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Factors Influencing University Students' Attitude and Behavioral Intention Towards Online Learning Platform in Chengdu, China

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Abstract

This research aims to determine the factors influencing university students' attitudes and behavioral intention towards online learning platforms in Chengdu, China. The conceptual framework has been adopted from the theoretical studies and research models of the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT). A sample of 450 respondents was collected from online questionnaires using the multi-stage sampling technique of probability and non-probability sampling method for quantitative research to reach target respondents of experienced university students. The collected data were analyzed using the Structural Equation Model (SEM) and Confirmatory Factor Analysis (CFA) to confirm the model fit and hypothesis testing. The results revealed that social influence was the most influential factor in behavioral intention, followed by attitude. The statistical finding shows no significant influence of facilitating conditions on behavioral intention. In addition, the antecedent of attitude was perceived usefulness. Therefore, the management of universities, lecturers, and marketing partitioners should emphasize building positive direct experience and ensuring benefits from using online learning platforms to formulate favorable attitudes, recommend to other peers, and encourage the usage behavioral intention for university students.

Keywords: Attitude, Behavioral intention, Online learning platform, University Students, China

Introduction

The usage of online learning tools has increased recently from the "new normal" situation due to the COVID-19 pandemic. New normal is adapting ways of living, interaction, and socialization with other people in COVID-19 to prevent the spreading while the disease cannot be cured (YLM, 2020). COVID-19 has rapidly spread worldwide, starting in early 2020 (Cortez & Johnston, 2020). This pandemic has disrupted all international and domestic businesses in all sectors, including the education system (Alon et al., 2020). Before the crisis, online classes or remote learning were optional or privileged some schools or universities gave. With COVID-19, the educational sections are pressured to rapidly migrate from traditional learning methods to online or virtual learning environments. Schools and universities are forced to close temporarily globally to contain and prevent the spreading of COVID-19. This pandemic has stimulated all schools and educational institutes globally to adopt new learning and education services to pursue students' education. With the emerging of digitalization, online learning is an alternative and suitable source of education. Online learning is an education that learners can access what they want, from anywhere in the World, and at any time that matches their schedule. With technology advancement, online learning can offer virtual socialization with peers, live or recording lectures from lecturers, and participation of their interests (Education, 2021). Online learning is supported by instructions from digital devices such as computers, laptops, tablets, or smartphones (Clark & Mayer, 2016). Online learning is not limited to academics learning but can also provide extracurricular activities for students' learning. However, delivering an effective and valuable online course can be a challenge because the class's level of engagement and interaction is not as great as in a physical classroom. The education institutions need to explore teaching-learning strategies that enable the replication of face-to-face interaction, in-person discussion, and question-and-answer sessions (Education, 2021). In addition to teaching-learning strategies, adequate digital competencies and facilities are also crucial for both teachers and students to operate and consistently update the learning platform's usage. Education institutes should ensure that all users understand the advantages of the learning platform and its operations. The online learning platform is a portal that consists of academic content presented through learning materials and live lectures on a specific topic. It can offer learning experiences that are engaging and interactive to the lecturers and learners (Ryan, 2020).

The ministry of education in China has fostered the educational instructions to utilize online learning platforms for an alternative teaching solution to relieve offline academic program disruption from class closure. Such a situation causes the educational institutions to widely use the online learning applications and platforms in China to facilitate learnings, activities, and training. By 2022, the size of online Chinese learners is expected to be more than 264 million users. The online education industry in China is anticipated to value over USD 87 billion (583 billion yuan) (Textor, 2021). Chengdu is the fourth-largest city in China that took part in the UNESCO Global

Network of Learning Cities (GNLC) program to develop the city as a learning city to promote lifelong learning for all. The learning resources incorporated in the learning service system will range from basic to higher education. By improving the service system and infrastructure, education would easily be accessed and extended to all families and communities in urban and rural areas (UIL, 2019). With the importance of online learning during the crisis, this study investigates the factors influencing university students' attitudes and behavioral intention towards online learning platforms, particularly in Chengdu, China. This research can serve as a reference point for universities, lecturers, and marketing partitioners to identify the drivers and plan appropriate approaches from the recommendations to build university students' willingness and behavioral intention to use online learning platforms.

Research Objectives

1. To determine the significance of influence between perceived ease of use and perceived usefulness on attitude towards online learning platform.
2. To determine the significance of influence between attitude, social influence, and facilitating conditions on behavioral intention towards online learning platforms.

Research Questions

1. What factors significantly influenced university students' attitudes and behavioral intention towards online learning platforms?
2. Which factor influences the strongest and weakest behavioral intention towards online learning platforms?

