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## Factors Impacting Online Learning Usage during Covid-19 Pandemic Among Sophomores in Sichuan Private Universities

Yingqu Cao <sup>1\*</sup>, Chanintorn Jittawiriyankoon <sup>2\*\*</sup>

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### Abstract

**Purpose:** This study examines factors impacting online learning usage among students in Sichuan private universities, China. The variables used to construct the conceptual framework are perceived ease of use, perceived usefulness, information quality, system quality, service quality, attitude toward using, satisfaction, behavioral intention and actual use. **Research design, data and methodology:** The quantitative approach (n=500) was conducted via online questionnaire, using judgmental sampling, quota sampling and convenience sampling. Before the data collection, index of item objective congruence (IOC) and Cronbach's Alpha reliability were accounted to validate content and pilot test (n=40). Afterwards, the data was analyzed in SPSS using descriptive statistics, confirmatory factor analysis (CFA) and structural equation modeling (SEM). **Results:** The results revealed that satisfaction had the strongest significant impact on behavioral intention. Other significant relationships were perceived ease of use and perceived usefulness on attitude toward using; information quality, service quality, attitude toward using on behavioral intention towards actual use. On the other hand, the relationship between system quality and behavioral intention was not significant. **Conclusions:** Academic practitioners were recommended to encourage online learning usage among students by developing better online learning system, technical support service and learning experience which led to successful adoption in higher education.

**Keywords :** Perceived Ease of Use, Perceived Usefulness, Information Quality, System Quality, Service Quality

**JEL Classification Code:** E44, F31, F37, G15

### 1. Introduction<sup>12</sup>

Even though online learning or e-learning had been used for over decades, it is the most recent format of distance education. Online education has taken place with the rise of internet which grants the better way of teaching and learning. Online learning offers many benefits for

instructors and learners to collaborate more actively and conveniently (Bouchrika, 2020). The COVID-19 pandemic forced rapid change in global higher education. Universities around the world, encountered with sudden restrictions on in-person classes and lectures, have rapidly expanded their existing online learning tools or adopted new ones. Many universities went completely online during the 2020 school year (Champagne & Granja, 2021).

<sup>1</sup> \*Yingqu Cao, PhD Candidate, Technology Education and Management, Graduate School of Business and Advanced Technology Management, Assumption University of Thailand. Email [yingqucao@gmail.com](mailto:yingqucao@gmail.com)

<sup>2</sup> \*\*Chanintorn Jittawiriyankoon, PhD TEM Program Faculty Member, Graduate School of Business and Advanced Technology Management, Assumption University of Thailand.

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University students in China were faced with the same rapid transition to online learning (Xue et al., 2020; Zhu & Liu, 2020). In January 2020, the Chinese government forced universities, along with other learning institutions, to cease in-person teaching activities, with most students were not allowed to return to campus due to the pandemic (Zhu & Liu, 2020).

The online education industry has been growing fast in China. Online learning industry based on end users in 2020 has raised by 46% to more than 400 million users. The time spent on online education has increased 60% during the pandemic in this region which encourages learning trend to take online programs and more people to become instructors for online classes, as physical distance is no longer a barrier (Kuo, 2021).

This research problem addresses how the experience of online learning platforms influences university students' intention to use and actual use of online learning. Many Chinese universities had not made a lot of use of online learning prior to the COVID-19, and were forced to implement online learning rapidly in response to the pandemic (Xue et al., 2020). As a result, this problem raises the question of what factors influencing online learning usage.

The research aims to examine student attitudes and perceptions leading to adoption of online learning at private universities in Sichuan Province, involving theories of TAM, UTAUT and IS Success Model. The objectives of the research include:

1. Investigating the impact of perceived ease of use (PEOU) and perceived usefulness (PU) on attitude toward using (ATT) an online learning platform.
2. Examining the role of information quality (IQ), system quality (SYQ), service quality (SEQ), attitude toward using (ATT), and user satisfaction (SAT), in the formation of behavioral intention (BI).
3. Determining the effect of behavioral intentions on actual system use (AU) of the online learning platform.
4. Making recommendations about the adoption of online learning platforms for university students in Sichuan province based on these investigations.

## 2. Literature Review

### 2.1. Online Learning

Online learning or e-learning explains a designed program or learning experience carried electronically with performance support content. An e-learning program incurs different type of formats, such as live or pre-recorded lecture content, video, quizzes, simulations, games, activities, and other interactive elements. The online learning service

segment plays an important role in the market, responding to its fast adoption of technology usage and integration. Online learning is viewed as a useful format which can exempt the various costs, comparing to traditional training, such as printing materials, physical infrastructure, onsite-staff and vice versa (Nair, 2021).

