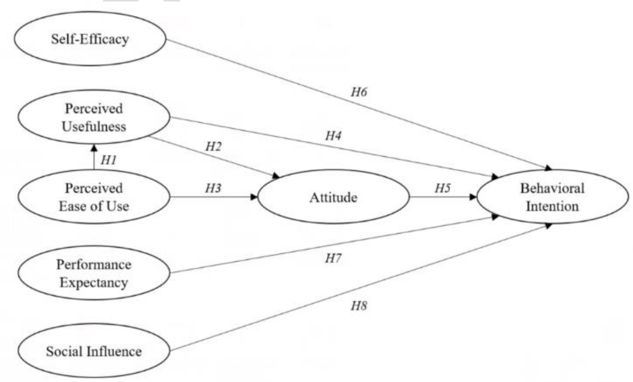

Figure 1: Conceptual Framework

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

3.2 Research Methodology

The researchers adopted the quantitative methodology to survey school of apparel students who had learned via e-learning way at Chengdu Textile College. The questionnaire method is an empirical research method to obtain the data. This was a confident approach for collecting data through well-designed questions, which consisted of three parts: screening questions, demographic information, and scale items on behavioral intention of e-learning. Cooper and Schindler (2014) thought that screening questions are helpful for researchers to screen whether the respondents have the knowledge or experience to attend the questionnaire. Further, a questionnaire usually contains information on respondents' demographic and lifestyle traits, so it can summarize or compare the attitude and intentions of the respondents (Polonsky & Waller, 2019). Moreover, the researcher employed the Likert scale rating between positive and negative to present a favorable or unfavorable attitude.

Before questionnaires were handed out to the target participants, three senior experts with Ph.D. and extensive experience were invited to examine the validity of the constructs in the research. Validity is the extent to which we can accurately and honestly measure the attributes of things. Then, internal consistency reliability, which is the consistency and stability of measurement results, was evaluated by Cronbach's Alpha approach. A pilot test with 30 students was surveyed to obtain reliability. Then, the questionnaire was distributed to accepted 488 respondents online from the target college following a validity and reliability assessment before mass data collection. Cronbach's Alpha values were greater than 0.70 (Sarmento & Costa, 2019). SPSS and Amos were applied to calculate and analyze the entire data. For the need of insurance of the validity and reliability of the model, the model fit measurement was implemented through Confirmatory Factor Analysis (CFA). Eventually, the Structural Equation Model (SEM) was used to prove connections among constructs.

3.3 Population and Sample Size

The target population of the research was students in the apparel School of Chengdu Textile College in Sichuan Province, China. Compared with simple models, 500 is the minimum sample size required for complex models (Williams et al., 2010). The calculator of the structural equation model resulted in a minimum sample size of 425 respondents, so 500 was primarily selected. However, 488 respondents were valid to proceeding the data analysis.

3.4 Sampling Technique

The researchers utilized a non-probability sampling which are judgmental, quota and convenience sampling. In the sampling procedure, judgmental sampling was initially implemented to choose 611 respondents from the target students who had experienced e-learning at Chengdu Textile College in the Sichuan Province of China and whose major was relevant to school of apparel. Later, a quota sampling method of 500 respondents was performed. Consequently, 488 questionnaires were qualified, and 12 questionnaires were unqualified. Finally, 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)	Sampling Units	Population Size Total = 611	Proportional Sample Unit Size Total = 500
School of Apparel	Freshman	149	122
	Sophomore	241	197
	Junior	221	181

Source: Created by the author.

4. Results and Discussion

4.1 Demographic Information

The demographic profile of the target 488 participants is presented in Table 2. For gender, female participants took the most of the total population proportion at 64.55%, while males accounted for 35.45%. Furthermore, costume art design had the maximum proportion of 43.65%, the leather art design was 30.94% and the embroidery design was 25.41%.