Literature Review

Perceived Ease of Use

Perceived ease of use is the extent to which an individual perceives that adopting the new technology is free of physical and mental effort (Davis, 1989). Gefen et al. (2003) has said that perceived ease of use measures the cognitive effort in learning and adopting the technology. It can also refer to the clarity and understandability of the system or technology that enable users to interact, engage and use the system with less mental effort (Ndubisi et al., 2003). Technology Acceptance Model (TAM) agrees that perceived ease of use on the new information technology impacts the technology's attitude and perceived usefulness from using the technology (Davis, 1989). In the study of Ngai et al. (2007), there is a significant direct impact of perceived ease of use on perceived usefulness and the attitude of university students toward using Web Course Tools (WebCT). In electronic learning, perceived ease of use also has a significant relationship with perceived usefulness and attitude for Korean university students (Park, 2009). Similar to the study on university students' intention to use Moodle platforms, there is a good correlation between perceived ease of use and perceived usefulness (Escobar-Rodriguez & Monge-Lozano, 2011). Thus, the following hypotheses were proposed as follows:

H_1: Perceived ease of use has a significant influence on perceived usefulness.

H_3: Perceived ease of use has a significant influence on attitude.

Perceived Usefulness

Perceived usefulness is the extent to which an individual perceived that adopting the new technology would enhance his or her work performance (Davis, 1989). Usefulness strongly relates to productivity. Ndubisi et al. (2003) claimed that using a system or technology in the workplace would improve productivity, task performance, and effectiveness. Perceived usefulness is one of the external factors that is said to be affected the individual's internal beliefs and attitude (Davis, 1989; Davis et al., 1989). The analysis of factors influencing the intention to use technology in university students showed that perceived usefulness is the highest interpreter of attitude towards technology, followed by perceived ease of use (Teo & Zhou, 2014). The study on e-learning also showed that the perceived usefulness of e-learning has a positive direct relationship with university faculty members' attitudes (Dos Santos & Okazaki, 2016). Another study on online learning adoption during the COVID-19 outbreak revealed that perceived usefulness positively influences the attitude towards using digital collaboration platforms (Singh et al., 2020). Thus, the following hypothesis was proposed:

H_2: Perceived usefulness has a significant influence on attitude.

Attitude

Attitude towards behavior is defined by Fishbein and Ajzen (1975) as the positive or negative feelings of an individual on the actions performed on a particular behavior. Individuals with a positive attitude towards behavior would create a desirable outcome, whereas a negative attitude would likely create an undesirable outcome (Fishbein & Ajzen, 2010). Various theories and previous studies can support the relationship between attitude and behavioral intention. A study by Dulle (2015) has proven that the UTAUT model can interpret the user acceptance and behavior in using open access. Users with a positive attitude are more likely to adopt the system than those who have a negative attitude. In the context of online learning and distance learning courses, students would have a positive attitude after course completion, leading to continuous intention to use online learning (Ilyas & Zaman, 2020; Kintu et al., 2017). Thus, the following hypothesis was proposed:

H_4: Attitude has a significant influence on behavioral intention.

Social Influence

Social influence can highly impact the decision-making of a customer. It can predict the behavior based on the feedback or recommendation received (Dholakia et al., 2004). Social influence is defined as an individual's belief that their peers, family, and social circle are deemed importation that their opinion is that adopting information technology is valuable (Venkatesh et al., 2003). Nair et al. (2015) has claimed that social influence has a significant influence on the intention to use a lecture capture system within the higher education industry. Likewise, there is a significant social influence on intention towards learning management system or e-learning by the university students (Ain et al., 2015; Tarhini et al., 2017). Social influence can be directly related to behavioral intention for both university students of undergraduate and postgraduate (McKeown & Anderson, 2016). Thus, the following hypothesis was proposed:

H_5: Social influence has a significant influence on behavioral intention.

Product Evaluation

The facilitating condition defined by Venkatesh et al. (2003) is the extent to which a user believes that his or her organization supports the essential technical infrastructure for using this technology. The technical infrastructure is not limited to system support but includes the resources, technical skills, and physical environment needed for effective adoption of continuous usage (Mazman & Usluel, 2010). Insufficient resources could demotivate or lead to an unfavorable decision for an individual to adopt the technology; thus, facilitating condition is one of the most influential factors towards behavioral intention (Raman & Don, 2013). Zhang (2016) has proven that facilitating condition is one factor that encourages the students' pleasure. With sufficient support and resources to access the system, it can create a positive evaluation for the students to use MOOC. Similar to the university students' usage intention of the learning management system, the facilitating conditions determined their usage (Hu & Lai, 2019). Thus, the following hypothesis was proposed:

H_6: Facilitating conditions have a significant influence on behavioral intention.