### 2.2. Technology Acceptance Model (TAM)

The technology acceptance model (TAM) was developed as an extension to the theory of reasoned action (TRA) in order to explain the adoption of technology by users in organizational contexts (Davis, 1989; Davis et al., 1989). The TAM has the key constructs and causal relationship of perceived usefulness, perceived ease of use and attitudes toward using technology. The attitude toward the use influences behavioral intention to use, which in turn contributes to actual system use the technology.

### 2.3. Information Systems Success Model (IS)

Information systems (IS) success model argues that behavioral intention to continue using online learning systems depends on perceived quality, including individual dimensions of information quality, system quality and service quality (Ramayah et al., 2010). Each of these three quality dimensions contributes to behavioral intention to continue to use the technology according to Ramayah et al. (2010). This model can be simplified and updated by DeLone and McLean (2003) elaborated that system quality directly impacts behavioral intention toward the learning system. Many studies have used IS model, particularly those concerned with continuance intention for technologies already in use (Daghan & Akkoyunlu, 2016; Ramayah & Lee, 2012).

### 2.4. Unified Theory of Acceptance and Use of Technology (UTAUT)

The unified theory of acceptance and use of technology (UTAUT) incorporates the main components and causal relationships of the framework, including effort expectancy, performance expectancy, social influence facilitating conditions, behavioral intention and actual usage (Chao, 2019). Effort expectancy and performance expectancy are defined essentially in the same way as perceived ease of use and perceived usefulness in the TAM framework. In addition, Chao (2019) integrates dimensions of self-efficacy, trust and perceived enjoyment as direct influencers, with perceived risk acting as a moderating factor. Furthermore, the model includes a satisfaction that has a direct influence on behavioral intention which is influenced by perceived enjoyment, effort expectancy and performance expectancy.

## 2.5. Perceived Ease of Use

Perceived ease of use (PEOU) is one of the variables that comes from the technology acceptance model (TAM) (Chuttur, 2009). An early definition of PEOU states that it is “the degree to which a person believes that using a particular system would be free of effort (Davis, 1989, p. 320).” This is similar to another study which states it is “the degree to which the prospective user expects the target system to be easy to use (Davis et al., 1989).” A slightly later elaboration on PEOU is influenced by other factors such as self-efficacy, objective usability and experience (Venkatesh & Davis, 1996). Later studies have essentially adopted Davis’s (1989) definition without any further modification (Fagan et al., 2008; Pan et al., 2005; Saadé & Kira, 2007; Sivo et al., 2018).

Studies on e-learning acceptance have included the attitude toward use (ATT) as a significant construct and have also generally showed that there is a positive relationship between PEOU and ATT (Al-Adwan et al., 2013; Farahat, 2012; Granić & Marangunić, 2019; Hanif et al., 2018; Siti et al., 2021; Sivo et al., 2018; Šumak et al., 2011). Thus, it appears in most online learning literatures that PEOU is a significant predictor of ATT which explains that students perceive the free of effort to use online learning platform will have a positive attitude toward using it as demonstrated by the following hypothesis.

**H1:** Perceived ease of use has a significant impact on attitude toward using online learning in Chinese higher education.

## 2.6. Perceived Usefulness

Perceived usefulness (PU) is one of the variables derived from TAM (Chuttur, 2009). Davis (1989) defined PU as “the degree to which a person believes that using a particular system would enhance his or her job performance.” A slightly modified definition of PU is that it is “the prospective user’s subjective probability that using a specific application system will increase his or her job performance within an organizational context (Davis et al., 1989).” PU describes the degree to which a student believes the benefits of using an online learning system would enhance his or her learning performance (Davis, 1989).

The relationship between PU and ATT was found the strongest effect within the TAM, which led to behavioral intention toward actual use of the online learning system (Chuttur, 2009; King & He, 2006; Yousafzai et al., 2007). Evidences from most literatures have confirmed the relationship and reviewed a significant, positive relationship between PU and ATT (Farahat, 2012; Granić & Marangunić, 2019; Siti et al., 2021; Sivo et al., 2018; Šumak et al., 2011).

Furthermore, it explains when students believe in the benefits of using online learning, they will have a positive attitude toward using it. The above statements stated in the following hypothesis:

**H2:** Perceived usefulness has a significant impact on attitude toward using online learning in Chinese higher education.

## 2.7. Information Quality

Information quality is a construct that comes from the information systems (IS) success model (sometimes called the DeLone and McLean or D&M model) (DeLone & McLean, 2003; Urbach & Müller, 2012). Information quality includes characteristics of the information provided by the system, including “accuracy, timeliness, completeness, relevance, and consistency (DeLone & McLean, 2003).” Information quality in this research is described as the content quality of learning program managed by the system. The quality of content is evaluated by students whether the institutions provide valuable information per their needs and expectations (Adeyinka & Mutula, 2010).

