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Determinants of College Students' Intentions and Usage Patterns in Online Learning

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Abstract

Purpose: This research paper investigates the main influences on students' online learning behavioral intention and use behavior in five universities in Chengdu. The conceptual framework proposes a causal relationship between facilitating conditions, performance expectancy, effort expectation, social influence, satisfaction, behavioral intention, and usage behavior. **Research design, data, and methodology:** The researcher used a quantitative method (n=500) to distribute a questionnaire to students in five universities. The questionnaire consisted of four main parts, which included screening questions and correlation measures for all variables. These questions were closed-ended questions created using a limited five-point Likert scale, and the data were analyzed using Structural Equation Modelling (SEM) and Confirmatory Factor Analysis (CFA), which included model fit, reliability, and validity of the constructs. **Results:** The results indicated that facilitating conditions, performance expectations, effort expectations, social influences, and satisfaction had a significant effect on behavioral intentions and use behavior, with effort expectations having the greatest effect on satisfaction, followed by performance expectations, satisfaction, facilitating conditions, and social influences, respectively. **Conclusions:** It can be seen that online learning can develop students' ability to learn independently, build a content-rich online self-study platform for students, integrate a variety of information and resources, and maximize the platform for students to exchange, communicate, and cooperate.

Keywords: Behavioral Intention, Use Behavior, Satisfaction, Online Learning

JEL Classification Code: E44, F31, F37, G15

1. Introduction

The Internet has made online learning possible. Many educators and researchers are interested in online learning programs to enhance and improve student learning while addressing the shortage of resources, facilities, and equipment, especially in higher education institutions. Online learning has become popular because it allows more flexible access to content and teaching methods anytime, anywhere. As the demand for quality education increases, more colleges and universities are trying to find ways to provide better online course content. Online education allows students to achieve their learning goals through efficient and convenient access to online technologies (email, learning management systems, discussion boards, video conferencing, social media, etc.) (Chen et al., 2010; Junco et al., 2010; Parsad & Lewis, 2008). At the same time, with the rapid development of online technologies, more and more students are choosing to learn online for various reasons, and assessment and evaluation techniques for online learning are important (Stallings, 2002).

Urdan and Weggen (2000) found through their research that online learning refers to web-based training, e-learning, distributed learning, virtual learning, or web-based teaching and learning. They also believe online learning is a branch of distance education that includes various technological applications such as computer and web-based learning classrooms, digital collaboration, and the learning process.

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Im et al. (2011) believe that online learning allows students to engage in self-regulated learning. They also believe that online learning allows students to hone their self-regulated learning skills through time management, regular review of study materials, actively seeking help from the teacher or classmates, completing assignments within a specified time frame, and reflecting on their learning process. The flexibility of online learning, which allows students to study at a time and place that suits their learning needs, is the main attraction for students to engage in learning. Some instructors and students report that they are better able to focus on the content of the course and less on other issues that may arise in a traditional classroom setting (Thomson, 2010). Students in online learning environments spend more time on learning tasks than those in traditional learning environments (Jaschik, 2009). Students can decide when and where to complete courses at their convenience, and both instructors and students can benefit from online learning 'anytime, anywhere,' where they are no longer synchronously bound to a specific building and schedule but instead have the freedom of mobility that an online educational experience provides (Mayadas et al., 2019).

Dabbagh and NannaRitland (2005) examined the differences between traditional and online learning environments through a comparative study. They argued that in traditional learning environments, the instructor's teaching method is linear, the knowledge imparted is controlled by the instructor and presented in real time, and the location and presence of the instructor and students limit the whole process of instruction. Conversely, online teaching is the process of carrying out a wide variety of teaching practices in an unconstrained and dynamic environment through asynchronous communication and real-time information using ever-evolving information and communication technologies. It is usually a student-centered instructional technology characterized by active learning (Baker, 2003; Browne, 2005). Therefore, the researcher used students with one year's experience of using online2 and learning in five higher education institutions in Chengdu, Sichuan Province, China, as the study population to explore the factors influencing students' behavioral intention to use online learning and their use behaviors.

