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Impacting Factors of Postgraduates' Behavioral Intention and Satisfaction in Using Online Learning in Chengdu University

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Abstract

Purpose: The study aims to investigate impacting factors of behavioral intention and satisfaction of postgraduate students in using online learning based on Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Information Systems Success (ISS). **Research design, data and methodology:** A quantitative method was applied to distribute questionnaire to 500 students of Chengdu University of China. Judgmental sampling, stratified random sampling, and convenience sampling were used as sampling techniques. Prior to data collection, index of item objective congruence (IOC) was ensured for all items at above 0.6. Cronbach's Alpha coefficient values as a pilot test were accepted at above 0.7. For the data analysis, confirmatory factor analysis (CFA) and structural equation model (SEM) were employed. **Results:** Behavioral Intention had the strongest significant effect on satisfaction, followed by social Influence, perceived ease of use, effort expectancy, perceived usefulness on behavioral intention. Additionally, perceived ease of use significantly affected on perceived usefulness. In opposite, the relationship between self-efficacy and behavioral intention was not supported. **Conclusions:** Academic researchers and school leaders would adapt the important factors impacting behavioral intention and satisfaction in the selection of online learning system to meet student's needs and their learning objectives.

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

JEL Classification Code E44, F31, F37, G15

1. Introduction

Based on the rapid enlargement of innovation and technology in China such as digital platform, internetinfrastructure and artificial intelligence, it hasprogressively improved online education as well as raised market competition. By 2020, the Chinese online education economy has expanded to approximately RMB 25.73 billion, including 14.12 million paying customers. In accordance with the statistical data, the measurement of the Chinese online education industry in 2024 is forecasted to reach RMB 49.05 billion, in consideration of during and the post COVID-19 pandemic (iResearch Institution, 2020). Despite of Chinese

online education has been advanced in recent years, the number of academic researchers in the field is scarce. Online learning is also gaining more attention from the Chinese government, especially Ministry of Education According to the previous academic works, the online teaching and learning platforms grant the great advantages in the digital intelligence era, especially under the circumstance of the coronavirus pandemic. Although massive number of universities have emphases the development and construction of the electronic instruction, they still encounter a certain degree of the issues which relate to

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deployment the effective online education. For example, the traditional education is viewed as more efficient than the electronic delivery. In addition, there has been a duplication of the teaching content in offline and online (Xiang, 2019). Electronic instruction has not been popular because of the low engagement and interaction (Li & Deng, 2020; Zhang & Wang, 2014). Moreover, the correlation of scientific investigations was not sufficient (Tian & Jiao, 2005). Most academic institutions in Southwest China have concentrated on undergraduate art design degrees which online education is considered to be not applicable to online teaching because it requires the physical practices and specific class environment (Dai, 2017).

Since 2020, participants who enrolled online courses had higher rates of attrition (varying from 20% to 50%) than those participating in traditional courses (Jazzar, 2012). Consequently, the researcher should appropriately measure the efficiency of online education. At psychological level, behavioral intention has been a powerful indicator for determining online learning adoption of students (Shin & Kang, 2015). The behavior of the learners is relatively changed and affected in terms of capability and engagement. Satisfaction encapsulates students' positive or enthusiastic expectations of their online learning experience or judgments (Nagy, 2018). This study is significant to academic researchers and higher education executives in evaluation of behavioral intention and satisfaction of students to adopt online learning in China.

2. Literature Review

2.1 Technology Acceptance Model (TAM)

The technology acceptance model has evolved from the theory of reasoned action (TRA) and has obtained reputation in effective measuring the important factors identifying the innovation and technology adoption (Davis et al., 1989). TAM encompasses the core characteristics of influencing factors for technology application such as perceived ease of use, perceived usefulness, behavioral intention and usage behavior (McCoy et al., 2007). Additionally, TAM has been systematically ascertained and approved by researchers and scholars in a multitude of domains and circumstances to characterize individuals' conviction throughout the comprehensive information technologies. (Giesbers, et al., 2013; Teo, 2009).

2.2 Unified Theory of Acceptance and Use of Technology (UTAUT)

Venkatesh et al. (2003) indicated that UTAUT represents for over seventy percent of the heterogeneity in behavioral intention and approximately fifty percent of the variability in actual use in a longitudinal study. According to this assumption, there are predominant latent variables which include performance expectancy, effort expectancy, social influence, and facilitating conditions to predict behavioral intention toward usage behavior (Shore et al., 2018). UTAUT has been utilized to characterize the participants' psychological and behavioral interaction towards the application of information system and technology (Venkatesh et al., 2003).