According to Ramayah et al. (2010), most of the research applied generic models that have modified IS success model in accordance with particular technology and research context. However, few studies have addressed the significant effect of IQ on continuance intention for online learning (Daghan & Akkoyunlu, 2016; Ramayah & Lee, 2012). In the updated IS success model, IQ has a significant and positive effect on behavioral intention (DeLone & McLean, 2003). Numerous studies have applied the IS success model to online learning environments have also supported the effect of IQ on BI (Efiloğlu Kurt, 2019; Freeze et al., 2010; Hsu, 2021; Lin, 2007; Thongsri et al., 2019). The theoretical relationship was derived to determine a hypothesis:

**H3:** Information quality has a significant impact on behavioral intention to use online learning in Chinese higher education.

## 2.8. System Quality

System quality (SYQ) is the second construct derived from the IS success model (DeLone & McLean, 2003; Urbach & Müller, 2012). System quality relates to the technological system in use, including characteristics of “ease of use, functionality, reliability, flexibility, data quality, portability, integration and importance (DeLone & McLean, 2003).” Another definition is “the desirable characteristics of an information system typically focus on usability aspects

and performance characteristics of the system under examination (Urbach & Müller, 2012).” The system quality incurs the platform selected by university to utilize an online learning which can provide ease of use, convenience and reliability.

Most evidence comes from the IS success model, where SYQ is the technical communication construct, and it is projected to have a positive, significant effect on BI (DeLone & McLean, 2003). This effect is observed in a meta-analysis of studies on the IS success model, which found SYQ had the second strongest effect on BI (after IQ). The literatures on e-learning adoption upheld this relationship, with the studies reviewed showing that there was a significant positive effect of SYQ on BI (Efiloğlu Kurt, 2019; Hsu, 2021; Lin, 2007; Thongsri et al., 2019). Consequently, H4 is formulated as:

**H4:** System quality has a significant impact on behavioral intention to use online learning in Chinese higher education.

## 2.9. Service Quality

Service quality (SEQ) was identified by DeLone and McLean (2003) as a key characteristic of the system, relating to aspects such as up-to-date hardware and software and service from technical support staff. SEQ is the perceived quality of support from support personnel, such as reliability and technical knowledge (Petter et al., 2008). The service quality is perceived by students on how the university provide technical support through using the online learning system.

SEQ will have a significant effect on BI, even though it is theoretically proposed to do so. However, this is not necessarily because the idea is invalid, but rather because it has not been tested very much in the context of online learning. Given many of the problems encountered during the rapid switch to online learning did require technical support (Mok et al., 2021; Zhu & Liu, 2020), it is very likely that SEQ may play more of a role than usual. In the context of this study, students intend to use online learning system when they receive high standard and responsive service from technical personnel. Thereby, the following hypothesis is stated:

**H5:** Service quality has a significant impact on behavioral intention to use online learning in Chinese higher education.

## 2.10. Attitude Toward Using

A general definition of attitude toward using is “a disposition to respond favorably or unfavorably to an object, person, institution or event (Ajzen, 2005, p. 3).” Furthermore, an attitude is essentially an evaluative disposition, and it is based on prior experiences and knowledge. Another definition is a psychological tendency that is expressed by evaluating a particular entity with some degree of favor or disfavor (Eagly & Chaiken, 1993, p. 1).” Attitude toward using is the individual’s evaluation and feelings about using the system (Davis et al., 1989).

The empirical evidence strongly supports the relationship between ATT and BI. General literature reviews showed evidence for the proposed relationship between these two key variables (Chuttur, 2009; King & He, 2006; Marangunić & Granić, 2015; Yousafzai et al., 2007). Individual studies focused on e-learning have explained that the attitude toward use among students is the favorably or unfavorably respond to an online learning which leads to an online learning adoption (Ajzen, 2005, p. 3; Al-Adwan et al., 2013; Farahat, 2012; Granić & Marangunić, 2019; Hanif et al., 2018; Siti et al., 2021; Sivo et al., 2018; Šumak et al., 2011). Therefore, H6 is stated as follows:

**H6:** Attitude toward using has a significant impact on behavioral intention to use online learning in Chinese higher education.

## 2.11. Satisfaction

User satisfaction is an element of the IS success model, (DeLone & McLean, 2003). Satisfaction (SAT) is identified are characteristics including repeat purchases or visits and user surveys as a way to measure satisfaction. A more detailed definition is the users’ level of satisfaction with reports, web sites and support services (Petter et al., 2008, p. 239). Satisfaction is the user’s perception of the system and their evaluation of the user experience and how well it met their expectations (Chiu et al., 2007).

The relationship between SAT and BI showed a positive and significant effect (Calli et al., 2013; Chao, 2019). There were also several empirical studies using the IS success model which showed that SAT contributed to BI (Chiu et al., 2007; Lin, 2007). This research intensified that satisfied students will have an intention to use online learning. Moreover, the high satisfaction of students in using online learning encourage them to have a willingness to use it. Accordingly, H7 is proposed as follow:

**H7:** Satisfaction has a significant impact on behavioral intention to use online learning in Chinese higher education.