Table 2: Demographic Profile

Demographic and General Data (N=488)		Frequency	Percentage
Gender	Male	173	35.45%
	Female	315	64.55%
Major Direction	Costume Art Design	213	43.65%
	Leather Art Design	151	30.94%
	Embroidery Design	124	25.41%

4.2 Confirmatory Factor Analysis (CFA)

Confirmatory factor analysis (CFA) was applied in the research. CFA differs from other approaches to examining hypothetical constructs by evaluating precise hypotheses in a deductive mode (Hoyle, 2000). Cronbach's Alpha values were greater than 0.70 (Sarmento & Costa, 2019).Factor loading pertains to standard terms for coefficients among the group of independent variables or the structure (Heckler & Hatcher, 1996). As seen in Table 3, the total factor loading results were beyond 0.50, the composite reliability was more than 0.70, and the average variance extracted (AVE) was above 0.50 (Hair et al., 2010). Thus, all CFA results were entirely acceptable.

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	0.820-0.867	0.925	0.711
Perceived Ease of Use	(Sahin et al., 2022)	4	0.817-0.865	0.903	0.699
Perceived Usefulness	(Sahin et al., 2022)	4	0.725-0.772	0.831	0.552
Attitude	(Bailey et al., 2022)	5	0.718-0.838	0.883	0.602
Performance Expectancy	(Tarhini et al., 2017)	5	0.663-0.783	0.848	0.529
Social Influence	(Tarhini et al., 2017)	4	0.735-0.805	0.853	0.593
Behavioral Intention	(Tarhini et al., 2017)	5	0.659-0.808	0.863	0.560

The goodness of fit is determined through the significance and permissible value of the factor load of each item (Hair et al., 2006). GFI, AGFI, NFI, CFI, TLI, and RMSEA were essential model fit indicators in CFA measurement. The convergent and discriminant validity were confirmed to be the value of this investigation, which was indicated in Table 4. As a result, the overall measures employed in the CFA assessment for this scientific study had perfect goodness of fit. Moreover, the findings of model measurement provided discriminant validity and validation to assess the validity of later structural model estimates.

Table 4: Goodness of Fit for Measurement Model

Index	Acceptable Values	Statistical Values
CMIN/DF	< 3.00 (Hair et al., 2010)	1.497
GFI	> 0.90 (Bagozzi & Yi, 1988)	0.925
AGFI	> 0.80 (Filippini, 1998)	0.910
RMSEA	< 0.05 (Hu & Bentler, 1999)	0.032
CFI	> 0.90 (Marsh et al., 2004)	0.975
NFI	> 0.90 (Bentler & Bonett, 1980)	0.929
TLI	> 0.90 (Bentler & Bonett, 1980)	0.972
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.

The discriminant validity is demonstrated in Table 5. The quantity specified diagonally is the mean square root of the mean, with no correlation greater than 0.80 across any two latent variables (Liu et al., 2009). The result showed that the discriminant validity was validated using these quantitative data.

Table 5: Discriminant Validity

	SE	PEOU	PU	ATT	PE	SI	BI
SE	**0.834**						
PEOU	0.232	**0.763**					
PU	0.271	0.146	**0.824**				
ATT	0.282	0.211	0.277	**0.801**			
PE	0.223	0.263	0.246	0.436	**0.733**		
SI	0.306	0.258	0.388	0.351	0.392	**0.784**	
BI	0.246	0.181	0.285	0.383	0.414	0.343	**0.713**

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

4.3 Structural Equation Model (SEM)

SEM is an empirical data-based multivariate statistical approach that estimates the structure and evaluates hypothesis testing through verification methods. SEM is applied to validate the measurement as well as structural models. The measurement model is critical because it tests the validity of the observable variables used to measure the latent variables. A structural model uses path analysis to find the greatest goodness-of-fit and hypothesized interactions among endogenous and exogenous variables.

