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Meizi Huang
[1]Corresponding Author, PhD Candidate, Graduate School of Innovative Technology Management, Assumption University, Thailand
Email: hmeizi6219321@gmail.com

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Abstract

This research aims to investigate factors for adoption of ubiquitous learning (u-learning) in higher education in China in the wake of the COVID-19 pandemic. Literature and theoretical models for adoption of ubiquitous learning were examined to find the key factors that would influence ubiquitous learning adoption which include performance expectancy, effort expectancy, social influence, facilitating conditions, intention to use and actual use. The research uses a quantitative, survey-based research design, employing online data collection. The study applied multistage sampling. First, a non-probability sampling method, judgmental sampling was used to draw a population of Chinese higher education students in Sichuan, China at three institutions: – Sichuan Normal University Fine Arts College, Sichuan University of Arts and Sciences Academy of Art and Design, and Dazhou Vocational and Technical College Art Department. Second, stratified random sampling was applied to calculate the number of students to represent each program. Lastly, a sample size of 420 was determined based on the ratio of the number of students in each institution to the total number of populations, were selected through convenience sampling. For analysis of data, Confirmation Factor Analysis (CFA) and structural equation modeling (SEM) were utilized. The analysis showed that intention to use has the strongest effect on actual system use. Furthermore, effort expectancy, facilitating conditions, and social influence except performance expectancy were found to positively affect the intention to use u-learning. Hence, policymakers, universities executives, and educators are recommended to consider these factors to ensure technology adoption success.

Keywords: ubiquitous learning, performance expectancy, effort expectancy, social influence, facilitating conditions

Introduction

E-learning or online learning is an online technology has been used in teaching and learning (Wang et al., 2018). E-learning has been widely accepted as educational tools. The e-learning has been increased during the pandemic. Around 9,000 online courses using Ubiquitous learning (u-learning) is an expansion that can be assessed through computers and mobile devices connected to the internet. U-learning is technological platform that supports learning anytime anywhere (Ogata et al., 2009). U-learning provides streaming and real-time interaction with better visual and audio output quality than a common e-learning format. Thus, students in higher education can benefit from the flexibility and functions the platform can offer to improve remote learning efficiency (Hwang, et al., 2008).

Research Objectives

1. To determine the factors influencing usage intention and actual use of ubiquitous learning in higher education in China
2. To investigate which factor has the strongest influence on usage intention and actual use of ubiquitous learning

Research Questions

1. What are factors influencing usage intention and actual use of ubiquitous learning in higher education in China?
2. Which factor has the strongest influence on usage intention and actual use of ubiquitous learning?

Significance of the Study

The finding of this study is significant for both government and stakeholders in higher education in China, considering that u-learning plays an important role during Covid-19 pandemic. The greater demand for students to use u-learning justifies the need for more effective remote learning approaches. Hence, government and universities that apply the recommended approach obtained from the results in this study will be able to enhance students' learning efficiency. Policymakers, practitioners and educators will be guided on what factors should be emphasized to improve students' u-learning adoption.

Literature Review

The literature review identifies the related theories and definitions of variables used in this study, which includes performance expectancy, effort expectancy, social influence, facilitating conditions, usage intention and actual system use.

Related Theories

Theory of Planned Behavior (TPB)

This paper adopted the theory of planned behavior (TPB) which was constructed from the theory of reasoned action or TRA. The model is a foundation of behavioral intentions or proactive determinations to act or perform some behavior. that Ajzen (1991) proposed that the three factors that would influence behavioral intention formation were attitudes toward using the technology, subjective norms (shared beliefs in behaving in a specific situation), and perceived behavioral control (the perception of the difficulty of decreeing a behavior).

Technology Acceptance Model (TAM)

The technology acceptance model (TAM) was theorized to describe the adoption of new technology in the organizational development context (Davis et al., 1989). The model is composed of attitudinal behavior which are perceived usefulness and perceived ease of use of the technology. Hence, TAM was developed from TPB and explained the relationships among attitudes, behavioral intentions and actual system use (Davis, 1985). In this study, two variables were derived from TAM which are behavioral intention and the actual system use (Davis, 1985; Davis et al., 1989).