2.3 Information Systems Success (ISS)

Information system success (ISS) is characterized as the quality of technology, related to its performance. Multiple independent indicators have been identified as dependent success measurements which is essential to the use of particular information technology (DeLone & McLean, 2003). Freeze et al. (2010) have identified significant association between information quality, system quality, service quality, behavioral intention, satisfaction, and system used in ISS model. The ISS model has been acknowledged in various social science studies to frame the vital significances of the successful technology adoption.

2.4 Perceived Ease of Use

Perceived ease of use corresponds to a participant's perception of his/her effort in utilizing technology (Davis, 1989). Based on Chen and Barnes (2007), perceived usefulness and perceived ease of use have a solid influence on behavioral intentions. Numerous investigations presented a significant association between perceived ease of use and perceived usefulness throughout the implementation of innovative information technology (Chen, 2008; Heijden et al., 2003; Kim et al., 2007; Wang et al., 2003). Many researchers suggested that perceived ease of use was a significant indicator for perceived usefulness. Chang et al. (2012) discovered that perceived ease of use influenced a participant's' willingness to employ technology. Based on the discussion, hypotheses are proposed:

H1: Perceived ease of use has a significant effect on perceived usefulness of postgraduate students in using online learning.

H4: Perceived ease of use has a significant effect on behavioral intention of postgraduate students in using online learning.

2.5 Self-Efficacy

Self-efficacy is described as the assessment of an individual in his/her capability and competency to execute some performance (Cheung & Vogel, 2013). Cheon et al. (2012) characterized self-efficacy as the degree to which

students could use the online learning system to accomplish an educational activity and performance. Self-efficacy could be considered as a dimension of behavioral intention in an online communication and e-learning system. It has been incorporated as a determinant of behavioral intention in a framework for digital and information technology's utilization. (Henry & Stone, 1995; Venkatesh & Davis, 2000; Yi & Hwang, 2003). Consequently, a hypothesis is set:
H2: Self-efficacy has a significant effect on behavioral intention of postgraduate students in using online learning.

2.6 Perceived Usefulness

Perceived usefulness signals the intensity of the confidence when individuals execute the particular information technology system to accomplish work which could facilitate their productivity (Saade & Bahli, 2005). According to some academic research, perceived usefulness enhances an individual 's behavioral intention to maintain their learning process and performance (Alamri, 2021). Many researchers explore perceived usefulness as a motivational factor that drive behavioral intention to use a technology (Kim & Kwahk, 2007). Rahman and Sloan (2015) investigated the acceptance of digital or mobile technology systems, which explains when users perceive the obtained benefits from the use of a technology, they would express the willingness to use. Thus, a hypothesis is proposed:
H3: Perceived usefulness has a significant effect on behavioral intention of postgraduate students in using online learning.

2.7 Effort Expectancy

Effort expectancy relates to the level of effort requisite to employ technology. It is defined as a degree of anticipated exertion in employing a particular technology system both physically and psychologically. Effort expectancy could be a incentivize mechanism that can enhance users' productivity (Ghalandari, 2012). UTAUT hypothesized that effort expectation is a determinant of behavioral intention which has been received widely attention from many academic researchers. It has been established as a significant determinant of behavioral intention to use a technology (Bardakc, 2019; Teo & Noyes, 2014). According to previous literatures, effort expectation could anticipate behavioral intention to the application of the certain system technology (Dwivedi et al., 2019). Hence, a proposed hypothesis is derived.
H5: Effort expectancy has a significant effect on behavioral intention of postgraduate students in using online learning.

2.8 Social Influence

Social influence is a psychological occurrence that specifies the conditions around a person which his/her mentality is associated with social or external pressures (Nuttavuthisit & Thøgersen, 2017). The confidence of an individual recognizes the significance of other persons' perspectives in considering whether or not to implement technology or system is described as social influence (Benmessaoud et al., 2011). A variety of the academic literatures have identified that the positive impact of social influence on behavioral intention to adopt the specific innovation (Taylor & Todd, 1995; Venkatesh & Brown, 2001; Venkatesh et al., 2003). Numerous investigations concluded that social influence is one of the most significant components that drives behavioral intention (Hao, 2013; Mtebe & Raisamo, 2014). As a result, it can be assumed that:
H6: Social influence has a significant effect on behavioral intention of postgraduate students in using online learning.

