INFLUENCING FACTORS OF BEHAVIORAL INTENTION AND SATISFACTION OF ONLINE LEARNING AMONG UNDERGRADUTES IN CHENGDU UNIVERSITY OF CHINA

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Abstract

The objective of this research is to investigate the behavioral intention and satisfaction of students towards online learning, in order to provide corresponding theoretical support for future planning and implementation of teaching reform. Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Information Systems Success (ISS) were applied to build a research model, consisted of perceived ease of use, perceived usefulness, self-efficacy, effort expectancy, social influence, behavioral intentions, and satisfaction. The multistate sampling techniques used were judgmental sampling, stratified random sampling, and convenience sampling. The target population and sample size were collected by distributing online questionnaire to 500 undergraduate students, majoring in economics, physical science, art design, and bioengineering in Chengdu university of China. Item- Objective Congruence (IOC) for the content validity and Cronbach's Alpha for reliability analysis were conducted before processing of the data collection. Afterwards, the descriptive analysis, Confirmatory Factor Analysis (CFA) and Structural Equation Model (SEM) were accounted. The results showed a significant relationship between perceived ease of use and perceived usefulness towards behavioral intention, and social influence on behavioral intention towards satisfaction. For non-significant relationships, there were self-efficacy and effort expectancy on behavioral intention. Academic researchers and education’s stakeholders should extend the study to ensure the high-quality online learning system for increasing the level of behavioral intention and satisfaction of the system.

Keywords: Undergraduate, Online Learning, Behavioral Intention, Satisfaction, Technology Adoption Model

Introduction

The Internet had been introduced to China in 1994, and the nationwide public internet was primarily accomplished in 1996. Thus, comprehensive online learning has commenced and is continuing to expand in China. Because the Chinese internet in the 90s is still in its early stages, the functionality of network software and hardware had not been upgraded. As the consequence, the quality of online learning was relatively mediocre, and the experience was not very enjoyable for the participant in the past (Guan & Li, 2014). With the technological advancement of the online and intelligence devices, as well as the advancement of mobile platforms, online learning has established an extraordinarily and advantageous aspects. Live classes have progressively appeared and increased, which also relates to brand-new business strategy (Chen & Bao, 2014; Fan, 2017). Among these, online education began to be actively investigated and realized in 2017, as a result of the advent of new content dissemination techniques such as live broadcasts and short films (Chen & Bao, 2014; Jiang, 2021). With the emergence of the novel coronavirus pandemic, the globe has entered an era of massive online education. Furthermore, the worldwide pandemic outbreak in 2020 exacerbated several colleges to make a hasty migration to online learning rather than attending lectures in person Online learning has changed the face of lecturing and learning worldwide. In comparison with the physical classroom, online learning may not deliver full effectiveness as some programs might need physical interaction for best performance of students such as arts, architecture, engineering, sports, medical practice etc. Learning effectiveness of students is required to be monitored closely during and after Covid-19 period (Aristovnik et al., 2020).

Objectives of the Study

The research objectives are described as follows;

1. To examine the significant effect between perceived ease of use and perceived usefulness of online learning among undergraduates in Chengdu University.

2. To examine the significant effects among self-efficacy, perceived usefulness, perceived ease of use, effort expectancy, social influence and behavioral intentions to use online learning among undergraduates in Chengdu University.

3. To examine the significant effect between behavioral intention and satisfaction of online learning among undergraduates in Chengdu University.

Research Framework

Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Information Systems Success (ISS) were applied to construct a research framework. It is composed with six independent variables which are perceived ease of use, perceived usefulness, self-efficacy, effort expectancy, social influence and behavioral intentions, and one dependent variable which is satisfaction per shown in Figure 1.