## 2.12. Behavioral Intention (BI)



Behavioral intention (BI) can be defined as “the strength of one’s intention to perform a specific behavior (Davis et al., 1989)” such as use an information system. BI is a primary construct of TAM and UTAUT model which signified that BI is the subjective probability of an individual performing a behavior (Venkatesh & Davis, 2000). In this research, behavioral intention explains willingness of student in using online learning or probability of a student performing a behavior of online platform usage (Venkatesh & Davis, 2000).

The final relationship of most technology adoption model is a relationship between BI and AU (Davis et al., 1989; DeLone & McLean, 2003). BI is proposed to have a significant, positive effect on AU. Not all studies incorporate both variables, as many did not test actual technology usage (Chuttur, 2009). Therefore, it is a common finding that BI positively effect AU (King & He, 2006; Marangunić & Granić, 2015; Petter & McLean, 2009; Yousafzai et al., 2007). Based on this evidence, the final hypothesis of the study is that:

**H8:** Behavioral intention has a significant impact on actual use of online learning in Chinese higher education.

### 2.13. Actual System Use

The actual system use (AU) simply represents the performance of the actual behavior being measured (Ajzen, 2005; Davis et al., 1989; Fishbein & Ajzen, 1975). In the context of technology adoption model, the actual behavior has been widely investigated (Davis, 1989; Davis et al., 1989). In this research, the actual system use is the choice to use the online learning system. Actual use can also be the frequency or degree of the use of the system (Efiloğlu Kurt, 2019, p. 1175). AU refers to whether and how much the individual actually uses the information system.

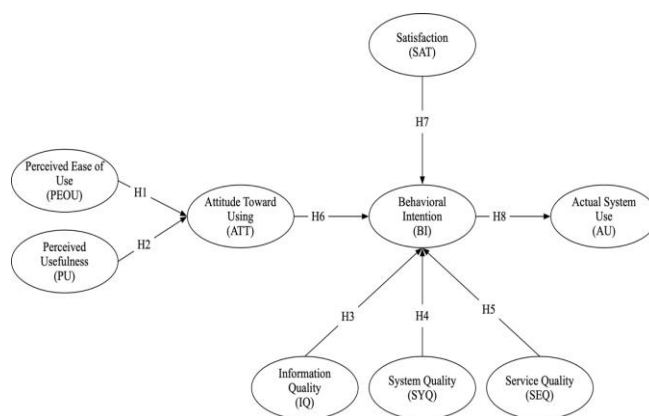
This research implies the actual system use is the choice to use the online learning system among students. Actual use also explains the frequency or degree of the use of the system (Efiloğlu Kurt, 2019). Lin et al. (2013) studied on behavioral use of e-learning system among students, which interpreted that actual use of a technology can be derived from numerous factors especially in UTAUT model which has been widely adopted. In addition, actual behavior presents as a final outcome of an adoption behavior.

## 3. Research Methods and Materials

### 3.1. Research Framework

The conceptual framework was adopted based on three theoretical models. Firstly, TAM involves perceived

usefulness, perceived ease of use, attitudes toward using technology, behavioral intention and actual system use (Davis, 1989). Secondly, Ramayah et al. (2010) argued that behavioral intention to continue using online learning systems depends on perceived quality, including individual dimensions of information quality, system quality and service quality. Lastly, Chao (2019) incorporates satisfaction that had a direct influence on behavioral intention. Consequently, the conceptual framework is constructed as in Figure 1.



**Figure 1:** Conceptual Framework

The conceptual framework is developed on how perceived ease of use (PEOU) and perceived usefulness (PU) impact attitude towards using (ATT), and how information quality (IQ), system quality (SYQ), service quality (SEQ), attitude toward using (ATT), and satisfaction (SAT) impact behavioral intentions (BI) towards actual use (AU) of online learning system. Hence, 9 variables and 8 hypotheses were proposed.

### 3.2. Methodology

The quantitative approach was used to distribute online survey to 500 respondents. The questionnaire was designed into three parts. Firstly, screening questions were used to qualify the target group. Secondly, the demographic questions were used to define the characteristics of the respondent. Lastly, 5-point Likert Scale was applied to measure items used in this research.

Prior to the data collection, content validity was reserved by index of item objective congruence (IOC) of three experts with an average scale of .70 or higher, indicating that the item measures the attribute or variable (Sireci, 1998). The pilot study of 40 samples was approved by Cronbach’s Alpha. The acceptable value of alpha coefficient for each structure must be greater than or equal to 0.60 (Nunnally & Bernstein, 1994), resulting all items

reserved. Later, the questionnaire was distributed to the target group. The sampling techniques used were judgmental sampling, quota sampling, and convenience sampling. After the data collection, the data was analyzed in SPSS using descriptive statistics, confirmatory factor analysis (CFA) and structural equation modeling (SEM).