Unified Theory of Acceptance and Use of Technology (UTAUT)

The third model used in the conceptual framework of this study is the unified theory of acceptance and use of technology (UTAUT). Venkatesh et al. (2003) attested that the UTAUT was developed from the change of technology adoption during the 1990s to early 2000s when leisure technology and internet usage started to grow rapidly. The UTAUT model incorporates the dimensions of previous behavioral frameworks of TRA, TPB, TAM, and other models which describe the acceptance of information technologies. For example, TAM demonstrated the technology usage in organizational circumstances (Davis et al., 1989), whereas the UTAUT integrates multiple contexts, individual and leisure usage of technology (Venkatesh et al., 2003).

Definition of Terms

Performance Expectancy

Performance expectancy is conceptualized from motivation into actions that leads to results or the belief of desirable output, which encourage individuals to perform (Vroom, 1964). In the context of this paper, performance expectancy is learning expectancy (Chen, 2011) that is similarly to perceived learning benefits. It is identified as the degree of belief among learners that ubiquitous learning can enhance their study performance. (Diep et al., 2016).

Effort Expectancy

A dimension of effort expectancy depends on how much effort the individual expects to complete a task (Isaac et al., 2001). In the context of learning expectancy, it is associated with the ease of using the information technology, resulting in good or bad attitude towards using it (Venkatesh et al., 2003). Effort expectancy has been projected as a key factor for voluntariness to use u-learning among learners (Honarpisheh & Zualkernan, 2013).

Social Influence

Social influence is defined as the degree to which an individual is influenced by other people to adopt technology (Venkatesh & Morris, 2000). It considers the feedback of a social group presented as norm which can influence an individual’s behavior. (Cialdini & Trost, 1998). Two dimensions describe this influence which are social norms and social identity. Social norms are defined as shared beliefs about how individual members of a group should behave in specific situations (Elster, 1989). Social identity refers to the ways that people's self-concepts are based on their membership in social groups (Leaper, 2011). The social group can, directly and indirectly, impact one’s attitude and action (Hwang, 2016). In this study, the adoption of u-leaning can be influenced by their instructors, classmates, and university requirement policy.

Facilitating Conditions

Facilitating conditions are signified as a perceived behavioral control, which means individual perceive in controlling results from their behavior. It extends to the supportive environment which helps them to perform task for favorable outcome (Ajzen, 1991). Facilitating conditions for u-learning can be obtained from hardware and software infrastructure provided by the school or university. In addition, training and technical support on the system can assist users to operate the system smoothly (Tan, 2013).

Usage Intention

Behavioral intention is an intrinsic and explicit motivation to engage in one's behavior which differs from various casual factors (Fishbein & Ajzen, 1975). Usage intention is a key output in technology adoption model. According to some studies on usage intention in the context of e-learning, mobile learning, and ubiquitous learning, initial usage intention can be extended to continued usage (Cho et al., 2009). Good and bad attitude towards usability can determine whether users will use a technology or not. Furthermore, usage intention can be strongly governed not only by the external factors, but also by the characteristics of technology itself (Wang et al., 2018).

Actual System Use

Actual system use is the usage behavior of the ubiquitous learning system. It is based in the concept of behavior in which users finally interact with the technology (Venkatesh et al., 2003). Many researchers only considered behavioral intention, and some studies measured attitude toward use rather than directly link it to an actual system use as the consequence variable. Actual usage of e-learning or mobile learning can better explain this acceptance behavior (Chen, 2011).

Relationship Between Variables and Research Hypotheses

Performance Expectancy and Usage Intention

The UTAUT advocated that performance expectancy positively effect on behavioral intention for technologies, which was supported by meta-analysis of previous studies (Venkatesh et al., 2003). Furthermore, many researchers have indicated that performance expectancy has a significant impact on online learning adoption (Araújo et al., 2017; Cho et al., 2009; Diep et al., 2016; Honarpisheh & Zualkernan, 2013; Joo et al., 2014; Moreno et al., 2017; Nikou & Economides, 2017; Olasina, 2019; Salloum & Shaalan, 2019; Shin et al., 2011; Tarhini et al., 2017; Wu & Lederer, 2009). Consequently, H1 is formulated as:

Hypothesis 1: Performance expectancy have a positive effect on usage intention for ubiquitous learning.