The combined values of CMIN/DF, GFI, AGFI, CFI, NFI, TLI, and RMSEA are beyond the permissible limits, and these numbers showed that the model fits. They are calculating and adjusting with AMOS, as shown in Table 6.

Table 6: Goodness of Fit for Structural Model

Index	Acceptable Criterion	Statistical Values
CMIN/DF	< 3.00 (Hair et al., 2010)	1.707
GFI	> 0.90 (Bagozzi & Yi, 1988)	0.911
AGFI	> 0.80 (Filippini, 1998)	0.897
RMSEA	< 0.05 (Hu & Bentler, 1999)	0.038
CFI	> 0.90 (Marsh et al., 2004)	0.964
NFI	> 0.90 (Bentler & Bonett, 1980)	0.917
TLI	> 0.90 (Bentler & Bonett, 1980)	0.960
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.

4.4 Research Hypothesis Testing Result

From the evaluated results in table 7, compared with other constructs, perceived usefulness had the most significant influence on attitude with β at 0.499 (t-value at 8.320 ***). Next, perceived ease of use had the second significant impact on perceived usefulness, with β at 0.383

(t-value at 7.196 ***). Then, performance expectancy significantly affected the behavioral intention with β at 0.357 (t-value at 6.678 ***). Followed by perceived usefulness, it had a significant effect on the behavioral intention with β at 0.325 (t-value at 3.263 **). Moreover, perceived ease of use affected attitude with β of 0.292 (t-value at 2.009 *). Furthermore, the attitude significantly influenced the behavioral intention with 0.254 (t-value at 4.215 ***). Moreover, social influence impacted behavioral intention with 0.141 (t-value at 2.968 **). Ultimately, self-efficacy had the significant effect on the behavioral intention with 0.104 (t-value at 2.292 *).

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-Value	Result
H1: PEOU → PU	0.383	7.196 ***	Supported
H2: PU → ATT	0.499	8.320 ***	Supported
H3: PEOU → ATT	0.292	2.009 *	Supported
H4: PU → BI	0.325	3.263 **	Supported
H5: ATT → BI	0.254	4.215 ***	Supported
H6: SE → BI	0.104	2.292 *	Supported
H7: PE → BI	0.357	6.678 ***	Supported
H8: SI → BI	0.141	2.968 **	Supported

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

The hypotheses testing result can be expansively described in Table 7.

The correlation outcome of **H1** supports the hypothesis that the impact of PEOU on PU is substantial, with a standardized coefficient value of 0.383. Davis (1993) mentioned that PEOU might be a necessary prerequisite for PU.

Regarding **H2,** the hypotheses testing supported PU as the most crucial element in ATT, with a standardized coefficient value of 0.499 and the highest value in this study. A clear relationship between PU and ATT toward usage of e-learning can influence instructors and students to utilize technology (Teo, 2011).

For the **H3,** it is confirmed that PEOU significantly influenced ATT with a common coefficient value of 0.292. According to Heijden (2000), a crucial predictor of attitude toward using technology is PEOU.

Furthermore, in the **H4,** the results confirm that PU considerably impacts learners' BI, with the standardized coefficient value at 0.325. It was illustrated by a study by Park et al. (2012) that PU substantially correlates with ATT and BI.

H5 demonstrates that ATT contributes to BI in this study, indicating the standardized coefficient value at 0.254. It was developed by Yu and Yu (2010); ATT considerably impacts BI toward learning based on the web.

Analysis for **H6,** the finding validates the hypothesis of SE on BI, indicating the 0.104 standardized coefficient value. SE was identified by Downey (2006) as an essential factor that has an impact on adopters' BI.

Subsequently, the hypothesis that PE had a substantial effect on BI was supported by the relevant statistical results for **H7,** with the standardized coefficient value of 0.357. Multiple studies from Venkatesh et al. (2003) have demonstrated that action inclination in various areas, for instance, social media and online learning, was significantly correlated with PE. Backed by Chiu and Wang (2008), PE supports a consistent usage inclination to use online study. Furthermore, e-learning not only assisted individuals in completing studies quickly and simply, but it also boosted technical ability and behavioral expression.