### 3.3. Population and Sample Size

The population of this study was second-year students at three private university in Sichuan, China namely, Sichuan Normal University Fine Arts College, Sichuan University of Arts and Sciences Academy of Art and Design Dazhou Vocational and Technical College Art Department. The statistical software of Soper (n.d.) was input with the expected effect size (0.2), the expected level of statistical power (0.8), the number of latent variables (8), the number of observed variables (27), and the probability scale (0.05). The recommended minimum sample size was 460. However, the researchers consider sample size of this study to be 500 participants to avoid error and insufficient data for the analysis. The data were collected between February to August 2021.

### 3.4. Sampling Technique

The three steps of sampling techniques were used. Firstly, the judgmental sampling is accounted to selecting second-year students in three private universities in Sichuan, China. Secondly, quota sampling was applied to calculating ratio from total students at each school (Table 1). Lastly, convenience sampling was used for the survey distribution via online channels including student mailing lists and social media groups.

**Table 1:** Quota Sampling

University	Estimated Students	Sample Size	Percentage
Sichuan Normal University Fine Arts College	2,400	136	27.2%
Sichuan University of Arts and Sciences Academy of Art and Design	6,000	336	67.2%
Dazhou Vocational and Technical College Art Department	500	28	5.6%
	8,900	500	100%

Source: Created by the author

The demographic results presented most participants were female of 51.8% (259), whereas male was 48.2% (241). The major group of participants were living in Sichuan of 75.4% (377) and outside Sichuan of 24.6% (123). Most participants had other occupation or activities besides study between 2 and 6 hours per week of 31.4% (157), followed by less than 2 hours per week of 26.6% (133), up to 2 hours per day of 18.8% (94), between 2 and 6 hours per day of 10.6% (53), more than 5 hours per day of 7.4% (37), and no activities of 5.2% (26) as presented in Table 2.

**Table 2:** Demographic Profile

Demographic and Behavior Data (N=500)		Frequency	Percentage
Gender	Male	241	48.2%
	Female	259	51.8%
Hometown	In Sichuan	377	75.4%
	Outside Sichuan	123	24.6%
Occupation and Other Activities	No activities	26	5.2%
	Less than 2 h per week	133	26.6%
	Between 2 and 6 h per week	157	31.4%
	Up to 2 h per day	94	18.8%
	Between 2 and 6 h per day	53	10.6%
	More than 6 h per day	37	7.4%

Source: Created by the author

### 4.2. Confirmatory Factor Analysis (CFA)

CFA was applied for a measurement model analysis. Hair et al. (2006) guided that the significance of factor loading of each item and acceptable values in signifying the goodness of fit. Factor loadings were higher than 0.50 and p-value of lower than 0.05. Furthermore, in case of Average Variance Extracted (AVE) was less than 0.5 but Composite Reliability (CR) was higher than 0.7, the convergent validity of the construct was still adequate (Fornell & Larcker, 1981) as shown in Table 3.

The square root of average variance extracted is determined that all the correlations are greater than the corresponding correlation values for that variable as of Table 4. Measurement model was tested using the fit model including CMIN/DF = 2.773, GFI = 0.902, AGFI = 0.872, NFI = 0.871, CFI = 0.912, TLI = 0.893, and RMSEA = 0.060. All estimates were acceptable with no model adjustment required. Therefore, the convergence validity and discriminant validity were ensured. All results are shown in Table 5.1.

## 4. Results and Discussion

### 4.1. Demographic Information

**Table 3:** Confirmatory Factor Analysis Result, 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	Sivo (2018)	3	0.849	0.782 - 0.846	0.851	0.655
Perceived Usefulness	Sivo (2018)	3	0.800	0.657 - 0.823	0.804	0.580
Information Quality	Lin (2007)	3	0.722	0.659 - 0.717	0.724	0.467
System Quality	Lin (2007)	3	0.834	0.779 - 0.800	0.834	0.626
Service Quality	Lin (2007)	3	0.739	0.642 - 0.756	0.741	0.490
Attitude Toward Using	Sivo (2018)	3	0.799	0.654 - 0.832	0.804	0.580
Satisfaction	Calli et. al. (2013)	3	0.698	0.629 - 0.702	0.702	0.440
Behavioral Intention	Calli et al. (2013), Sivo (2018)	3	0.765	0.572 - 0.830	0.790	0.563
Actual Use	Sivo (2018)	3	0.851	0.778 - 0.861	0.852	0.658

Note: CR = Composite Reliability, AVE = Average Variance Extracted

Source: Created by the author

**Table 4:** Discriminant Validity

	SAT	ATT	BI	IQ	SYQ	SEQ	AU	PU	PEOU
SAT	<b>0.663</b>								
ATT	0.346	<b>0.762</b>							
BI	0.602	0.291	<b>0.750</b>						
IQ	0.364	0.133	0.441	<b>0.683</b>					
SYQ	0.215	0.111	0.254	0.426	<b>0.791</b>				
SEQ	0.392	0.251	0.487	0.387	0.250	<b>0.700</b>			
AU	0.516	0.231	0.302	0.224	0.501	0.225	<b>0.811</b>		
PU	0.410	0.302	0.436	0.378	0.243	0.443	0.236	<b>0.761</b>	
PEOU	0.173	0.124	0.246	0.179	0.138	0.122	0.151	0.150	<b>0.809</b>