Effort Expectancy and Usage Intention

UTAUT, as developed from TPB and TAM, stated the casual relationships between effort expectancy and usage intention (Davis et al., 1989; Venkatesh et al., 2003). This statement is also supported by many empirical research (Honarpisheh & Zualkernan, 2013; Sung et al., 2015; Tarhini et al., 2017). Some studies discovered an insignificant association between effort expectancy and usage intention (Chen, 2011; Joo et al., 2014; Salloum & Shaalan, 2019). Nevertheless, the relationship between effort expectancy and usage intention has been confirmed by studies and evidence from the literatures. The theoretical relationship is derived to determine a hypothesis:

Hypothesis 2: Effort expectancy have a positive effect on usage intention for ubiquitous learning.

Social Influence and Usage Intention

Social influence has been found to positively impact the usage intention for technology system (Ajzen, 1991; Venkatesh et al., 2003). Numerous studies supported this empirical relationship (Honarpisheh & Zualkernan, 2013; Hwang, 2016; Nikou & Economides, 2017; Olasina, 2019; Salloum & Shaalan, 2019; Sung et al., 2015; Tarhini et al., 2017). However, some studies rejected the relationship between social influence and usage intention in other technology adoption. For example, the case of mobile learning in South Korea, the distance learning of students in Business Administration programs and vice versa (Chao, 2019; Joo et al., 2014; Moreno et al., 2017). The context of study tends to produce different outcome based on its population of interest. From u-learning perspective, this study hypothesizes social influence has a positive effect on usage intention for ubiquitous learning as stated in the following hypothesis:

Hypothesis 3: Social influence have a positive effect on usage intention for ubiquitous learning.

Facilitating Conditions and Usage Intention

UTAUT suggests facilitating conditions as an essential factor that directly affects usage intention (Venkatesh et al., 2003). Some studies have attested that facilitating conditions can potentially impact on e-learning adoption. Even though there are mixed findings, most of studies indicate positive relationship between facilitating conditions and usage intention for e-learning (Fakhoury & Aubert, 2017; Joo et al., 2014; Kuciapski, 2016; Moreno et al., 2017; Raja Yusof et al., 2017). Some other studies proved that facilitating conditions could lead directly to actual use. (Salloum & Shaalan, 2019; Tan, 2013). Thus, this study looked further into the impact of facilitating conditions on usage intention (Tarhini et al., 2017) as stated in the following hypothesis:

Hypothesis 4: Social Facilitating conditions have a positive effect on usage intention for ubiquitous learning.

Usage Intention and Actual System Use

Ajzen (1991), Davis et al., (1989) and Venkatesh et al. (2003) have proven the direct relationship between usage intentions and actual system use. Some studies have examined usage intention as the final variable of the structural pathway, whereas others have tested other factors with usage intention toward actual usage as the final variables (Chen, 2011; Joo et al., 2014; Olasina, 2019; Wu & Lederer, 2009). The empirical studies investigating the casual relationship of usage intention towards actual usage behavior have supported this study. Thus, the following hypothesis is set:

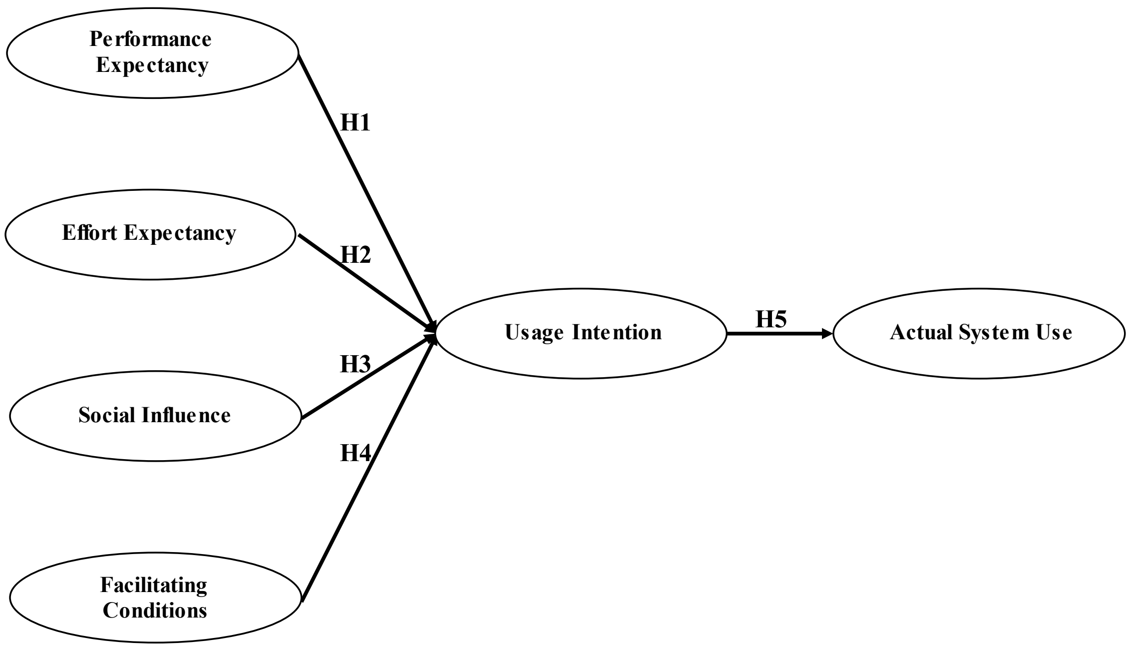
Hypothesis 5: Usage intention have a positive effect on actual system use of ubiquitous learning.

Conceptual Framework

The conceptual framework as shown in Figure 1 indicates the six variables of the study which include performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), intention to use (UI) and actual system use (SU). These variables are considered the factors affecting the adoption of ubiquitous learning (u-learning) in the wake of the COVID-19 pandemic in Chinese higher and from which the five hypotheses for this study were derived to test if there is relationship between these variables.

Figure 1

Conceptual Framework of the ubiquitous learning adoption



Note. Constructed by the author (2021).

Research Methodology

Research Design

This study applied quantitative approach with multi-stage sampling design. Firstly, judgmental sampling was carried out to draw a population of Chinese higher education students in Sichuan, China from three institutions namely Fine Arts College, Arts and Sciences Academy of Art and Design, and Dazhou Vocational and Technical College Art Department. Stratified sampling was then applied to determine the number of students to represent each program of study in these three institutions. Lastly, the sample size was determined using convenience sampling. Before collecting the data, Item- Objective Congruence (IOC) Index and pilot test of 30 students were tested to confirm validity and reliability. Afterwards, Confirmation Factor Analysis (CFA) and Structural Equation Modeling (SEM) were applied to analyze the data, using factors loading, fit model, convergent and discriminant validity.

Research Population and Sample

The target population are students in higher education in China, both Chinese and international students. As of 2019, approximately 30.3 million students enrolled at around 2,688 institutions in China (Textor, 2020). The sample size determination was based on the selected analysis method which is structural equation modeling (SEM). SEM requires a larger sample size than standard regression-based statistical methods (Westland, 2010). The minimum sample size requires 200 (Soper, 2020). However, in this study, a sample size of 420 was determined based on the ratio of the number of students in each institution to the total number of populations as shown in Table 1.

Table 1

Population and Sample Size by Programs

Programs	Approximate Population Size (Total Students)	Sample Size
Sichuan Normal University Fine Arts College	2,400	113
Sichuan University of Arts and Sciences Academy of Art and Design	6,000	283
Dazhou Vocational and Technical College Art Department	500	24
Total	**8,900**	**420**

Note. Constructed by the author (2021).