2. Literature Review

2.1 Facilitating Conditions

Facilitating conditions are the factors in the environment that influence a person's support for the resources and aspirations available to perform a behavior (Venkatesh et al., 2012). This includes the level and type of support provided to the individual user, which strongly influences the user's motivation and subsequent adoption of the technology (Paola Torres Maldonado et al., 2010; Yu & Land, 2005). In the case of online learning, students perceive online support to be a very important factor (Miller & Lu, 2003; Moore, 2003). Lee (2010) found through his research that when students are engaged in online learning if they are supported in the areas of online registration, course selection, online technology guidance, and timely feedback from their instructors, in their opinion, online learning is easy to use. In addition, Kim and Lee (2011) argued that when students use websites to check their progress in online learning, they show positive levels of satisfaction with the course.

Research has found that students' frequency of using technology for learning and their intention to continue using it is greatly facilitated by students' internet access and digital resources (Chiu & Wang, 2008; Nikou & Economides, 2017). Lai (2015) found through his research that recommending useful technology resources, providing guidance on how to use these resources, and actively encouraging students to use these resources are three forms of support that positively predicted students' intention to learn online. Critical success factors for online learning refer to satisfaction with student learning outcomes and social and cognitive presence (Joo et al., 2011). To better understand learning outcomes, we can include 'satisfaction' related to positive feelings or attitudes towards technology use (Liaw & Huang, 2013; Richardson et al., 2017). Research on student satisfaction may be important in developing students' intentions to enroll in online courses (Alraimi et al., 2015; Bhattacherjee, 2001).

H1: Facilitating Conditions has a significant impact on satisfaction.

H8: Facilitating conditions has a significant impact on use behavior.

2.2 Performance Expectancy

According to Brown et al. (2016), performance expectancy is the extent to which the use of technology provides benefits to consumers and leads to improved performance. Deng et al. (2010) found that when a system performs in a way that provides experiential and emotional value, it decreases the user's satisfaction. When this system provides useful functionality, it increases the user's satisfaction. When users perceive a system as useful or helpful, they are satisfied and want to continue using it (Bhattacherjee, 2001). Performance expectancy elicits a stronger intention to use because users' satisfaction with a service or technology depends on their expectations of its performance (Choi et al., 2011; Diep et al., 2016; Wang et al., 2016).

Martirosyan et al. (2015) noted that when students are satisfied, their academic performance and outcomes improve. Dhaqane and Afrah (2016) also found that satisfaction promotes student academic performance and student retention. In addition, Tang and Austin (2009) argued that technology is used in the classroom as a useful instructional device without guaranteeing that it will improve student satisfaction or achievement. However, satisfaction is essential, and therefore, satisfaction should be focused on issues related to performance expectations (Suldo et al., 2015). According to Sinclaire (2014), it was found that satisfaction is the result of the learning process and belongs to one of the conditions of success in higher education. Therefore, satisfaction can improve academic performance, motivate students to participate more actively in their studies and improve their classroom performance. This fact is recognized by Lo (2010), who argues that higher satisfaction requires more challenging teaching techniques as a way of stimulating students to think and learn, in addition to Winberg and Hedman (2008), who found through their research that the identification of satisfaction is essential to ensure the academic performance of students.

H2: Performance expectancy has a significant impact on satisfaction.

H4: Performance expectancy has a significant impact on behavioral intention.

2.3 Effort Expectancy

According to Venkatesh et al. (2003), effort expectancy refers to the ease of using a technology, which makes users feel relaxed when they use a technology with only a little effort, and it can also be considered as ‘the degree to which the system in question is judged to be easy to use. Cimperman et al. (2016) showed that the antecedents of effort expectancy are ease of use, complexity, and perceived ease of use. Chiu and Wang (2008) considered effort expectancy as the perceived ease of use by learners when using a system. They showed that the antecedents of effort expectancy are ease of use, complexity, and perceived ease of use. They also argued that effort expectancy is the extent to which learners perceive that no effort is required when using a system. According to Saadé and Bahli (2005), performance expectancy was found to be positively influenced by effort expectations (similar to perceived ease of use in the Technology Acceptance Model (TAM)). On the other hand, Venkatesh et al. (2003) stated that effort expectancy positively affects behavioral intention and its indirect effect through attitude.