Eventually, the hypothesis that SI had a significant effect on BI was corroborated by the statistical results for **H8,** with a standardized coefficient value of 0.141. Previous research determined that SI closely connects with BI (Venkatesh et al., 2003).

5. Conclusions and Recommendation

5.1 Conclusion and Discussion

This investigation aimed to explore different factors that affected perceived usefulness, attitude, and behavioral intention regarding e-learning of college students from apparel schools in Chengdu Textile College in the Sichuan province of China. The statistical data was collected from 488 valid participants who had ever used an e-learning platform. From the outcome, all hypotheses were supported. Perceived usefulness influences attitude with the highest significant coefficient value among all. According to Venkatesh (2000), as stated by the Technology Acceptance Model, several information technology researchers have proven the active effect of perceived usefulness on the attitude associated with using information technology systems. Moreover, attitude affects the behavioral intention of e-learning adoption positively and significantly. It was acknowledged by Davis (1993) that attitude is regarded as a fundamental component of predicting future action and has a close relationship with action tendency. Furthermore, perceived ease of use affects perceived usefulness powerfully. Liu et al. (2009) show a casual and practical link between perceived ease of use and perceived usefulness. Consequently, performance expectancy, perceived usefulness, social influence, and self-efficacy significantly impact behavioral intention.

5.2 Recommendation

With the progress of innovative technology, college learning methods changed considerably. Simultaneously, in the post-pandemic era, e-learning was sprouting. Through the quantitative research on the usefulness, attitude, and behavioral intention of e-learning in Chengdu Textile College of China, the research findings suggested that more consideration should be paid to students' psychology, technology application, and social impact, including correlations among self-efficacy, perceived ease of use, perceived usefulness, attitude, performance expectancy, social influence as well as behavioral intention.

Regarding performance expectancy, students should be respected, and an art curriculum should be set up and transform teacher-centered education into a student-centered teaching mode. In order to inspire students' innovative thinking, students' characteristics, interests, and advantages should be integrated, individual art learning and self-learning should be guided, and art learning methods should be endowed with diversity, technology, and flexibility. Concerning perceived usefulness and perceived ease of use, students could be encouraged to think about problems and solve problems. Based on the platform for e-learning, they could raise problems and gradually solve them. Further, the technical support of e-learning, course technical training, and hardware support was fully considered so that learners could operate quickly and efficiently to build a good learning attitude and impact the positive intention of electronic learning. To establish a correct understanding and a positive attitude towards e-learning, schools should give sufficient attention to the publicity of the school's educational philosophy, educational, academic exchanges, and cultural activities in electronic or online forms, such as video publicity, cloud lectures, cloud exhibitions, online lectures, etc., to enhance students' experience and feelings of e-learning, to promote the integration and acceptance from e-learning.

Challenges and opportunities of e-learning coexist. School administrators and teaching implementers should attach full importance to e-learning, change educational ideas, innovate educational methods, make e-learning platforms a new and efficient means of art education, foster technology transformation, and realize the innovation of art wisdom. Based on these assumptions, it provides reference and inspiration for the electronic learning and promotion of in higher institutions in southwest China.

5.3 Limitation and Further Study

Firstly, the sample profile of the investigation was restricted to a small scale of a single college, which could not generalize the representativeness for other college students. It should be referred to with caution. In future investigations, it was recommended to consider other colleges or regions to obtain more objective and comprehensive data. Secondly, a future survey might integrate other investigation theories into the conceptual framework, such as the theory of planned behavior (TPB). Thus, it would promote sustainable investigation and innovative findings toward e-learning. Consequently, this investigation focused on students' e-learning in college education but ignored e-learning and practice in industry or companies. Later, it could view e-learning from the aspect of students' learning growth and career requirement for examination and analysis.

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