Research Instrument

A questionnaire was distributed to students who participated in the study. There are three parts in a questionnaire. Firstly, question 1 and 2 are screening questions which include "Are you using ubiquitous learning?" and "Are you studying at Sichuan Normal University Fine Arts College or Sichuan University of Arts or Sciences Academy of Art and Design or Dazhou Vocational and Technical College Art Department?" Secondly, question 3 to 24 applied 5-point Likert scale (strongly disagree to strongly agree) to measure six (6) latent variables and twenty-two (22) observed variables which includes performance expectancy (4), effort expectancy (5), social influence (4), facilitating conditions (3), intention to use (3) and actual use (3). Lastly, question 25 to 28 is used for demographic profile of respondents which includes gender, age and how many years of e-learning experience.

Results and Discussion

Demographic Information

The number of female participants is the 222 (52.8%), and the number of male participants is 198 (47.2%). Majority of respondents are 18 to 25 years old which account for 95% (399) of total respondents, followed by 26 to 33 years old which account for 4.3% (18)

and 3 (0.7%) are aged 34 to 41 years old. There are 234 (55.7%) who have 6-12 months e-learning experience, 117 (27.9%) with 12-18 months e-learning experience, 14 (3.33%) have more than 18 months e-learning experience and, 55 (13.1%) with less than six months e-learning experience. Table 2 summarizes the demographic data.

Table 2

Demographic Information

Demographic Profile Data (N=420)		Frequency	Percentage
Gender	Male	198	47.2%
	Female	222	52.8%
Age	18 – 25 years old	399	95.0%
	26 – 33 years old	18	4.3%
	34 – 41 years old	3	0.7%
	42 – 49 years old	0	0%
	49 years old and above	0	0%
E-learning Experience	Less than 6 months	55	13.1%
	6 to12 months	234	55.7%
	12 to 18 months	117	27.9%
	More than 18 months	14	3.3%

Note. Constructed by the author (2021).

Confirmatory Factor Analysis (CFA)

CFA was applied prior for analyzing the measurement model with structural equation model (SEM). The CFA results showed that all items in each variable are significant and have factor loading that indicates discriminant validity. Hair et al. (2006) suggested that the significance of factor loading of each item and acceptable values can define the goodness of fit. The factor loadings are higher than 0.50 and p-value is lower than 0.05. Additionally, Fornell and Larcker (1981) recommended that the convergent validity must be confirmed by Composite Reliability (CR) and must be greater than the cut-off point of 0.7 and Average Variance Extracted (AVE) higher than the cut-off point of 0.4. The results of CFA and AVE are shown in Table 3.

Table 3

Convergent Validity

Variables	Source of Questionnaire	No. of Item	Cronbach's Alpha	Factors Loading	CR	AVE
Performance Expectancy (PE)	Chao (2019)	4	0.826	0.632– 0.819	0.829	0.550
Effort Expectancy (EE)	Chao (2019)	5	0.829	0.625 – 0.777	0.832	0.498
Social Influence (SI)	Tarhini et al. (2017)	4	0.787	0.641 – 0.743	0.789	0.484
Facilitating Conditions (FC)	Raja Yusof et al. (2017)	3	0.898	0.843 – 0.877	0.899	0.748
Usage Intention (UI)	Chao (2019)	3	0.744	0.665 – 0.724	0.745	0.493
Actual System Use (SU)	Venkatesh and Davis (1996)	3	0.751	0.633 – 0.755	0.757	0.511

Note. CR = Composite Reliability, AVE = Average Variance Extracted, *=p-value<0.05.

In Table 4, AVE shows that all the correlations are greater than the corresponding correlation values for that variable. Furthermore, indicators for the fitness of the model were tested in goodness-of-fit index (GFI), adjusted goodness-of-fit index (AGFI), normalized fit index (NFI) Tucker-Lewis index (TLI), comparative fit index (CFI), root mean square error of approximation (RMSEA) and root mean square residual (RMR). All are greater than acceptable values as shown in Table 5. The results illustrated in Table 3-5 also confirm the construct validity were validated as the convergent and discriminant validities.