2.9 Behavioral Intention

Behavioral intention represents the encouragement and the willingness to perform certain behavior or to use an information technology (Davis, 1989). Behavioral intention is the level to which a participant is encouraged to perform a specific behavior. It is hypothesized to be a causative characteristic of behavior and attitude. (Ajzen, 1991; Cheung & Vogel, 2013). Several social scientists specified that the behavioral intention to use massive open online courses can influence students' learning satisfaction (Pozón-López et al., 2020). The favorable experience has a considerable effect on satisfaction, and behavioral intention has a positive and significant impact on satisfaction (Wu et al., 2017). Eom et al. (2019) determined that behavioral intention is the vital exogenous or independent variable to satisfaction. Thereby, the following hypothesis is obtained:
H7: Behavior intention has a significant effect on satisfaction of postgraduate students in using online learning.

2.10 Satisfaction

According to the academic work from Locke (1969), satisfaction is categorized as a psychosocial behavior or willingness patterns associated with a participant 's assessment of the quality or benefits of a specific product or service. In this study, satisfaction demonstrates students' positive or optimistic preconceptions of their online education's experience or observations (Nagy, 2018). Satisfaction represents the level of favorable feeling, generated from the specific technological system usage (Lin & Hsieh, 2006; Nagy, 2018). Furthermore, satisfaction is illustrated to be an acceptance to use a specific system technology (Oliver, 1993).

3. Research Methods and Materials

A quantitative method was applied to distribute online questionnaire for the data collection. The conceptual framework is based on three key theories which are Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Information Systems Success (ISS).

3.1 Research Framework

Seven variables used are perceived ease of use, perceived usefulness, self-efficacy, effort expectancy, social influence, behavioral intentions, and satisfaction per shown in Figure 1. Three previous literatures were reviewed to propose a conceptual framework of this study. Firstly, Shin and Kang (2015) examined the mobile learning management system usage and found the significant impact among perceived ease of use, perceived usefulness, behavioral intention and satisfaction. Secondly, the report of Cheung and Vogel (2013) showed that self-efficacy significantly influenced behavioral intention to use e-learning system. Thirdly, Maphosa et al. (2020) evaluated UTAUT model to confirm significant relationship between effort expectancy, social influence and behavioral intention to use WhatsApp to deliver a lecture during Covid-19.

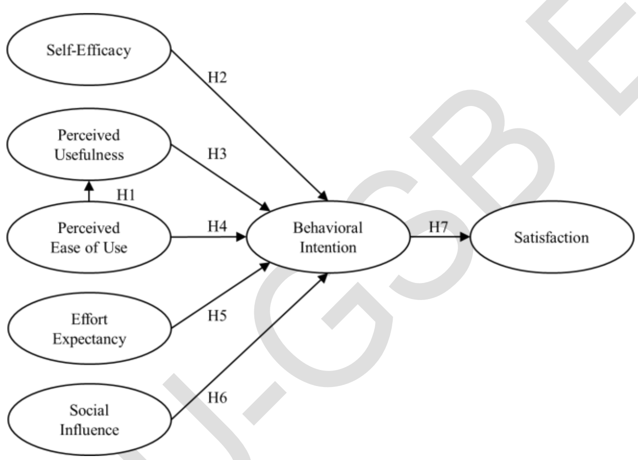

Figure 1: Conceptual Framework

Seven hypotheses are summarized per below:
H1: Perceived ease of use has a significant effect on perceived usefulness of postgraduate students in using online learning.
H2: Self-efficacy has a significant effect on behavioral intention of postgraduate students in using online learning.
H3: Perceived usefulness has a significant effect on behavioral intention of postgraduate students in using online learning.
H4: Perceived ease of use has a significant effect on behavioral intention of postgraduate students in using online learning.
H5: Effort expectancy has a significant effect on behavioral intention of postgraduate students in using online learning.
H6: Social influence has a significant effect on behavioral intention of postgraduate students in using online learning.
H7: Behavior intention has a significant effect on satisfaction of postgraduate students in using online learning.