Behavioral Intention

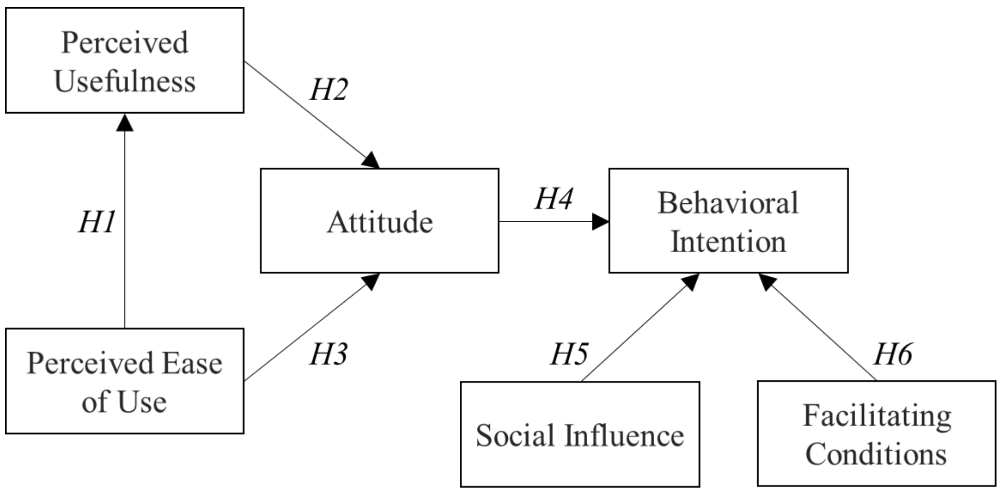
Intention drives the behavior of an individual. Behavioral intention is a motivational factor determining whether an individual desires to perform a particular behavior (Ajzen, 1991). It tends to perform or not perform a particular action shortly (Ajzen & Fishbein, 1980). The intention or desired behavior can predict actual behavior (Venkatesh et al., 2003). In the information technology context, Yi et al. (2016) have defined behavioral intention as the tendency of a user to perform a specific behavior resulting from technology usage intention. It can measure or predict the user acceptance and adoption of new or existing technology.

Research Framework

Based on the previous research model and theories of technology acceptance model (TAM) developed by Davis (1989) and the unified theory of acceptance and use of technology (UTAUT) developed by Venkatesh et al. (2003), the author has adapted the conceptual framework to explain the factors influencing university students' attitude and behavioral intention towards online learning platform in Chengdu, China. The conceptual framework constructs are perceived ease of use, perceived usefulness, attitude, social influence, facilitating conditions, and behavioral intention.

Figure 1

Conceptual Framework



Note. Constructed by the author (2021).

Research Methodology

Research Design

The study has employed a quantitative research approach by using a questionnaire as a survey tool for data collection. Prior to the distribution of the questionnaire, the reliability was ensured by conducting an Item-Objective Congruence (IOC) test with three experts and a pilot test of Cronbach's Alpha with 45 respondents. The questionnaires were distributed via email to the selected universities' student councils for primary data collection. The representatives from the student council were asked for a favor in distributing the questionnaires linked randomly to the university students until establishing the proportionate sample size. The questionnaire comprises three sections. The first section is screening questions to narrow down and ensure that the respondents have met the target respondents. The second section measures baseline and independent variables, using the Five-point Likert scale (5= strongly agreed, 4= Agreed, 3=Neutral, 2= Disagreed, and 1= Strongly Disagreed). In the last section, demographic information of the target respondents is collected.

The data collection was analyzed by using statistical package software of SPSS and AMOS 26.0. The analyses performed were Confirmatory Factor Analysis (CFA) and Structural Equation Model (SEM) for each construct's convergent and discriminant validity and test the influence significance among the constructs.

Population and Sample Size

The target population for this study is university students studying in the Top 5 universities of Chengdu, China, and have to experience using online learning platforms for more than a year to ensure the students are familiarized with the platform. BCUR ranks top 5 universities based on their performance in four dimensions: teaching and learning, research, social service, and internationalization (ARWU, 2019). In this study, the sample size determinant is by parameter values to calculate via A-priori Sample Size Calculator for Structural Equation Models from danielsoper's website (Soper, 2019). The parameter values conditioned for the sample size calculation are six latent variables and 29 observed variables with a probability level of 0.05. The result showed that the recommended minimum sample size for Structural Equation Models is 403 samples; therefore, 450 samples were collected to ensure the minimum requirement and population representation.

Sampling Technique

The study employed a multi-stage sampling of probability and non-probability sampling methods for this quantitative research method. Purposive sampling was used in the first stage to select the top five universities in Chengdu, which each of these five universities were considered a group or stratum. Secondly, proportionate stratified sampling is applied to allocate sample size to each group based on the number of students, as shown in table 1. This method would allow the appropriate representation of sample size from a large population (Fottrell & Byass, 2008). Finally, purposive and convenience sampling was applied at the third stage to select respondents with experience in using online learning platforms for more than a year based on the proportional sample size from each group.

Pilot Test

Cronbach's Alpha reliability test was applied to measure items of each variable in the questionnaire. The researcher performed pilot testing by collecting 48 responses and examining them using SPSS AMOS version 26 as a statistical tool. The results of Cronbach's Alpha Coefficient are in Table 1. The obtained reliability scores ranged from 0.705 to 0.922, while the acceptable level is >0.7 or higher (Nunnally, 1967); this confirmed the internal consistency as per the reliability test.