Table 4

Discriminant Validity

	PE	EE	SI	FC	UI	SU
PE	**0.742**					
EE	0.070	**0.706**				
SI	0.023	0.542	**0.696**			
FC	0.082	0.454	0.452	**0.865**		
UI	0.038	0.480	0.455	0.443	**0.702**	
SU	0.051	0.579	0.500	0.549	0.408	**0.715**

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

Table 5

Goodness of Fit for Confirmatory Factor Analysis (CFA)

Index	Acceptable Values	Statistical Values
CMIN/DF	< 3.00 (Hair et al., 2006)	1.343
GFI	≥ 0.90 (Hair et al., 2006)	0.948
AGFI	≥ 0.90 (Hair et al., 2006)	0.932
NFI	≥ 0.90 (Arbuckle, 1995)	0.936
CFI	≥ 0.90 (Hair et al., 2006)	0.983
TLI	≥ 0.90 (Hair et al., 2006)	0.979
RMSEA	< 0.05 (Browne & Cudeck, 1993)	0.029
RMR	< 0.05 (Hair et al., 2006)	0.016
Model summary		**In harmony with empirical data**

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, NFI, normalized fit index, TLI = Tucker-Lewis index, CFI = comparative fit index, RMSEA = root mean square error of approximation, and RMR = root mean square residual

Structural Equation Model (SEM)

Structural Equation Modeling (SEM) is used to test relationship among constructs in a proposed model and validate the measurement of the structure coefficient (Hair et al., 2010). Table 6 explicates the fit model for Structural Equation Model (SEM). Chi-square/degrees-of-freedom (CMIN/DF) ratio should not be less than 3.00 and GFI, AGFI, NFI, CFI and TLI should be higher than 0.9 (Hair et al., 2010; Arbuckle, 1995; Browne & Cudeck, 1993). SEM was calculated and adjusted by SPSS AMOS version 26. The fit indices were in harmony with empirical data which are CMIN/DF = 1.812, GFI = 0.926, AGFI = 0.906, NFI = 0.912, CFI = 0.958, TLI = 0.951 and RMSEA = 0.044.

Table 6

Goodness of Fit for Structural Equation Model (SEM)

Index	Acceptable Values	Statistical Values
CMIN/DF	< 3.00 (Hair et al., 2006)	1.812
GFI	≥ 0.90 (Hair et al., 2006)	0.926
AGFI	≥ 0.90 (Hair et al., 2006)	0.906
NFI	≥ 0.90 (Arbuckle, 1995)	0.912
CFI	≥ 0.90 (Hair et al., 2006)	0.958
TLI	≥ 0.90 (Hair et al., 2006)	0.951
RMSEA	< 0.05 (Browne & Cudeck, 1993)	0.044
RMR	< 0.05 (Hair et al., 2006)	0.020
Model summary		**In harmony with empirical data**

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, NFI, normalized fit index, TLI = Tucker-Lewis index, CFI =

comparative fit index, RMSEA = root mean square error of approximation, and RMR = root mean square residual

Research Hypothesis Testing Result

The regression weights with t-value were measured to determine the significance of each construct as shown in Table 7. All hypotheses were supported with a significance at p = 0.05 except H1 with β value of 0.007. Usage intention has the strongest impact on actual system use at 0.801, followed by the effect of effort expectancy (β =0.423), facilitating conditions (β = 0.342), and social influence (β = 0.260) on usage intention.

Table 7

Hypotheses Testing Result of the Structural Model

Hypothesis	Standardized path coefficient (β)	t-value	Testing result
H1: Performance Expectancy (PE) => Usage Intention (UI)	0.007	0.161	Not Supported
H2: Effort Expectancy (EE) => Usage Intention (UI)	0.423	5.417*	Supported
H3: Social Influence (SI) => Usage Intention (UI)	0.260	3.478*	Supported
H4: Facilitating Conditions (FC) => Usage Intention (UI)	0.342	5.717*	Supported
H5: Usage Intention (UI) => Actual System Use (SU)	0.801	10.107*	Supported