Cao et al. (2013) used the TAM/UTAUT model to indirectly explain how traditional educational technology and social media applications can improve student engagement, academic performance, and learning satisfaction. Students perceive their use of traditional educational technology as the easiest way to obtain learning outcomes (perceived ease of use and effort expectations), which favors student performance, engagement, and satisfaction (Al-Gahtani et al., 2007; Cao et al., 2013; Hu et al., 2003; Venkatesh et al., 2003). Several studies have shown that performance expectancy and effort expectations positively affect satisfaction (Chao, 2019; Phuong et al., 2020). Sheila and Hidayati (2021) study found that satisfaction as a mediator variable strongly affects the relationship between the independent variables (performance expectancy and effort expectancy) and intention to continue using as a dependent variable. Oliver (1980), based on the expectancy-confirmation theory, argued that effort expectancy is a determinant of satisfaction because effort expectancy provides a baseline for individuals to form evaluative judgments about the focal technique.

H3: Effort expectancy has a significant impact on satisfaction.

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

2.4 Social Influence

Venkatesh et al. (2003) considered social influence as a person's perception of the importance of other people's beliefs in trying to persuade them to use a new technology and defined social influence in the UTAUT model as an individual's evaluation of the relevance of adopting a new technological tool. The function of social influence is investigated according to the existing research base, which includes the influence of family members, colleagues, and friends on individual adoption behaviors (Shen et al., 2019). This leads to the conclusion that social influence is a key predictor of behavioral intention (Lu et al., 2020). Social influence can affect users' behavioral intentions in various situations (Kim & Lee, 2020; Salloum & Shaalan, 2018; Yunus et al., 2021).

In other words, social influence refers to the social pressure from the external environment that surrounds an individual, and this external environmental social pressure may influence an individual's perceptions and behaviors towards engaging in certain behaviors. Even when people do not want to engage in a certain behavioral activity, they may engage in an activity as a result of being influenced by the opinions of others. Therefore, it is reasonable to expect that social influence directly affects behavioral intentions (Venkatesh et al., 2003). Venkatesh and Davis (2000) suggest that the effects of social influence will only take place in coercive environments. Less impact in voluntary environments. Reviewing the previous literature, many researchers agree that in the context of e-learning technologies, students' decisions to adopt and embrace e-learning are usually influenced by pressure from other students, teachers, and family members (Cheung & Vogel, 2013; Chu & Chen, 2016; Lin et al., 2013; Marchewka et al.,

2014; Sharma et al., 2016; Tosuntas et al., 2015).
H6: Social influence has a significant impact on behavioral intention.

2.5 Satisfaction

Cigdem and Ozturk (2016) argued that satisfaction is a critical factor in the study of consumer behavior as it causes a significant impact on business performance by causing a sustained increase in product usage and improving product profitability and margins. Satisfaction can, therefore, be used to assess the success of a system. Behavioral intention regarding the reuse of the system has had a positive impact (Mohammadi, 2015). Some earlier studies have shown that satisfaction positively influences behavioral intention to use technology from the perspective of online course learning (Alraimi et al., 2015; Joo et al., 2018; Shahijan et al., 2016). For example, from a MOOC perspective, the relationship between satisfaction and behavioral intention in quality online web-based learning is positively mediated (Ayala et al., 2014; Udo et al., 2011). Wani et al. (2017) stated that if the user's satisfaction is higher, the user has a stronger behavioral intention.

Petter et al. (2008) through their study found that satisfaction is the level of pleasure that the user gets when using the information system level of its support services. Also, in the latest information system success model, they argued that using the system precedes satisfaction. If this elicits satisfaction, it will ultimately lead to higher behavioral intentions. In previous studies, researchers have also found that satisfaction positively affects users' behavioral intention to use e-learning services (Almaiah & Alismaiel, 2019; Alshurideh et al., 2019). Specifically, Almarashdeh et al. (2010) also support the idea that satisfaction can positively and significantly impact the actual use of online learning systems.
H7: Satisfaction has a significant impact on behavioral intention.

2.6 Behavioral Intention

Nabity-Grover et al. (2020) argued that behavioral intention could be expressed as the level of commitment of an individual to engage in a behavior. Therefore, researchers' behavioral intentions towards online teaching and learning can be measured by their commitment to reach educational goals through their acceptance and use of online technological resources (Ab Jalil et al., 2019). Cimperman et al. (2016) found that behavioral intention is the extent to which a person has consciously planned whether to perform certain future behaviors. On the other hand, usage behavior refers to the intensity or frequency with which a user uses aspects of information technology.