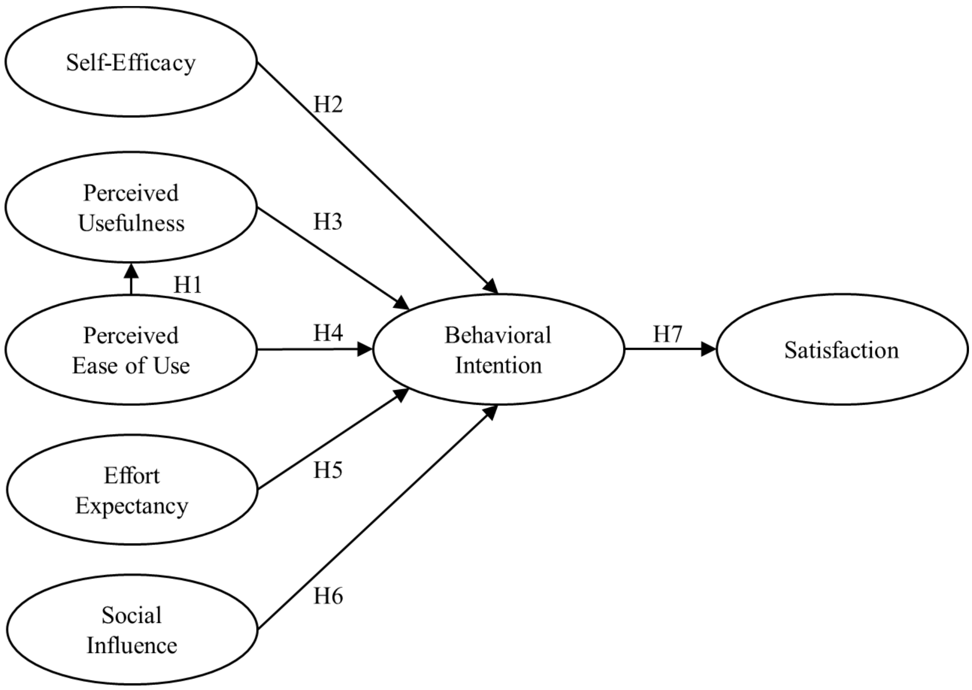

Figure 1 Conceptual Framework

Significance of the Study

Regarding to the fact that online learning has become extremely adopted in Chinese public colleges, there is a challenge of complexity with the instructional implementation, as evidenced by instructors' misconceptions of students' psychological requirements. Moreover, the academic administrations in organizational strategy departments who deploy online learning urged that online learning is an inconsistency phenomenon. These limitations would have a negative influence on the effectiveness of online education. Based on the above situation, it has the obvious significance for us to conduct corresponding research.

Literature Review

1. Technology Acceptance Model (TAM)

Numerous efforts have been devoted by social scientists and researchers who endeavors to construct and evaluate the theoretical matrices for anticipating the technological acceptance for the mankind (Cheon et al., 2012). The majority of academic achievements for the online learning have accurately forecasted the technology adoption of behavioral intention which developed form the theories based on the technology acceptance model by Davis (1989) which explains the user’s journey on the use of a new technology. TAM presents key variables which are perceived ease of use, perceived usefulness, attitudes toward using and behavioral intention (Davis et al., 1989).

2. Unified Theory of Acceptance and Use of Technology (UTAUT)

The unified theory of acceptance and use of technology (UTAUT) is an adoption and utilization for technology system which has been established by Venkatesh et al. (2003). The primary function of the UTAUT model is to characterize authentical motivations to utilize an information system or application software and certain subsequent employment of the behavioral interaction. According to this assumption, there are predominant latent variables which include performance expectancy, effort expectancy, social Influence, and facilitating conditions towards behavioral intention and use behavior (Venkatesh et al., 2003).

3. Information Systems Success (ISS)

DeLone and McLean (1992) originally established the ISS theory, and they have enhanced this framework several years later in the reaction of condemnation from other scholars. The ISS model has been acknowledged in amounts of social science academic achievements and generally regarded amongst the exploration of information systems adoption studies. Information quality, system quality, service quality, behavioral intention, satisfaction, and net system benefit are the crucial variables of ISS framework (DeLone & McLean, 2002).

4. Perceived Ease of Use

Perceived ease of use is characterized as the correspondence toward a participant's perception that the use of target technology requires the minimum effort (Davis, 1989).