Note: *=p-value<0.05

Figure 2 exhibits the result of structural model. H1 showed no support in the relationship between performance expectancy and usage intention with standard coefficient value of 0.007 in the structural pathway. This result is consistent with the arguments presented by many researchers (Araújo et al., 2017; Cho et al., 2009; Diep et al., 2016; Honarpisheh & Zualkernan, 2013; Joo et al., 2014; Moreno et al., 2017; Nikou & Economides, 2017; Olasina, 2019; Salloum & Shaalan, 2019; Shin et al., 2011; Tarhini et al., 2017; Wu & Lederer, 2009) who confirmed that usage intention has no positive effect on performance expectancy.

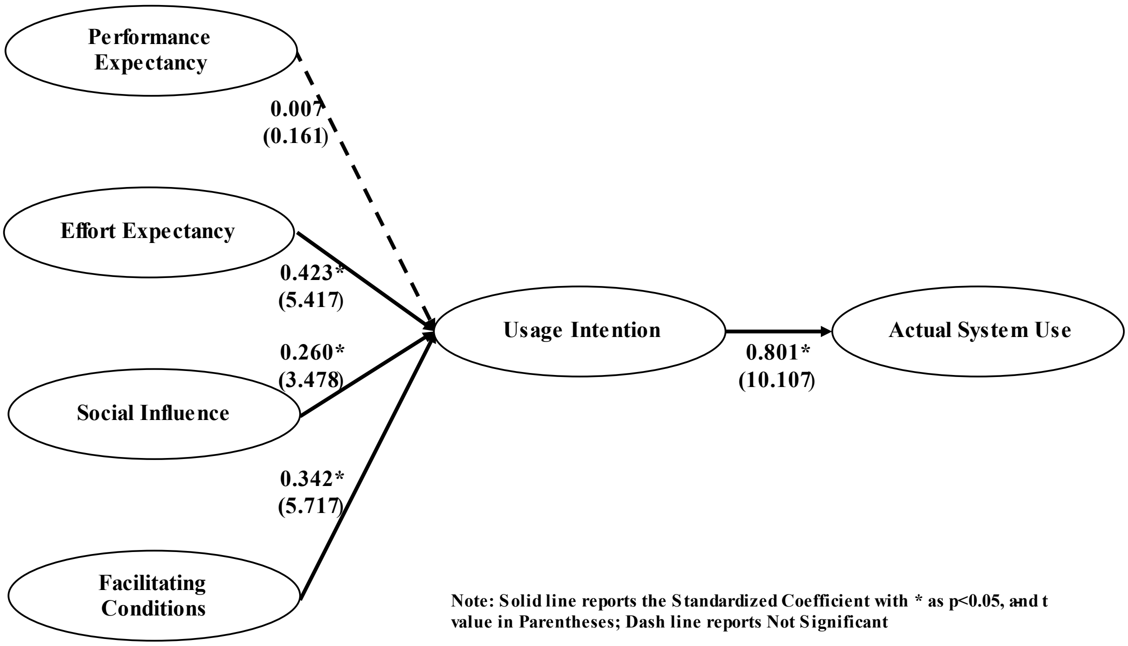
However, results of the SEM analysis show that effort expectancy positively affects usage intention, and which supports H2 in this study, with a standard coefficient value of 0.423. Chen et al. (2021) confirmed that the user-friendly function of technology can encourage learners to use online learning as the level of effort is minimized. H3 has a standard coefficient value of 0.260, which can be postulated that social influence positively affects usage intention of u-learning. Supported by a number of literature (Honarpisheh & Zualkernan, 2013; Hwang, 2016; Nikou & Economides, 2017; Olasina, 2019; Salloum & Shaalan, 2019; Sung et al., 2015; Tarhini et al., 2017), it is believed that learners are encouraged by their social circles such as instructors and classmates to use the system.