In a way, behavioral intention reflects the extent to which students intend and are willing to continue to use online learning, while usage behavior refers to the actual use of online learning by students in their academic studies; therefore, it can be assumed that students' behavioral intentions lead to online learning usage behavior (Zacharis & Nikolopoulou, 2022). Nicholas-Omoregbe et al. (2017) found that students' behavioral intentions in adopting e-learning systems and their usage behavior are positively correlated and ultimately lead to better grades. Bagozzi (1981) also argued that usage behavior is the extent to which an individual uses technology to accomplish various tasks.
H9: Behavioral intention has significant impact on use behavior.

3. Research Methods and Materials

3.1 Research Framework

The hypothetical framework of this study was adapted from three theoretical models. Firstly, Chao C-M (2019) developed and empirically tested a model to predict the factors influencing students' behavioral intention to use m-learning by examining the UTAUT model, which explores behavioral intention to use m-learning from a consumer perspective. Secondly, Tan (2013) also explained Taiwanese university students' acceptance of English e-learning websites by examining the Unified Theory of Technology Acceptance and Usage, which aims to explore the demand for English e-learning websites among Taiwanese university students. The third one is to explore the key drivers of students' and teachers' e-learning satisfaction according to (Teo & Wong, 2013). The conceptual framework of this study is shown in Figure 1.

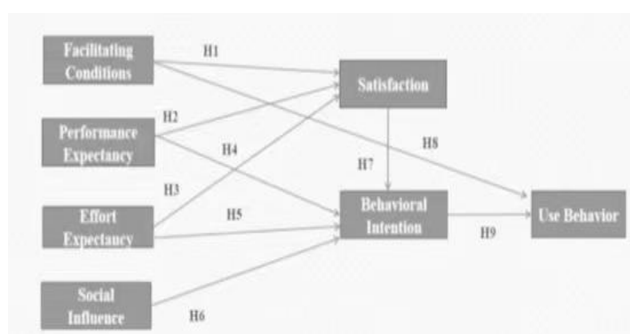

Figure 1: Research Conceptual Framework

H1: Facilitating Conditions has a significant impact on satisfaction.
H2: Performance expectancy has a significant impact on satisfaction.

H3: Effort expectancy has a significant impact on satisfaction.
H4: Performance expectancy has a significant impact on behavioral intention.
H5: Effort expectancy has a significant impact on behavioral intention.
H6: Social influence has a significant impact on behavioral intention.
H7: Satisfaction has a significant impact on behavioral intention.
H8: Facilitating conditions has a significant impact on use behavior.
H9: Behavioral intention has significant impact on use behavior.

3.2 Research Methodology

The researcher used a quantitative non-probability sampling method and created an online questionnaire through Questionnaire Star. This made distributing and collecting data from the target population easy and fast. The respondents were students from five universities in Chengdu. The data collected will be used to analyze the key factors significantly influencing students' intention and behavior toward online learning. The survey consists of three parts. A screening question was used to determine the characteristics of the respondents. Next, a 5-point Likert scale was used to measure five proposed variables ranging from strongly disagree (1) to agree (5) to analyze all four hypotheses strongly. Finally, demographic questions included gender, age, and educational background. Expert scoring and pilot testing of the Index of Item and Goal Congruence (IOC) was conducted on 50 respondents to conduct the pilot test.

In addition, the researcher conducted validity and reliability tests using Cronbach's alpha method. After the reliability test, a questionnaire was distributed to the target respondents, and an impressive 500 responses were received, ensuring a large and diverse sample size. The researcher then analyzed the collected data through SPSS AMOS 29.0. The researcher then used Confirmatory Factor Analysis (CFA) to test the accuracy and validity of the convergence. Nine hypotheses between the seven variables in the conceptual framework were illustrated through an overall test analysis of the given data. Model fit measures were calculated to ensure the validity and reliability of the model. Finally, the researcher used Structural Equation Modelling (SEM) to test the effects of the variables.