Table 1

Population and Sample Size by University

University	Source	Population of Students	Proportional Sample Size
Sichuan University	SCU (n.d.)	60,400	138
University of Electronic Science and Technology of China	UESTC (n.d.)	38,000	87
Southwest Jiaotong University	SWJTU (2019)	43,541	99
Southwestern University of Finance and Economics	SWUFE (n.d.)	21,140	48
Southwest Petroleum University	SWPU (n.d.)	34,413	78
Total		**197,494**	**450**

Results and Discussion

Demographic Information

Among 450 respondents, 53.1 percent (239) were male, and 46.9 percent (211) were female. Respondents were the majority at the age of 25 to 30 years old at 35.8 percent (161), followed by below 25 years old at 26.7 percent (120), 31 to 35 years old at 21.6 percent (97), 35 to 40 years old at 10.9 percent (49), and above 40 years old at 5.1 percent (23). The university degrees undertaken by respondents were bachelor's at 30.4 percent (137), Master's at 46 percent (207), and doctoral degree at 23.6 percent (106). The academic year of respondents mainly was in the second year at 43.1 percent (194), the third year at 30.7 percent (138), the fourth year at 17.3 percent (78), first year at 5.8 percent (26), and above the fourth year at 3.1 percent (14).

Confirmatory Factor Analysis (CFA)

Confirmatory factor analysis, or CFA, is a measurement model that focuses on determining the correlations between observed and unobserved variables in the framework to validate discriminant and convergent validity (Jöreskog, 1969). The convergent validity was assessed by Composite Reliability (CR), Average Variance Extracted (AVE), and factor loading. The recommended value of CR is at 0.6 or higher (Hair et al., 2017), AVE at 0.4 or higher (Fornell & Larcker, 1981), and factor loading at 0.5 or higher (Chen & Tsai, 2007). Table 2 has presented the statistical values from CFA, which affirmed the convergent validity and internal consistency from Cronbach's alpha value higher than 0.7 (Santos, 1999).

Table 2

Confirmatory Factor Analysis (CFA), Composite Reliability (CR), and Average Variance Extracted (AVE)

Variables	Source of Questionnaire (Measurement Indicator)	No. of Item	Cronbach's Alpha	Factors Loading	CR	AVE
Perceived ease of use (PEOU)	Lee et al. (2015), Rotchanakitumnuai and Speece (2009)	6	0.851	0.667–0.722	0.852	0.489
Perceived usefulness (PU)	Lee et al. (2015)	5	0.861	0.669–0.807	0.862	0.557
Attitude (AT)	Lee et al. (2015)	5	0.866	0.685–0.804	0.867	0.566
Social Influence (SI)	Alam et al. (2020)	4	0.764	0.565–0.726	0.769	0.457
Facilitating Conditions (FC)	Alam et al. (2020)	5	0.889	0.601–0.929	0.874	0.589
Behavioral Intention (BI)	Hsiao and Tang (2014), Kirat Rai et al. (2020)	4	0.765	0.643–0.684	0.765	0.450

Note: Composite Reliability (CR) and Average Variance Extracted (AVE)

Discriminant validity must be ensured before the research hypothesis testing (Hamid et al., 2017). AVE is used to assess discriminant validity. According to the Fornell-Lacker criterion, the square root of AVE should be compared and exceed the correlations coefficient of the measured constructs. As shown in Table 3, the AVE square root for each construct was greater than inter-construct correlations; hence discriminant validity is affirmed.

Table 3

Discriminant Validity

	PEOU	PU	AT	SI	FC	BI
PEOU	**0.699**					
PU	0.423	**0.746**				
AT	0.133	0.319	**0.752**			
SI	0.430	0.485	0.358	**0.676**		
FC	-0.038	0.011	-0.019	0.013	**0.767**	
BI	0.436	0.427	0.332	0.731	0.013	**0.671**

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

Structural Equation Model (SEM)

SEM is a statistical method that measures the fit of the structural research model and its path into the comprehensive framework of covariance structure analysis (Dragan & Topolšek, 2014). The goodness of fit (GoF) explains the degree of research model fit relative to the observed values from the structural equation model (Schermelleh-Engel et al., 2003). Table 4 has illustrated the fit indices used for measurement, statistical value, and comparison to the acceptable threshold. All fit indices were above the acceptable threshold; hence the structural model fitness is affirmed, as shown in table 4.

Table 4

Goodness of Fit

Index	Criterion	Statistical Value
CMIN/DF	< 3.00 (Hair et al., 2006)	1.589
GFI	≥ 0.90 (Hair et al., 2006)	0.924
AGFI	≥ 0.90 (Hair et al., 2006)	0.907
NFI	≥ 0.90 (Arbuckle, 1995)	0.911
CFI	≥ 0.90 (Hair et al., 2006)	0.965
TLI	≥ 0.90 (Hair et al., 2006)	0.960
RMSEA	< 0.05 (Browne & Cudeck, 1993)	0.049
RMR	< 0.05 (Hair et al., 2006)	0.036

Note: 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

The regression weight was then used to measure the significance of the causal relationship between variables (Fornell & Larcker, 1981). The hypothesis testing results indicated that all proposed hypotheses were supported at the significant level of p=0.05, except for H3 and H5. Perceived ease of use had a more significant influence on attitude than perceived usefulness. Furthermore, social influence was the strongest predictor of behavioral intention on online learning platforms, followed by attitude and facilitating conditions. The causal relationships are illustrated in Table 5. The variables can explain the variation of behavioral intention by 88.3%, as shown in figure 2.