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

Source: Created by the author

**Table 5.1:** Goodness of Fit for Confirmatory Factor Analysis (CFA)

Index	Acceptable Values	Values
CMIN/DF	< 3.00 (Hair et al., 2006)	2.773
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.902
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.872
NFI	≥ 0.80 (Wu & Wang, 2006)	0.871
CFI	≥ 0.80 (Bentler, 1990)	0.912
TLI	≥ 0.80 (Sharma et al., 2005)	0.893
RMSEA	< 0.08 (Pedroso et. al., 2016)	0.060

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: Created by the author

### 4.3. Structural Equation Model (SEM)

SEM was applied to examine casual relationships among variables for hypotheses confirmation in this research (Jöreskog & Sörbom, 1993). SPSS AMOS was employed to define the fit degree of a structural model. For structural model, the results showed Chi – Square ( $\chi^2/df$ ) of 2.957, Goodness-of-fit statistic (GFI) = 0.863, Adjusted

Goodness-of-fit statistic (AGFI) = 0.827, Normed Fit Index (NFI) = 0.857, Comparative Fit Index (CFI) = 0.899, Tucker-Lewis index (TLI) = 0.882, and Root Mean Square Error of Approximation (RMSEA) = 0.063. Accordingly, the structural model presented model fit as concluded in Table 5.2.

**Table 5.2:** Goodness of Fit for Structural Equation Model (SEM)

Index	Acceptable Values	Values
CMIN/DF	< 3.00 (Hair et al., 2006)	2.957
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.863
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.827
NFI	≥ 0.80 (Wu & Wang, 2006)	0.857
CFI	≥ 0.80 (Bentler, 1990)	0.899
TLI	≥ 0.80 (Sharma et al., 2005)	0.882
RMSEA	< 0.08 (Pedroso et. al., 2016)	0.063

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: Created by the author

### 4.4. Research Hypothesis Testing Result

The regression weights and R<sup>2</sup> variance verified significant relationship as displayed in Table 6 when p is equal to 0.05. Satisfaction had the strongest significant impact on behavioral intention at the value of  $\beta = 0.599$  and t-value = 9.213\*. Secondly, perceived usefulness had significant effect on attitude toward using at the value of  $\beta = 0.348$  and t-value = 6.301\*. Thirdly, there was a significance relationship between service quality and behavioral intention at the value of  $\beta = 0.295$  and t-value = 6.300\*. Next, behavioral intention and actual use were

supported at the level of  $\beta = 0.201$  and t-value = 3.994\*. Fifthly, information quality had a significant impact on behavioral intention at the value of  $\beta = 0.162$  and t-value = 3.945\*. Sixthly, there was a support relationship between attitude toward using and behavioral intention at the value of  $\beta = 0.096$  and t-value = 2.635\*. Lastly, perceived ease of use had a significant impact on attitude toward using at the value of  $\beta = 0.120$  and t-value = 2.348\*. On the other hand, there was no significant relationship between system quality and behavioral intention. In conclusion, the significance was confirmed H1, H2, H3, H5, H6, H7 and H8, whereas H4 was found not supported.

**Table 6:** Hypothesis Result of the Structural Model

Hypotheses	Paths	Standardized Path Coefficients ( $\beta$ )	t-value	Tests Result
H1	PEOU $\rightarrow$ ATT	0.120	2.348*	Supported
H2	PU $\rightarrow$ ATT	0.348	6.301*	Supported
H3	IQ $\rightarrow$ BI	0.162	3.945*	Supported
H4	SYQ $\rightarrow$ BI	0.029	0.834	Not Supported
H5	SEQ $\rightarrow$ BI	0.295	6.300*	Supported
H6	ATT $\rightarrow$ BI	0.096	2.635*	Supported
H7	SAT $\rightarrow$ BI	0.599	9.213*	Supported
H8	BI $\rightarrow$ AU	0.201	3.994*	Supported

Note: \*p<0.05

Source: Created by the author

The results from Table 6 and Figure 2 indicated that:

H1: The standardized path coefficient between perceived ease of use and attitude toward using was 0.120 (t-value = 2.348\*). Therefore, H1 was supported.

H2: Perceived usefulness significantly impacted attitude toward using as the standardized path coefficient was 0.348 (t-value = 6.301\*). Henceforth, H2 was supported.

H3: The standardized path coefficient between information quality and behavioral intention was supported with the value of 0.162 (t-value = 3.945\*).