Regarding H4, the positive relationship of facilitating conditions on usage intention was found with the standard coefficient value of 0.342. It has been confirmed by many studies

(Fakhoury & Aubert, 2017; Joo et al., 2014; Kuciapski, 2016; Moreno et al., 2017; Raja Yusof et al., 2017) that the supportive environment can encourage the intention of learners to use u-learning. H5 presents the strongest relationship between usage intention and actual system use of u-learning in Chinese higher education with the standard coefficient value of 0.801. It confirms the theoretical models of TPB, TAM and UTAUT and previous literatures (Ajzen, 1991; Davis et al.,1989; Venkatesh et al., 2003; Chen, 2011; Joo et al., 2014; Olasina, 2019; Wu & Lederer, 2009) which affirms that learners' intention can lead to actual use of the system as they increase their performance.

Figure 2

The Results of Structural Equation Modeling Analysis



Note. *represents Standardized Coefficient with p-value lower than 0.05

Direct, Indirect and Total Effects of Relationships

The AMOS program measures the relationship between all variables including the direct, indirect and total effects. The direct effect refers to the pathway between two variables without mediator of the measurement model. On the other hand, an indirect effect reflects the relationship between two variables and moderates at least by one variable (Raykov & Marcoulides, 2000). In this study, there is a variable that directly affects actual system usage, which is usage intention with a significant effect value 0.801 while there are some indirect effects that show usage intention as moderator of relationship. The significant indirect effect shows that performance expectancy has an effect on actual use of system with a value of 0.006, followed by effort expectancy (0.339), social influence (0.208) and facilitating conditions (0.274). To sum up, all symbolized the total effect of each structural pathway as shown in Table 8.

Table 8

Direct, Indirect and Total Effects of Relationships

Independent Variables	Dependent Variables							
	Usage Intention (UI)				Actual System Use (SU)			
	Direct Effect	Indirect Effect	Total Effect	R^2	Direct Effect	Indirect Effect	Total Effect	R^2
Performance Expectancy (PE)	0.007	-	0.007	0.753	-	0.006	0.006	0.642
Effort Expectancy (EE)	0.423	-	0.423		-	0.339	0.339	
Social Influence (SI)	0.260	-	0.260		-	0.208	0.208	
Facilitating Conditions (FC)	0.342	-	0.342		-	0.274	0.274	
Usage Intention (UI)	-	-	-		0.801	-	0.801	

Note. Constructed by the author (2021).

Conclusion

Because online learning usage has increased and has become a common platform worldwide in digital era, the factors that drive adoption of this related technology have been widely investigated by many scholars. As technology have been created to assist people for various reasons such as convenience, timesaving and cost-minimizing, it is important that users of these technologies understand clearly their intention, adoption and actual use of these technologies. This research explored the use of TPB, TAM and UTAUT, which have been used to examine the adoption of technology among u-learning users. The major factors examined in this study include performance expectancy, effort expectancy, social influence, facilitating conditions that impact usage intention; behavioral intention that can influence actual system usage of u-learning in Chinese higher education was also examine.

This study applied quantitative approach with multi-stage sampling technique which includes judgmental, stratified random and convenience sampling. The target population is students from top three higher education institutes in Sichuan, China. A sample size of 420 was determined based on the ratio of the number of students in each institution to the total number of populations. A questionnaire was distributed to students via offline and online channels. Prior to data collection, Item- Objective Congruence (IOC) Index and pilot test of 30 students were tested for validity and reliability. For data analysis, Confirmation Factor Analysis (CFA) and Structural Equation Modeling (SEM) were applied.

The results obtained from CFA and SEM revealed that usage intention has the strongest impact on actual usage. Effort expectancy, facilitating conditions and social influence positively affect usage intention. However, this study contradicts results of studies that posits performance expectancy positively affects actual use among u-learning users as result was found insignificant.

Recommendations

Policymakers, university executives and educators must consider each factor to assure students would engage in u-learning more efficient and they develop positive technology experience by providing them with effective communication channels, creative online classes and usage training for new users.

Suggestions for Further Studies

It is recommended that further studies be conducted that will explore other factors such as individual cognitive and psychological factors e.g., self-esteem, self-efficacy, which can also produce different perspectives and results. Other suggestions may include other groups as participants like high school students or use of other platforms.

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