Table 5

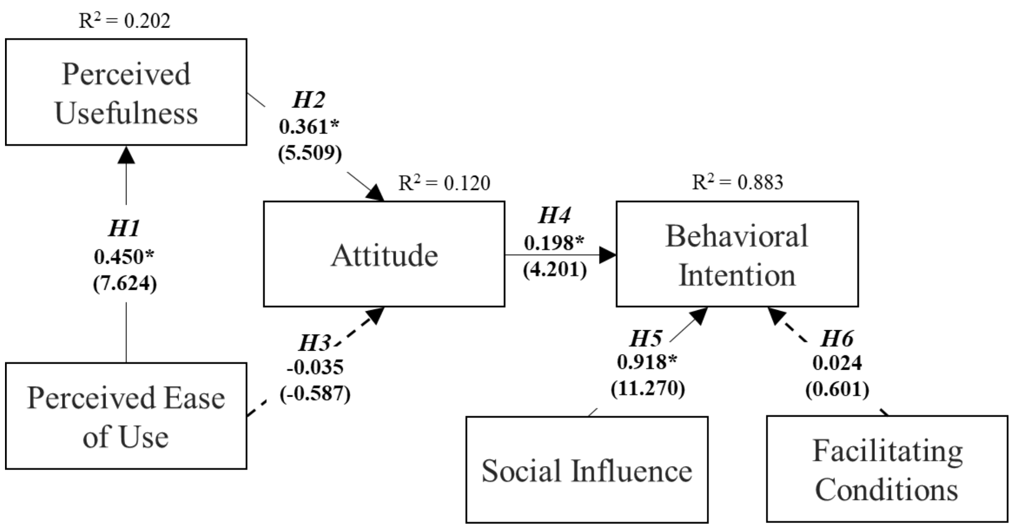
Hypotheses Result of the Structural Model

Hypothesis	Standardized path coefficient (β)	t-value	Test result
H1: Perceived ease of use (PEOU) → Perceived usefulness (PU)	0.450	7.624*	Supported
H2: Perceived usefulness (PU) → Attitude (AT)	0.361	5.509*	Supported
H3: Perceived ease of use (PEOU) → Attitude (AT)	-0.035	-0.587	Not Supported
H4: Attitude (AT) => Behavioral intention (BI)	0.198	4.201*	Supported
H5: Social influence (SI) => Behavioral intention (BI)	0.918	11.270*	Supported
H6: Facilitating conditions (FC) => Behavioral intention (BI)	0.024	0.601	Not Supported

Note. *=p-value<0.05

Figure 2

The Results of Structural Model



Note: Solid line reports the Standardized Coefficient with * as $p<0.05$, and t-value in Parentheses; Dash line reports Not Significant.

From the results of hypothesis testing in table 5, four out of six hypotheses were supported. In H1, perceived ease of use has a significant influence on perceived usefulness, which implies that if the e-learning platform is free of effort while using, clear, and understandable, the students would be able to engage in the system and enhance their work performance. In addition, the system will be perceived as applicable when the students understand and acknowledge the value received. This finding was consistent with the study of Escobar-Rodriguez and Monge-Lozano (2011), Ndubisi et al. (2003), and Ngai et al. (2007). H2 has also supported TRA theory and TAM theory that perceived usefulness significantly influences attitude towards the technology.

Moreover, the relationship of perceived usefulness towards attitude was significant and more substantial compared to perceived ease of use in H3. This finding is consistent with the papers of Dos Santos and Okazaki (2016), Singh et al. (2020), and Teo and Zhou (2014), and Venkatesh and Bala (2008). The student tends to adopt new technology from its functionality rather than its ease of use. The finding in H4 can also prove that the positive attitude derived from the ability to seek information and enhance performance from online learning platforms can strongly influence individuals' behavior. This positive correlation is aligned with the findings of Ilyas and Zaman (2020), Kintu et al. (2017), and Zhou et al. (2020). From the H5 result, social influence was the strongest predictor of behavioral intention on the online learning platform. Venkatesh et al. (2003) believe that social influence would be significantly impacted in a mandatory environment, which in this instance, online learning platform is also considered mandatory for educational institutions nowadays. This direct relationship between social influence and behavioral intention among undergraduate and postgraduate students has adhered to the studies of McKeown and Anderson (2016) and Tarhini et al. (2017). Lastly, facilitating conditions have no significant influence on behavioral intention. This finding contradicts Hu and Lai (2019) and Zhang (2016), which have concluded a correlation. However, this lack of significant influence is supported by Buabeng-Andoh and Baah (2020), Isaias et al. (2017), and Tarhini et al. (2017); this implies that the availability of infrastructure, network access, or other resources were not the determinants of the students' behavioral intention. The required infrastructure and resources are fundamentally mandatory for the educational institutions to provide to support the student's usage of the online learning platform. Hence, the results from hypothesis testing have highlighted that educational institutions or universities should emphasize stipulating the social norm or mandatory usage of the online learning platform and promoting the benefits and user-friendly usage environment to enhance attitude, directly and indirectly, influence students' behavioral intention.