3.2 Methodology

The questionnaire distribution was methodized as quantitative approach and had directly given to administrative office to promote to 500 postgraduate students of Chengdu University of China via WeChat. The questionnaire has three parts with 31 questions. Research instruments embedded three sections, involving screening questions, five-point Likert scale (ranging from 1 to 5 for strongly disagree to strongly agree), and demographic information. Before proceeding the data collection, index of item objective congruence (IOC) was accounted, resulting all measuring items were remained at the value 0.6 or above. Cronbach's Alpha coefficient values from the 50 participants as a pilot test were accepted at above 0.7 (Nunnally & Bernstein, 1994).

3.3 Population and Sample Size

The population aims to target postgraduate students, majoring in economics, physical, art design, and bioengineering of Chengdu University of China who have been using online learning. A minimum sample size was calculated via Soper (2022), an online statistical calculator, which requires at least 425 participants. However, 500 samples are considered to be collected to ensure adequate data size for further handling mission values and employing statistical analysis.

3.4 Sampling Technique

To collect the data, the sampling techniques were employed. Firstly, judgmental sampling was applied to choose postgraduate students, majoring in economics, physical, art design, and bioengineering of Chengdu University of China, who have been using online learning. Secondly, stratified random sampling was calculated to properly divide each sample group per total of students in each major, showing in Table 1. Lastly, convenience sampling was executed to distribute online questionnaire to the 500 students via administrative office to promote via WeChat application.

Table 1: Number of target population

Subjects	Population Size (Total = 969)	Proportional Sample Size (Total = 500)
Economic	218	112
Physical	91	47
Art Design	306	158
Bioengineering	354	183

Source: Created by the author.

3.5 Reliability Test

According to Table 2, fifty participants were involved for the pilot test, which resulted Cronbach's Alpha coefficient values, ranging between 0.839 to 0.935. The results confirmed the internal consistency of the variables and the reliability for each item with the value of 0.70 or above (Nunnally & Bernstein, 1994). CA of each construct in this study, including perceived ease of use (PEOU) = 0.911, perceived usefulness (PU) = 0.898, self-efficacy (SE) = 0.889, effort expectancy (EE) = 0.935, social influence (SI) = 0.922, behavioral intention (BI) = 0.839, and satisfaction (SS) = 0.909.

Table 2: Consistency of the Scale Test (n=50)

Variables	Source of Questionnaire	No. of items	Cronbach's Alpha	Strength of Association
Perceived Ease of Use	Vululleh (2018)	5	0.911	Excellent
Perceived Usefulness	Vululleh (2018)	5	0.898	Very Good
Self - Efficacy	Cheung and Vogel (2013)	3	0.889	Very Good
Effort Expectancy	Tan (2013)	4	0.935	Excellent
Social Influence	Vululleh (2018)	4	0.922	Excellent
Behavioral Intention	Maphosa et al. (2020)	3	0.839	Very Good
Satisfaction	Al-Azawei and Lundqvist (2015)	5	0.909	Excellent

Source: Constructed by author.

3.6 Data Analysis

The data collection was subjected to 500 participants, who are postgraduate students, majoring in economics, physical, art design, and bioengineering of Chengdu University of China. The data were analyzed through SPSS AMOS statistical software. Confirmatory Factor Analysis (CFA) was conducted to examine factor loadings, composite reliability, convergence validity, discriminant validity and goodness of fit of the measurement model. Structural model was executed under Structural Equation Model (SEM) to determine significant relationships and hypotheses of this research.

4. Result and Discussion

4.1 Demographic Profile Summary

Table 3 shows the summary of demographic profile of respondents (n=500) in this study. The majority of participants were male (53.0%), whereas females were 47.0%. For the postgraduate programs, there was Master degree of 80.0%, and Doctoral Degree of 20.0%. Additionally, most respondents were 26 years old and above at 62.4%, while the least was 21 years old or below of 8.2%.

Table 3: Demographic Profile of Respondents

N=500	Demographic Profile	Percentage
Gender	Male	53.0%
	Female	47.0%
Year of Postgraduate Study	Master Degree	80.0%
	Doctoral Degree	20.0%
Age	21 years old or below	8.2%
	22-23 years old	13.6%
	24-25 years old	15.58%
	26 years old or above	62.4%

Source: Constructed by author.