According to the TAM, actual behavior is determined by the behavioral intention for the specific application, which is characterized by perceived usefulness and perceived ease of use. According to Davis (1993) and Teo (2009), perceived ease of use has a positive impact on perceived usefulness. According to Venkatesh and Davis (2000), perceived usefulness is indeed regulated by perceived ease of usage. Furthermore, a variety of previous academic research have determined that perceived ease of use had an impact on behavioral intention (Çelik, 2008; Lee, 2009; Kesharwani & Tripathy. 2012; Abbad, 2013). Accordingly, the proposed hypotheses are established:

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

H4: Perceived ease of use has significant effect behavioral intention.

5. Self-efficacy

Self-efficacy refers to individuals' belief of their abilities to orchestrate and accomplish goals (Bandura, 1982). Self-efficacy has been incorporated as a determinant of behavioral intention for digital and information technology utilization. (Henry & Stone, 1995; Venkatesh & Davis, 2000; Yi & Hwang, 2003). Self-efficacy is a fundamental characteristic that stems from participants' perceptions regarding to their capabilities to implement their behavioral intention (Cheung & Vogel, 2013). Henceforth, we hypothesize:

H2: Self-efficacy has a significant effect on behavioral intention.

6. Perceived Usefulness

Perceived usefulness is defined as the extent to which a student is convinced to use an online learning as it can facilitate his or her learning achievements (Shin & Kang, 2015). Based on TAM, perceived usefulness is a strong significant component determining attitude towards use, and behavioral intention (Liaw & Huang, 2003). A number of academic investigations incorporated perceived usefulness as a constitution of the technology acceptance model which can predict behavioral intention (Rajan & Baral, 2015; Wu & Wang, 2005; Yunus & Mohammad, 2017). Consequently, a following hypothesis is proposed:

H3: Perceived usefulness has a significant effect on behavioral intention.

7. Effort Expectancy

Effort expectancy could be conceptualized as the extent of convenience associated with the employment of the system and technology (Bardakc, 2019). UTAUT signified effort expectancy as an instantaneous determinant of behavioral intention. Many antecedent academic researchers have established that effort expectancy is a significant determinant of behavioral intention to use particular technology (Teo & Noyes, 2014). According to academic achievements, effort expectation could anticipate behavioral intention to the employment of the certain technology system (Dwivedi et al., 2019). Hence, H5 is set:

H5: Effort expectancy has a significant impact on behavioral intention.

8. Social Influence

Social influence explains how other persons can influence individuals to adopt the system technology (Venkatesh et al., 2003). Social influence is a considerable effect on behavioral intention to implement certain technologies (Barrane et al., 2018; Chao, 2019; Dwivedi et al., 2019; Tao, 2011). Alam and Uddin (2019) demonstrated that behavioral intention might have been affected by how family and friends, as influencers, can convince users to use a technology. Therefore, social influence is a significant indicator for behavioral intention. Based on the above evidences, a hypothesis is constructed:

H6: Social influence has a significant effect on behavioral intention.

9. Behavioral Intention

Behavior intention is the level to which a participant has a strong will to perform a specific behavior. It is hypothesized to be a causative characteristic of behavior and attitude (Ajzen, 1991). Shin and Kang (2015) encountered that behavioral intention is a significant forecaster of user's satisfaction and performance in online learning. Several social scientists stated that the behavioral intention for the employment of massive open online courses can generate the considerable influence on students' learning (Pozón-López et al., 2019). Consequently, the hypothesis is demonstrated:

H7: Behavior intention has a significant effect on satisfaction.

10. Satisfaction

Satisfaction in this study can be implied as the students' positive or optimistic preconceptions of their online education experience or observations (Nagy, 2018). Satisfaction is constituted in the theory of planned behavior (Ajzen, 1991). Satisfaction represents the level of enjoyment generated from the use of specific technological system whether or not such system match or exceed user's expectation (Lin & Hsieh, 2006). Accordingly, satisfaction is illustrated to be an acceptance, a consideration or a psychological reaction to a particular technology (Oliver, 1993).