Conclusions and Recommendations

This study aims to determine the factors influencing university students' attitudes and behavioral intention towards online learning platforms in Chengdu, China. The factors studied were perceived ease of use, perceived usefulness, attitude, social influence, facilitating conditions, and behavioral intentions. The conceptual framework and its factors were developed based on TAM and UTAUT and previous empirical research. The data was gathered from 450 sets of questionnaire distribution to the target respondents of university students studying in Top 5 universities of Chengdu, China, who have experience using online learning platforms for more than a year. The collected data was analyzed using Confirmatory Factor Analysis (CFA) and Structural Equation Model (SEM) to confirm the reliability and validity of constructs, ensure model fit, and test the proposed research hypotheses. All factors in the conceptual model had significantly influenced behavioral intention, except for perceived ease of use that has no direct influence on attitude and no direct influence of facilitating conditions on behavioral intention. Therefore, four out of six hypotheses were supported. Social influence was the most substantial factor in behavioral intention towards online learning platforms, followed by attitude. Finally, the attitude of the university students was driven by perceived usefulness and indirectly driven by perceived ease of use.

The significant factors that management of universities, lecturers, and marketing partitioners should emphasize when enhancing students' behavioral intention to use online learning platforms were a social influence, attitude, perceived usefulness, and perceived ease of use that indirectly influence through attitude, respectively. Although using an online learning platform is gradually required for learning, universities should focus on delivering a positive experience from using an online learning platform to build favorable word-of-mouth or recommendation from peers to peers. For instance, creating a community or classroom in an online platform allows interaction, engagement, and appraisal among peers to build close relations and satisfaction. The usefulness of the learning platform should be ensured and promoted. The platform should enable the students to seek beneficial information required for their studies quickly. The information can be shared from classroom resources and materials or among peers. The universities can also open for students' feedback on the functionality or assistance needed from using the online learning platform to support students' proper needs and wants.

Limitation and Further Study

There are limitations to this study that should be extended in future research. For example, the researcher may develop a conceptual framework based on different research theories such as expectation confirmation theory of information system continuance (ECT-IS) or the information systems successful model (ISSM) to explore other key drivers that can drive or help understand students' satisfaction, post-purchase behavior, and perception on usefulness and ease of use. In addition, the scope of the research population can be widened to other geographical areas of China or other countries, which may result in different findings and recommendations.

References

Ain, N., Kaur, K. & Waheed, M. (2015). The influence of learning value on learning management system use: an extension of UTAUT2. *Information Development*, *32*(5), 1306-1321.

Ajzen, H. & Fishbein, M. (1980). *Understanding attitudes and predicting social behavior*. PrenticeHall.

Ajzen, I. (1991). Theories of cognitive self-regulation the theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179-211.

Alam, M.Z., Hu, W., Hoque, M.R. & Kaium, M.A. (2020). Adoption intention and usage behavior of mHealth services in Bangladesh and China: A cross-country analysis. *International Journal of Pharmaceutical and Healthcare Marketing*, *14*(1), 37-60. https://doi.org/10.1108/IJPHM-03-2019-0023

Alon, I., Farrell, M. & Li, S. (2020). Regime type and COVID-19 response. *FIIB Business Review*, 1-9. https://doi.org/10.1177/2319714520928884

Arbuckle, J. (1995). *AMOS: Analysis of Moment Structures User's Guide*. Small Waters.

ARWU. (2019). *Best Chinese Universities Ranking • Overall Ranking – 2019*. Shanghai Ranking. http://www.shanghairanking.com/Chinese_Universities_Rankings/Overall-Ranking-2019.html

Browne, M. W., & Cudeck, R. (1993). Alternative ways of assessing model fit. In K. A. Bollen, & J. S. Long (Eds.), *Testing structural equation models* (pp. 136-162). Sage.

Buabeng-Andoh, C., & Baah, C. (2020). Pre-service teachers' intention to use learning management system: an integration of UTAUT and TAM. *Interactive Technology and Smart Education, 17*(4), 455-474. https://doi.org/10.1108/ITSE-02-2020-0028

Chen, C.F. & Tsai, D.C. (2007). How destination image and evaluative factors affect behavioral intentions? *Tourism Management, 28*(4), 1115-1122. https://doi.org/10.1016/j.tourman.2006.07.007.

Clark, R. C., & Mayer, R. E. (2016). *e-Learning and the Science of Instruction: Proven Guidelines for Consumers and Designers of Multimedia Learning*. John Wiley & Sons.

Cortez, R. & Johnston, W. (2020). The coronavirus crisis in B2B settings: crisis uniqueness and managerial implications based on social exchange theory. *Industrial Marketing Management, 88*, 125-135.