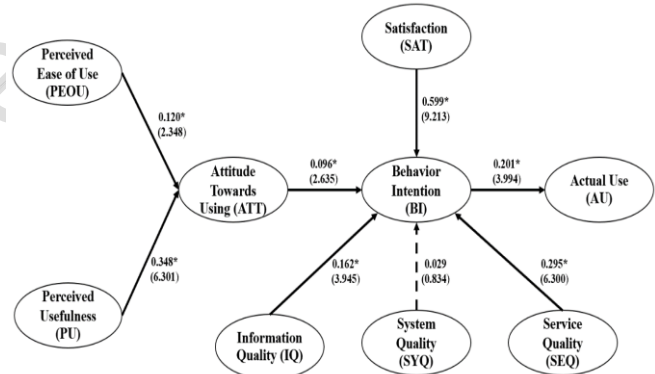
H4: There was no significant relationship between system quality and behavioral intention due to the standardized path coefficient was 0.029 (t-value = 0.834).

H5: Service quality and behavioral intention was significant at the standardized path coefficient of 0.295 (t-value = 6.300\*). Thereby, H5 was supported.

H6: The standardized path coefficient between attitude toward using behavioral intention was 0.096 (t-value = 2.635\*). Therefore, H6 was supported.

H7: The standardized path coefficient between student satisfaction and behavioral intention was 0.599 (t-value = 9.213\*). As a result, H7 was strongly supported.

H8: Behavioral intention and actual use had the standardized path coefficient at 0.201 (t-value = 3.994\*). As a result, H8 was supported.



**Figure 2:** The Results of Structural Model

### 4.5. Direct, Indirect and Total Effects of Relationships

The direct, indirect and total effect of the relationship were shown in Table 7. Satisfaction directly affects behavioral intention at 0.599 and indirectly affects actual use at 0.121. Service quality directly affects behavioral intention at 0.295 and indirectly affects actual use at 0.059. System quality directly affects behavioral intention at 0.029 and indirectly affects actual use at 0.006. Information quality directly affects behavioral intention at 0.162 and indirectly affects actual use at 0.033. Attitude toward using directly affects behavioral intention at 0.096 and indirectly affects actual use at 0.019.



Perceived usefulness directly affects attitude toward using at 0.348 and indirectly affects behavioral intention at 0.034 and actual use at 0.007. Perceived ease of use directly

affects attitude toward using at 0.120 and indirectly affects behavioral intention at 0.012 and actual use at 0.002. Behavioral intention has a direct effect on actual use at 0.201.

**Table 7:** Direct (DE), Indirect (IE) and Total Effects (TE)

Independent Variable	Dependent Variables											
	Attitude Toward Using (ATT)				Behavior Intention (BI)				Actual Use (AU)			
	DE	IE	TE	R <sup>2</sup>	DE	IE	TE	R <sup>2</sup>	DE	IE	TE	R <sup>2</sup>
SAT	-	-	-	.135	.599	-	.599	.482	-	.121	.121	.041
SEQ	-	-	-		.295	-	.295		-	.059	.059	
SYQ	-	-	-		.029	-	.029		-	.006	.006	
IQ	-	-	-		.162	-	.162		-	.033	.033	
PU	.348	-	.348		-	.034	.034		-	.007	.007	
PEOU	.120	-	.120		-	.012	.012		-	.002	.002	
ATT	-	-	-		.096	-	.096		-	.019	.019	
BI	-	-	-		-	-	-		-	.201	-	

Source: Created by the author

## 5. Conclusions and Recommendation

### 5.1. Discussion and Recommendation

The recommendations generalize findings with implications for theories and practices for academic practitioners to improve online learning adoption among students in higher education. Firstly, satisfaction had the strongest significant impact on behavioral intention as consistent with previous literatures (Calli et al., 2013; Chao, 2019; Chiu et al., 2007; Lin, 2007). The results imply that students who has high satisfaction will have an intention to use online learning. Therefore, academic practitioners are enquired to provide effective online learning system and service support to students in order to encourage their usage. Secondly, perceived usefulness significantly impacted attitude toward using per the evidence of many studies (Chuttur, 2009; King & He, 2006; Yousafzai et al., Farahat, 2012; Granić & Marangunić, 2019; Siti et al., 2021; Sivo et al., 2018; Šumak et al., 2011). Thereby, universities should promote the benefits and how online system can enhance their learning performance to build positive attitude toward using it among students.

Thirdly, universities should focus on providing high quality of service for online learning usage such as software installment, manual guide, training and help desk support in order to ensure behavioral intention of students to response with the research findings that service quality had a significant impact on behavioral intention (Mok et al., 2021; Zhu & Liu, 2020). Fourthly, behavioral intention had a significant impact on actual use which was proven by many researchers in technology adoption topics (Davis et al., 1989; DeLone & McLean, 2003; Chuttur, 2009; King & He, 2006; Marangunić & Granić, 2015; Petter & McLean, 2009;

Yousafzai et al., 2007). The researchers also confirmed this relationship and further suggested the educators could develop relevant factors to enhance intention to use of students such as ease-of-use system, technical service support and effective communication on online learning system.