4.2 Confirmatory Factor Analysis (CFA)

The measurement model was examined in CFA, showing the fit results as of Table 4, including CMIN/df = 2.238, GFI = 0.899, AGFI = 0.876, NFI = 0.902, CFI = 0.943, TLI = 0.935, and RMSEA = 0.050. Accordingly, the convergent validity and discriminant validity were confirmed by the fit model.

Table 4: Goodness of Fit for Measurement Model

Index	Acceptable Values	Statistical Values of Postgraduate students
CMIN/DF	< 3.00 (Hair et al., 2006)	796.627/356 = 2.238
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.899
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.876
NFI	≥ 0.80 (Wu & Wang, 2006)	0.902
CFI	≥ 0.80 (Bentler, 1990)	0.943
TLI	≥ 0.80 (Sharma et al., 2005)	0.935
RMSEA	< 0.08 (Pedroso et al., 2016)	0.050
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, NFI = Normed Fit Index, CFI = Comparative Fit Index, TLI = Tucker-Lewis Index, and RMSEA = Root Mean Square Error of Approximation.
Source: Constructed by author.

4.3 Convergent validity

Per Table 5, the convergent validity can be assessed in the measurement model of CFA. In this research, the factor loading of each item was significant of the value greater than 0.50 and p-value of lower than 0.05 (Hair et al., 2006). The results confirmed the internal consistency of the variables and the reliability for each item with the value of 0.70 or above (Nunnally & Bernstein, 1994). Furthermore, Average Variance Extracted (AVE) is recommended to be 0.4 or over. Composite Reliability (CR) is acceptable at the value of 0.6 or above (Fornell & Larcker, 1981).

Table 5: Confirmatory Factor Analysis Result, Composite Reliability (CR) and Average Variance Extracted (AVE)

Variable	Factor Loading >0.5	t-value>1.98 & p-value<0.5	CA >0.7	CR (pc) >0.6	AVE (pv) >0.4
PEOU	0.558-0.741	10.849-13.763	0.805	0.809	0.461
PU	0.735-0.818	16.121-17.781	0.877	0.878	0.589
SE	0.592-0.997	15.827-16.994	0.879	0.900	0.758
EE	0.589-0.763	12.266-15.758	0.800	0.800	0.503
SI	0.635-0.687	11.956-11.779	0.764	0.765	0.449
BI	0.662-0.762	13.000-13.832	0.748	0.752	0.503
SS	0.697-0.802	15.493-18.064	0.857	0.859	0.550

Source: Constructed by author

4.4 Discriminant Validity

According to Fornell and Larcker (1981), discriminant validity was examined by the calculation of the square root of each AVE which it is larger than all inter-construct/factor correlations as of Table 6. Thus, the discriminant validity is supportive. As a result, convergent and discriminant validity were validated to assure construct validity.

Table 6: Discriminant Validity

	SS	PU	SE	PEOU	EE	SI	BI
SS	**0.742**						
PU	0.683	**0.768**					
SE	0.119	0.112	**0.871**				
PEOU	0.536	0.459	0.076	**0.679**			
EE	0.628	0.683	0.131	0.626	**0.709**		
SI	0.517	0.485	0.112	0.635	0.631	**0.670**	
BI	0.698	0.589	0.145	0.618	0.701	0.582	**0.710**

Source: Constructed by author

4.5 Structural Equation Model (SEM)

SEM was applied to measure structural model of this study. Before the adjustment, the structural model was unacceptable fit. After the adjustment, the fit results of the model were Chi-Square ($X2$/df) = 2.979, Goodness-of-fit statistic (GFI) = 0.867, Adjusted Goodness-of-fit statistic (AGFI) = 0.837, Normed Fit Index (NFI) = 0.870, Comparative Fit Index (CFI) = 0.909, Tucker-Lewis Index (TLI) = 0.895, and Root Mean Square Error of Approximation (RMSEA) = 0.063 as presented in Table 7.