Research Methodology

Researchers conducted quantitative approach, using online questionnaire distribution to the target group. Research instruments were compiled into three sections including screening questions, Five-point Likert scale of measuring items, and demographic information.

1. Population and Sample Size

The target population of this empirical research was undergraduate students, majoring in economics, physical, art design, and bioengineering of Chengdu University of China. Additionally, the sample size was determined by Soper (2022)' s online statistical software which recommended the minimum sample size at least 425. However, to minimize the tendency of missing data and error, researchers considered a proper sample size to be 500.

2. Sampling Technique

The sampling techniques were the combination of probability and nonprobability approaches which include judgmental sampling, stratified random sampling, and convenience sampling. Firstly, judgmental sampling was applied to select undergraduate students, majoring in economics, physical, art design, and bioengineering of Chengdu University of China. Secondly, stratified random sampling was calculated in a proportion of each major as demonstrated in Table 1. Lastly, convenience sampling was organized to distribute online survey to 500 participants via WeChat application.

Table 1 The Proportional Scale for the Stratified Random Sampling

Subjects	Population Size (Total = 4781)	Proportional Sample Size (Total = 500)
Economic	1709	179
Physical	743	78
Art Design	1343	140
Bioengineering	986	103

Source: Created by the author

Results and Discussion

1. Demographic Information

The demographic profile of 500 participants were gender, year of study and age. Most of participants were female (57.6%) whereas males were 42.4%. For the year of undergraduate study, third year was 39.8%, second year was 22.8%, fourth year was 19.6%, and first year was 17.8%. The participants were majorly between 18 to 20 years old of 63.2%, while the least group is over 26 years old at 1.2%. The details of demographic profile are presented in Table 2.

Table 2 Demographic Results

N=500	Demographic Profile	Percentage
Gender	Male	42.4%
	Female	57.6%
Year of	First Year	17.8%
Undergraduate Study	Second Year	22.8%
	Third Year	39.8%
	Fourth Year	19.6%
Age	18-20 years	63.2%
	21-22 years	18.6%
	23-24 years	11.0%
	25-26 years	6.0%
	Over 26 years	1.2%

Source: Created by the author

2. Confirmatory Factor Analysis (CFA)

CFA was implemented to assess the fit degree of a measurement model in this research. The results of the initial model showed acceptable model fit as presented in Table 3.

Table 3 Goodness of Fit for Measurement Model

Index	Acceptable Values	Statistical Values
CMIN/DF	< 3.00 (Hair et al., 2006)	503.734/356 = 1.415
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.938
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.924
NFI	≥ 0.80 (Wu & Wang, 2006)	0.922
CFI	≥ 0.80 (Bentler, 1990)	0.976
TLI	≥ 0.80 (Sharma et. al., 2005)	0.972
RMSEA	< 0.08 (Pedroso et al., 2016)	0.029
Model summary		**Acceptable Model Fit**

Source: Created by the author

CFA results revealed the constructs have coefficient of internal consistency under Alpha Cronbach's value above 0.7 which is considered high reliability and acceptable (Nunnally & Bernstein, 1994). All measuring items in each construct are significant and have factor loading to prove discriminant validity. Hair et al. (2006) noted that factor loadings are greater than 0.50 and p-value of lower than 0.05. Additionally, Fornell and Larcker (1981) confirmed that the Composite Reliability (CR) is greater than the cut-off values of 0.6 and Average Variance Extracted (AVE) is higher than the cut-off point of 0.4. The summary of CFA, CR and AVE of this study is shown in Table 4.