Fifthly, information quality was another key variable that drives behavioral intention which explained that the quality of content in online learning system was assessed by students could enhance their interest of using it (DeLone & McLean, 2003; Urbach & Müller, 2012; Adeyinka & Mutula, 2010). Accordingly, universities should ensure to develop meaningful and engagement content (i.e., games, quizzes, competitions etc.), relating to online learning system to avoid boredom or low adoption rate. Sixthly, students expect that online learning system should be free of effort to use which explains that perceived ease of use significantly impact attitude toward using the system. Easy-to-use online learning platform can generate positive attitude toward using it. Thus, the institution could source the appropriate learning software from service providers and registered for a trial session to ensure the user’s friendly function before full deploying it (Al-Adwan et al., 2013; Farahat, 2012; Granić & Marangunić, 2019; Hanif et al., 2018; Siti et al., 2021; Sivo et al., 2018; Šumak et al., 2011).

Next, attitude toward using significantly impacted behavioral intention. Previous studies on e-learning affirmed that the attitude toward use among students is the favorably or unfavorably respond to an online learning which leads to an online learning adoption (Ajzen, 2005, p. 3). (Al-Adwan et al., 2013; Farahat, 2012; Granić & Marangunić, 2019; Hanif et al., 2018; Siti et al., 2021; Sivo et al., 2018; Šumak et al., 2011). Consequently, academic management could consider to provoke a favorably respond

to attract student's behavioral intention such as promoting on how online learning system can improve their learning efficiency. Lastly, the relationship system quality and behavioral intention was not supported in this study which contradicted with many researchers (Efiloğlu Kurt, 2019; Hsu, 2021; Lin, 2007; Thongsri et al., 2019). It can be assumed that students were not a decision maker who select the online learning software. However, academic practitioner should conduct system quality survey to get better insights on why this factor is not significant.

## 5.2. Conclusion

This study achieved its objectives in investigating factors impacting online learning usage among second-year students in Sichuan private universities, China. TAM, IS success model and UTAUT technology adoption model were adapted to construct a conceptual framework. Variables used are perceived ease of use, perceived usefulness, information quality, system quality, service quality, attitude towards using, satisfaction, behavioral intention and actual use. The population and sample size were 500 participants. The quantitative approach was applied by distributing online questionnaire. The sampling techniques enquire probability sampling including judgmental sampling, quota sampling, and convenience sampling. Before collecting the data, IOC validity and Cronbach's Alpha reliability were accounted. After the data collection, CFA was used to measure factor loading, convergent validity, discriminant validity and goodness of fit model. Lastly, SEM was operated for relationships and hypotheses testing.

The findings revealed both support and non-support in relationship among factors. Firstly, satisfaction had the strongest significant impact on behavioral intention which explained satisfied students will have a high intention to use the online learning system. Secondly, perceived usefulness on attitude toward using which explained when students believe in using online learning can help them achieving their learning goals, they will have a positive attitude toward using it. Thirdly, service quality was a factor impacting behavioral intention. The reliability and responsive service from technical support staff can increase the level of intention to use online learning system among students. Fourthly, the relationship between behavioral intention and actual use was supported. This study also confirmed that behavioral intention of students can motivate them to performing a behavior of online platform usage. Fifthly, the relationship between information quality and behavioral intention was significant which signified that the perceived content quality can drive the students' intention to use online learning system. Sixthly, perceived ease of use significantly impacted attitude toward using which described that the

easy-to-use online learning system would build positive attitude toward using it. Next, there was a significant relationship between attitude toward using and behavioral intention which signified that positive attitude of students can lead to a high intention to use online learning system. On the other hand, the relationship between system quality and behavioral intention was not significant which contradicted with the hypothesis and previous literature reviews that the quality of online learning system can enhance students' behavioral intention.

## 5.3. Limitation and Further Study

There are several limitations in this research. Firstly, the used variables were scoped to the partial model of TAM, IS success model and UTAUT which can be extend to other variables in the model. The study did not address factors like curriculum design, course content, teaching style or course interaction which could also affect the student's attitude toward use of online learning, behavioral intentions and actual system use. Secondly, other level of education or geographical area in China possibly generates different hypotheses and results which researcher could elaborate the different sample group into such as secondary school in Shanghai or other countries. Thirdly, since the sample was mostly the sophomore in a faculty of arts, the behavior on online learning usage might be different to that of the students from other faculties, e.g., computer science, business administration, engineering etc. Next, since the study was conducted during Covid-19, the behavior on online learning usage might be interrupted and super volatile. On the other hand, other researchers can use this limitation as a unique interesting point of the study. Lastly, the future study can extend to qualitative methodology such as in-depth interview or focus group due to this method could provide better insights of the research results in comparison with quantitative analysis.

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