Davis, F.D. (1989). Perceived usefulness, perceived ease of use and user acceptance of information technology. *MIS Quarterly, 13*(3), 319-340.

Davis, F.D., Bagozzi, RP & Warshaw, P.R. (1989). User acceptance of computer technology: a comparison of two theoretical models. *Management Science, 35*(8), 982-1003.

Dholakia, U.M., Bagozzi, R.P. & Pearo, L.K. (2004). A social influence model of consumer participation in network-and small-group-based virtual communities. *International Journal of Research in Marketing, 21*(3), 241-263.

Dos Santos, L.M. & Okazaki, S. (2016). Planned e-learning adoption and occupational socialization in Brazilian higher education. *Studies in Higher Education, 41*(11), 1974-1994.

Dragan, D & Topolšek, D. (2014). Introduction to Structural Equation Modeling: Review, Methodology and Practical Applications. *Proceedings of the International Conference on Logistics & Sustainable Transport*. University of Maribor.

Dulle, F.W. (2015). The suitability of the unified theory of acceptance and use of technology (UTAUT) model in open access adoption studies. *Information Development, 27*(1), 32-45.

Education. (2021). *Online Learning - What Is It And How Does It Work?* https://www.educations.com/study-guides/study-online/

Escobar-Rodriguez, T. & Monge-Lozano, P. (2011). The acceptance of Moodle technology by business administration students. *Computers and Education, 58*(4), 1085-93.

Fishbein, M. & Ajzen, I. (1975). *Belief, attitude, intention, and behavior: an introduction to theory and research*. Addison-Wesley.

Fishbein, M., & Ajzen, I. (2010). *Predicting and changing behavior: The reasoned action approach*. Psychology Press.

Fornell, C. & Larcker, D.F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*, 39-50.

Fottrell, E. & Byass, P. (2008). Population survey sampling methods in a rural African setting: measuring mortality. *Population Health Metrics, 6*(1), 2.

Gefen, D., Karahanna, E. & Straub, D.W. (2003). Trust and TAM in online shopping: an integrated model. *MIS Quarterly*, *27*(1), 51-90.

Hair, J., Black, W., Babin, B., Anderson, R., & Tatham, R. (2006). *Multivariate data analysis* (6th ed.). Pearson Education.

Hair, J., Hollingsworth, C. L., Randolph, A. B., & Chong, A. Y. L. (2017). An updated and expanded assessment of PLS-SEM in information systems research. *Industrial Management & Data Systems, 117*(3), 442-458.

Hamid, M. R., Sami, W., & Sidek, M. (2017). Discriminant validity assessment: Use of Fornell & Larcker Criterion versus HTMT Criterion. *In Journal of Physics: Conference Series, 890*(1).

Hsiao, C.H. & Tang, K.Y. (2014). Explaining undergraduates' behavior intention of e-textbook adoption: Empirical assessment of five theoretical models. *Library Hi Tech, 32*(1), 139-163. https://doi.org/10.1108/LHT-09-2013-0126

Hu, X. & Lai, C. (2019). Comparing factors that influence learning management systems use on computers and on mobile. *Information and Learning Sciences, 120*(7/8), 468-488. https://doi.org/10.1108/ILS-12-2018-0127

Ilyas, A. & Zaman, M.K. (2020). An evaluation of online students' persistence intentions. *Asian Association of Open Universities Journal*, *15*(2), 207-222. https://doi.org/10.1108/AAOUJ-11-2019-0053

Isaias, P., Reis, F., Coutinho, C., & Lencastre, J.A. (2017). Empathic technologies for distance/mobile learning: An empirical research based on the unified theory of acceptance and use of technology (UTAUT). *Interactive Technology and Smart Education, 14*(2), 159-180.

Jöreskog, K. G. (1969). A general approach to confirmatory maximum likelihood factor analysis. *Psychometrika, 34*(2), 183-202. https://doi.org/10.1007/BF02289343

Kintu, M.J., Zhu, C. & Kagambe, E. (2017). Blended learning effectiveness: the relationship between student characteristics, design features and outcomes. *International Journal of Educational Technology in Higher Education, 14*(1), 1-20.

Kirat Rai, S., Ramamritham, K. & Jana, A. (2020). Identifying factors affecting the acceptance of government to government system in developing nations – empirical evidence from Nepal. *Transforming Government: People, Process and Policy, 14*(2), 283-303. https://doi.org/10.1108/TG-05-2019-0035

Lee, C.Y., Tsao, C.H. & Chang, W.C. (2015). The relationship between attitude toward using and customer satisfaction with mobile application services: An empirical study from the life insurance industry. *Journal of Enterprise Information Management*, *28*(5), 680-697. https://doi.org/10.1108/JEIM-07-2014-0077

Mazman, S.G. & Usluel, Y.K. (2010). Modeling educational usage of Facebook. *Computers and Education, 55*(2), 444-453.