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

Latent Variables	Source of Questionnaire	No. of Items	Cronbach's Alpha	Factors Loading	CR	AVE
Perceived Ease of Use (PEOU)	Vululleh (2018)	5	0.833	0.681-0.730	0.833	0.500
Perceived Usefulness (PU)	Vululleh (2018)	5	0.844	0.646-0.794	0.845	0.524
Self-Efficacy (SE)	Cheung & Vogel, (2013)	3	0.755	0.673-0.771	0.756	0.509
Effort Expectancy (EE)	Tan (2013)	4	0.877	0.773-0.831	0.879	0.646
Social Influence (SI)	Vululleh (2018)	4	0.826	0.689-0.808	0.827	0.545
Behavioral Intention (BI)	Maphosa et al. (2020)	3	0.715	0.590-0.749	0.724	0.469
Satisfaction (SS)	Al-Azawei & Lundqvist (2015)	5	0.810	0.620-0.716	0.811	0.462

Source: Created by the author.

Discriminant validity can approve construct validity of this study which was measured by calculating the square root of each AVE (Table 5). As a result, the value of discriminant validity is larger than all inter-construct/factor correlations, therefore, the discriminant validity is proved. Furthermore, the convergent and discriminant validity were supported (Fornell & Larcker, 1981).

Table 5 Discriminant Validity

	SS	PU	SE	PEOU	EE	SI	BI
SS	**0.680**						
PU	0.649	**0.724**					
SE	0.251	0.197	**0.714**				
PEOU	0.564	0.515	0.241	**0.707**			
EE	0.182	0.192	0.618	0.200	**0.804**		
SI	0.309	0.364	0.069	0.136	0.142	**0.739**	
BI	0.617	0.648	0.256	0.527	0.272	0.425	**0.685**

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

Source: Created by the author

3. Structural Equation Model (SEM)

Structural model was examined, using SEM to determine the goodness of fit model (Table 6). The findings were Chi–Square ($\chi 2$/df) = 2.839, goodness-of-fit index (GFI) = 0.889, adjusted goodness-of-fit index (AGFI) = 0.870, normalized fit index (NFI) = 0.837, comparative fit index (CFI) = 0.887, Tucker-Lewis index (TLI) = 0.876, and root mean square error of approximation (RMSEA) = 0.061.

Table 6: Goodness of Fit for Structural Model

Index	Acceptable Values	Statistical Values
CMIN/DF	< 3.00 (Hair et al., 2006)	1050.532/370 = 2.839
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.889
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.870
NFI	≥ 0.80 (Wu & Wang, 2006)	0.837
CFI	≥ 0.80 (Bentler, 1990)	0.887
TLI	≥ 0.80 (Sharma et al., 2005)	0.876
RMSEA	< 0.08 (Pedroso et. al., 2016)	0.061
Model summary		**Acceptable Model Fit**

Source: Constructed by the author

4. Hypothesis Testing Result

SEM produced the outcome of relationships and hypotheses, using the standardized path coefficient (β) and t-value at the significant value of $p<0.05$. As of Table 7, The significant results were that H1, H3, H4, H6 and H7, whereas non-significant results were H2 and H5.

Table 7 Hypothesis Result of the Structural Equation Model

Hypothesis	Standardized path coefficient (β)	t-value	Testing result
H1: PEOU → PU	0.515	8.549*	Supported
H2: SE → BI	0.090	1.909	Not Supported
H3: PU → BI	0.515	7.633*	Supported
H4: PEOU → BI	0.335	5.630*	Supported
H5: EE → BI	0.056	1.285	Not Supported
H6: SI → BI	0.256	5.386*	Supported
H7: BI → SS	0.720	9.862*	Supported

Note: * $p<0.05$

Source: Created by the author.

Table 7 is explained in accordance with hypotheses results per follows:

H1 presented a significant relationship at standard coefficient value of 0.515 (t-value = 8.549) which confirmed that perceived ease of use significantly affected perceived usefulness. According to the TAM, perceived ease of use directly impacted perceived usefulness in some studies (Davis, 1993; Teo, 2009; Çelik, 2008; Lee, 2009; Kesharwani & Tripathy. 2012; Abbad, 2013). Based on assumptions, undergraduate students believe the easy-to-use online learning system can produce greatly benefits and tends to adopt it.