Table 7: Goodness of Fit for Structural Model

Index	Acceptable Values	Statistical Values	
		Before Adjustment	After Adjustment
CMIN/DF	< 3.00 (Hair et al., 2006)	1501.092/370 = 4.057	1051.603/353 = 2.979
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.832	0.867
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.803	0.837
NFI	≥ 0.80 (Wu & Wang, 2006)	0.815	0.870
CFI	≥ 0.80 (Bentler, 1990)	0.853	0.909
TLI	≥ 0.80 (Sharma et al., 2005)	0.839	0.895
RMSEA	< 0.08 (Pedroso et al., 2016)	0.078	0.063
Model summary		Unacceptable Model Fit	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, NFI = Normed Fit Index, CFI = Comparative Fit Index, TLI = Tucker-Lewis Index, and RMSEA = Root Mean Square Error of Approximation.
Source: Constructed by author

4.6 Research Hypothesis Testing Result

Research hypothesis testing and results were determined by standardized path coefficient (β) and t-value of the SEM (Table 8). Most of hypotheses were significant at p-value less than 0.5, except H2 of the relationship between self-efficiency and behavioral intention which was not supported.

Table 8: Hypotheses Testing Result of the Structural Model

Hypothesis	standardized path coefficient (β)	t-value	Testing result
H1: PEOU → PU	0.289	5.983*	Supported
H2: SE → BI	0.068	1.566	Not Supported
H3: PU → BI	0.214	3.911*	Supported

H4: PEOU→ BI	0.447	6.983*	Supported
H5: EE → BI	0. 334	5.799*	Supported
H6: SI → BI	0.457	7.108*	Supported
H7: BI → SS	0.491	8.068*	Supported

Note: *=p-value<0.5
Source: Constructed by author.

The hypothesis testing results are explained per followings.

H1 showed that perceived ease of use significantly affected perceived usefulness at the value of standard coefficient = 0.289 (t-value = 5.983). The result was compiled with earlier studies that a preconception of postgraduate students on easy-to-use online learning system leads to the cognitive awareness of the system's benefits (Chang et al., 2012; Davis et al., 1989).

H2's result was a non-significant relationship between self-efficiency and behavioral intention with the standard coefficient value = 0.068 (t-value = 1.566). The outcome was opposed by many scholars (Cheon et al., 2012; Cheung & Vogel, 2013; Henry & Stone, 1995; Venkatesh & Davis, 2000; Yi & Hwang, 2003), which argued that self-efficacy is the degree to which students could use the online learning system to accomplish an educational activity or performance.

H3 affirmed the proposed hypothesis between perceived usefulness and behavioral intention with standard coefficient value = 0.214 (t-value = 3.911), which was also supported by previous literatures (Alamri, 2021; Kim & Kwahk, 2007; Rahman & Sloan, 2015; Saade & Bahli, 2005). In addition, the benefits of online learning system such as convenience, less time consuming and accessibility enhance students' behavioral intention to maintain their learning process and performance.

For **H4**, perceived ease of use had a significant effect on behavioral, representing the standard coefficient value = 0.447 (t-value = 6.983). The number of literatures agreed perceived ease of use corresponds to a student's perception in utilizing online learning system which is effortless and is an indicator of behavioral to use a system (Chen & Barnes, 2007; Chen, 2008; Davis, 1989; Heijden et al., 2003; Kim et al., 2007; Wang et al., 2003).

H5 supported the significant relationship between effort expectancy and behavioral intention with the standard coefficient value = 0.334 (t-value = 5.799). UTAUT has been proven for these key variables and significance which implied effortless online learning system can drive the willingness to use a system among postgraduate students (Bardakc, 2019; Dwivedi et al., 2019; Teo & Noyes, 2014).

H6 verified the significant effect of social influence on behavioral intention of using an online learning system, showing standard coefficient value = 0.457 (t-value = 7.108). Numerous investigations had a consensus that the impact of other persons such as teachers, family and classmates vitally affected student's behavioral intention to use online learning system (Hao, 2013; Mtebe & Raisamo, 2014).

The result of **H7** showed that behavioral intention of postgraduate students significantly affected satisfaction of online learning system usage, reflecting the value of standard coefficient = 0.491 (t-value = 8.068). From the finding, serval social scientists pointed that the behavioral intention to use online learning system can influence students' satisfaction (Ajzen, 1991; Cheung & Vogel, 2013; Pozón-López et al., 2020).

5. Conclusion, Recommendations and Limitations

5.1 Conclusion

Online learning system adoption has been widely explored among academic researchers in evaluation of behavioral intention and satisfaction of students to adopt online learning in China. The study achieved its research objective to investigate impacting determinants of behavioral intention and satisfaction of postgraduate students in using online learning, including perceived ease of use, perceived usefulness, self-efficacy, effort expectancy, social influence. For research methodology, a quantitative approach was made through the survey distribution to 500 students of Chengdu University of China. The findings were that behavioral intention had the strongest significant effect on satisfaction, followed by social influence, perceived ease of use, effort expectancy, perceived usefulness on behavioral intention. Additionally, perceived ease of use significantly affected on perceived usefulness. In opposite, the relationship between self-efficacy and behavioral intention was not supported.