McKeown, T. & Anderson, M. (2016). UTAUT: capturing differences in undergraduate versus postgraduate learning? *Education + Training, 58*(9), 945-965. https://doi.org/10.1108/ET-07-2015-0058

Nair, P.K., Ali, F. & Leong, L.C. (2015). Factors affecting acceptance and use of ReWIND: validating the extended unified theory of acceptance and use of technology. *Interactive Technology and Smart Education, 12*(3), 183-201.

Ndubisi, N.O., Gupta, O.K. & Massoud, S. (2003). Organizational learning and vendor support quality by the usage of application software packages: a study of Asian entrepreneurs. *Journal of Systems Science and Systems Engineering, 12*(3), 314-31.

Ngai, E.W.T., Poon, J.K.L. & Chan, Y.H.C. (2007). Empirical examination of adoption of WebCT using TAM. *Computers and Education, 48*(2), 250-67.

Park, S.Y. (2009). An analysis of the technology acceptance model in understanding university students' behavioural intention to use e-Learning. *Educational Technology and Society, 12*(3), 150-62.

Raman, A. & Don, Y. (2013). Preservice teachers' acceptance of learning management software: An application of the UTAUT2 model. *International Education Studies, 6*(7), 157–164.

Rotchanakitumnuai, S. & Speece, M. (2009). Modeling electronic service acceptance of an e-securities trading system. *Industrial Management & Data Systems, 109*(8), 1069-1084. https://doi.org/10.1108/02635570910991300

Ryan, B. (2020). *What is an online learning platform?* iDTech. https://www.idtech.com/blog/what-is-an-online-learning-platform

Santos, J.R.A. (1999). Cronbach's alpha: a tool for assessing the reliability of scales. *Journal of Extension, 37*(2), 1-5.

Schermelleh-Engel, K., Moosbrugger, H., & Müller, H. (2003). Evaluating the fit of structural equation models: Tests of significance and descriptive goodness-of-fit measures. *Methods of psychological research online, 8*(2), 23-74.

SCU. (n.d.). *About SCU*. http://en.scu.edu.cn/About_SCU.htm

Singh, A., Sharma, S. & Paliwal, M. (2020). Adoption intention and effectiveness of digital collaboration platforms for online learning: the Indian students' perspective. *Interactive Technology and Smart Education*. Advance online publication. https://doi.org/10.1108/ITSE-05-2020-0070

Soper, D. S. (2019). *A-priori sample size calculator for structural equation models*. Daniel Soper. https://www.danielsoper.com/statcalc/calculator.aspx?id=89

SWJTU. (2019). *SWJTU at a glance*. https://en.swjtu.edu.cn/ABOUT/SWJTU_at_a_Glance.htm

SWPU. (n.d.). *Important statistics of Southwest Petroleum University*. https://www.swpu.edu.cn/en/index/About_SWPU1/Statistics.htm

SWUFE. (n.d.). *SWUFE at a glance*. https://e.swufe.edu.cn/ABOUT/SWUFE_AT_A_GLANCE.htm

Tarhini, A., Masa'deh, R., Al-Busaidi, K.A., Mohammed, A.B. & Maqableh, M. (2017). Factors influencing students' adoption of e-learning: a structural equation modeling approach. *Journal of International Education in Business, 10*(2), 164-182. https://doi.org/10.1108/JIEB-09-2016-0032

Teo, T. & Zhou, M. (2014). Explaining the intention to use technology among university students: a structural equation modeling approach. *Journal of Computing in Higher Education, 26*(2), 124-142.

Textor, C. (2021). *Value of online education market in China 2012-2022*. Statista. https://www.statista.com/statistics/1014491/china-market-size-of-online-education/

UESTC. (n.d.). *Why UESTC*. https://en.uestc.edu.cn/About_UESTC/Why_UESTC.htm

UIL. (2019). *Chengdu, China*. Unesco. https://uil.unesco.org/city/chengdu

Venkatesh, V. & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision Sciences*, *39*(2), 273-315.

Venkatesh, V., Morris, M.G., Davis, G.B. & Davis, F.D. (2003). User acceptance of information technology: toward a unified view. *MIS Quarterly*, *27*(3), 425-478.

Yi, M., Jackson, J., Park, J. & Probst, J. (2016). Understanding information technology acceptance by individual professionals: toward an integrative view. *Information and Management, 43*(3), 350-363.

YLM, DR (2020). *Covid-19: what does the 'new normal' mean?* The Star. https://www.thestar.com.my/lifestyle/health/2020/05/21/Covid-19-what-does-the-039new-normal039-mean

Zhang, J. (2016). Can MOOCs be interesting to students? An experimental investigation from regulatory focus perspective. *Computers and Education*, *95*, 340-351.

Zhou, Q., Lee, C.S., Sin, S.C.J., Lin, S., Hu, H. & Fahmi Firdaus Bin Ismail, M. (2020). Understanding the use of YouTube as a learning resource: a social cognitive perspective. *Aslib Journal of Information Management*, *72*(3), 339-359. https://doi.org/10.1108/AJIM-10-2019-0290