H2 showed that self-efficacy had no significant effect on behavioral intention**,** supported by the value of standard coefficient value at 0.090 (t-value = 1.909). According to many scholars, self-efficacy has been united as a factor of behavioral intention in the context of technology and system adoption (Henry & Stone, 1995; Venkatesh & Davis, 2000; Yi & Hwang, 2003). The result signified that undergraduate students' opinion of their skills and control over the online learning system had no association with the willingness to use.

The result of **H3** confirmed a significant effect between perceived usefulness and behavioral intention, reflecting standard coefficient value of 0.515 (t-value = 7.633). This study can affirm that perceived usefulness is the extent to which a student is convinced to use an online learning as it can facilitate his or her learning achievements as evidenced in TAM (Shin & Kang, 2015; Liaw & Huang, 2003; Rajan & Baral, 2015; Wu & Wang, 2005; Yunus & Mohammad, 2017).

H4 was supported in a relationship between perceived ease of use and behavioral intention with the standard coefficient value at 0.335 (t-value = 5.630). Previous studies had a consensus on this result where it explained the perceptions of undergraduate students that online system is easy to use and they are more likely to adopt the use for their learning efficiency (Çelik, 2008; Lee, 2009; Kesharwani & Tripathy. 2012; Abbad, 2013).

H5 resulted the non-supported relationship between effort expectancy and behavioral intention with the standard coefficient value at 0.056 (t-value = 1.285). Accordingly, the hypothesis result was contradicted with many researchers that UTAUT signified effort expectancy is an instantaneous determinant of behavioral intention. Many literatures explain that students have no other options but are forced to adopt online learning during Covid-19 pandemic (Bardakc, 2019; Teo & Noyes, 2014; Dwivedi et al., 2019).

H6 proved the significant effect of social influence on behavioral intention to use online learning among undergraduate students at standard coefficient value of 0.256 (t-value

= 5.386). Social influence has an impact on behavioral intention to use an online learning system (Barrane et al., 2018; Chao, 2019; Dwivedi et al., 2019; Tao, 2011). Therefore, behavioral intention to use online learning system among undergraduate students has been affected by teachers, family and friends.

H7 reflected the strongest relationship among others, showing a significant effect between behavioral intention and satisfaction with the standard coefficient value at 0.720 (t-value = 9.862). Ajzen (1991) and Shin and Kang (2015) agreed that behavioral intention is a significant forecaster of user's satisfaction and performance in online learning among undergraduate students.

Conclusions, Recommendations and Limitations

1. Conclusions

The rapid growth of the technology advancement and Covid-19 pandemic have accelerated the online learning in higher education in China. This study contributes academically and practically on how behavioral intention to use could build satisfaction of using online learning system among undergraduate students. Three major theories were adopted, involving TAM, UTAUT and ISS. The findings showed that behavioral intention had the strongest significant effect on satisfaction. The relationship between perceived ease of use and perceived usefulness towards behavioral intention are supported. Also, social influence significantly affected behavioral intention. On the other hand, self-efficacy and effort expectancy had no significant effect on behavioral intention in this study.

2. Recommendations

Although online learning has been the only way to continue teaching and learning during Covid-19 pandemic, learning effectiveness is a key success of academic goals. For academic researchers, this study can add the extent knowledge of technology adoption in online learning context. Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Information Systems Success (ISS) are effective models for further investigations. The relationship between variables of perceived ease of use, perceived usefulness, self-efficacy, effort expectancy, social influence, behavioral intention and satisfaction has been enormously examined in social studies worldwide.

The recommendations are made in this part to guide the practices for both academic practitioners and educational management executors to strategize for better improvement of online learning engagement and learning effectiveness of students. The recommendations aim to be made in order to improve educational industry in accordance with online learning including investing to improve online learning system, improvement in gaining competitiveness after Covid-19, more features in online learning for higher student satisfaction and learning effectiveness assessment

3. Limitations and Future Research

TAM, UTAUT and ISS models are composed with many more variables to be examined such as attitude, facilitating conditions, usage behavior etc., Only quantitative method was applied in this study; thus, future research should consider to enquire qualitative approach such as interview, focus group for better insights. Moreover, this research achieved to answer the sample group of undergraduate students which can be expanded to others such as postgraduates.

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