The implications of this study were enlightened at the final conclusion. Firstly, perceived ease of use significantly affected perceived usefulness. Based on the original TAM, the relationship between these two variables is limited. However, several researchers have confirmed a cognitive awareness of users would perceive easy-to-use system technology associated with its benefits (Chang et al., 2012; Davis et al., 1989), which extend to an online learning system among students. Secondly, self-efficiency was predicted to be a factor affecting behavioral intention (Cheon et al., 2012; Cheung & Vogel, 2013; Henry & Stone, 1995; Venkatesh & Davis, 2000; Yi & Hwang, 2003). However, the result of this research was different. It can be assumed that self-efficacy was not relevant to student's willingness to use online learning system or they have no other choice because online education is the only way for them to continue their classes during Covid-19 pandemic.
Thirdly, the relationship between perceived usefulness and behavioral intention was supported as aligned with many

scholars (Alamri, 2021; Kim & Kwahk, 2007; Rahman & Sloan, 2015; Saade & Bahli, 2005). It supported the claim that benefits of online learning system offer motivation of students to use online learning system such as convenience, responsiveness and less time consuming. Fourthly, when students feel that online learning system is easy to use, they would adopt to use it to achieve their learning objectives as evidenced in previous studies (Chen & Barnes, 2007; Chen, 2008; Davis, 1989; Heijden et al., 2003; Kim et al., 2007; Wang et al., 2003).

Fifthly, the significant relationship between effort expectancy and behavioral intention was existed. It can be explained that students will have a motivation to engage online classes when they found it is easy to connect and serve their expectations in certain levels (Bardakc, 2019; Dwivedi et al., 2019; Teo & Noyes, 2014). Next, some researchers pointed the importance of others in referring students to use online learning system (Hao, 2013; Mtebe & Raisamo, 2014). In the early of pandemic, teachers need to brief all students on how to continue their study with the online system which arouses their behavioral intention to use for class attendance. Lastly, behavioral intention of postgraduate students had the strongest effect on satisfaction of online learning system usage in this study (Ajzen, 1991; Cheung & Vogel, 2013; Pozón-López et al., 2020). Postgraduate level requires some maturity to proceed a higher degree in the university and the course selection. They are affordable to drop or switch to another competitors. Therefore, satisfaction was found to be highly driven by behavioral intention in this study.

5.2 Recommendations

Online learning system had been viewed as a differentiation's strategy before the Covid-19 and was an option or selection for busy professionals or remote learners. After Covid-19, online learning is currently a new normal of business and education sectors at all level. Specially in academic sector, the priority has been shifted to the development and deployment of online learning system. Thus, it is a question on "How to win this game?". In the nature of higher education, the market is very competitive within and outside the country. To invest an effort on studying the factors impacting learners' behavioral intention and satisfaction might pay the price.

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 limitations for future study can guide new entry researchers to adapt the new research model in accordance with the findings of this study.

In addition, school executives and instructional leaders are recommended to deploy the effective online learning system by studying on which motivational factors that most and least important to actually produce behavioral intention and satisfaction of existing and prospective students. The integrated strategies of online learning are to be properly planned and executed to ensure a return on investment. A decision maker can select either global online learning platform or develop in-house platform in order to meet the need of learners. The alternative choices could be a conference platform which has been widely accepted such as Zoom or Skype. However, the global platforms are restricted in China but there are various Chinese developed platforms to be used such as WeChat or Superstar Software.

5.3 Limitations and Future Research

Researchers did not apply the full model of TAM, UTAUT and ISS. Thus, future researchers can consider to add more variables per appropriate to their topic such as performance expectancy facilitating conditions, attitude etc. Next, quantitative approach was selected for this study as it is less cost and less time consuming. Hence, the future study is suggested to employ qualitative method such as focus group or interview. Thirdly, the sample size was limited in China which has a unique educational culture. The online learning system has been tailored and used only inside the country. By investigating other countries with different culture and economy, there possibly produces different results. Lastly, the study limits to a sample of one university in some faculties only. Students in other fields of education may lead to the different result.

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