3.3 Population and Sample Size

The target population for this study was second to fourth-year undergraduate students with at least one year of experience with online learning at five selected universities in Chengdu, Sichuan, China. First-year undergraduate students were excluded from the target population because the researcher wanted to ensure that the respondents were familiar with online learning and had experience interacting with online learning. DeCuir-Gunby and Schutz (2017) argued that if an adequate sample size is to be determined for the study, then it depends on the researcher's statistical techniques, as each statistical technique has a minimum number of requirements for the study. While Kline (2016) stated that the minimum sample size requirement for SEM is 375. According to Soper (2019), who developed a calculator for the minimum sample size for structural equation modeling, the recommended minimum sample size was calculated to be 425. however, according to previous studies, the researcher collected 500 samples from five higher education institutes in Chengdu, Sichuan Province, to obtain better statistical results.

3.4 Sampling Technique

Saunders et al. (2007) argued that judgment sampling or purposive sampling is a non-probability sampling technique that enables the researcher to select the elements for the study. The researcher adopted a non-probability sampling method and used judgment sampling to select second to fourth-year undergraduate students with more than one year of online learning experience from five universities in Chengdu. Quota sampling was then conducted based on the total number of students in the five universities, as shown in Table 1. The researchers then distributed the questionnaires online using the convenience sampling method.

Table 1: Sample Units and Sample Size

University Name	Population Size	Proportional Sample Size
Sichuan University	60,000	151
Sichuan Normal University	38,000	96
Chengdu University of Techn ology	36,388	92
Sichuan University of Media and Communications	20,000	50
Southwest Jiaotong University	44,024	111
Total	**198,412**	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

The questionnaire was distributed among 500 students in five selected higher education institutions. The respondents included 238 female and 262 male students, representing 47.6 percent and 52.4 percent, respectively. The age level distribution was as follows: 163 students aged 18-20 years or

32.6 percent of the total number of respondents, 176 students aged 21-22 years or 35.2 percent of the total number of respondents, 141 students aged 23-24 years or 28.2 percent of the total number of respondents, and 20 students aged 25 years and above or 4 percent of the total number of respondents.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	238	47.6%
	Female	262	52.4%
Age	18-20years old	163	32.6%
	21-22years old	176	35.2%
	23-24years old	141	28.2%
	25years of age or older	20	4%

4.2 Confirmatory Factor Analysis (CFA)

Hoyle (2012) proposed Confirmatory Factor Analysis (CFA) as a statistical technique used to identify and examine hypothesis constructions, allowing for a detailed assessment of hypotheses in a deductive mode, which makes CFA superior to other strategies in analyzing hypothesis constructions. In this study, confirmatory factor analysis (CFA) was conducted. Since confirmatory factor analysis (CFA) describes an underlying construct that cannot be directly observed, it is a type of structural equation modeling that deals specifically with measurement models to test the relationship between observed and underlying variables. According to Tabachnick and Fidell (2007) and Comrey and Lee (1992), the critical values of factor loadings should start from 0.32 (weak), 0.45 (fair), 0.55 (good), 0.63 (very good) or 0.71 (excellent). Therefore, this study's critical value for factor loading was 0.50.

Table 3: Confirmatory Factor Analysis Result, Composite Reliability (CR) and Average Variance Extracted (AVE)

Variable	Source of Questionnaire (Measurement Indicator)	No. of Item	Cronbach's Alpha	Factors Loading	CR	AVE
Facilitating conditions (FC)	Timothy and Tosun (2003)	4	0.831	0.684-0.805	0.832	0.554
Performance Expectancy (PE)	Chao (2019)	4	0.854	0.740-0.811	0.854	0.595
Effort Expectancy (EE)	Chao (2019)	5	0.870	0.725-0.794	0.871	0.575
Social Influence (SI)	Tan (2013)	4	0.848	0.706-0.829	0.850	0.585
Satisfaction (SF)	Chao (2019)	5	0.877	0.714-0.819	0.876	0.587
Behavioral Intention (BI)	Tan (2013)	3	0.842	0.774-0.827	0.843	0.642
Use Behavior (UB)	Ab Jalil et al. (2019)	5	0.845	0.644-0.786	0.847	0.526

Additionally, Table 4 displays various goodness-of-fit indices such as CMIN/DF, GFI, AGFI, NFI, CFI, TLI, and RMSEA. Importantly, each of these indices significantly surpassed the acceptable threshold, providing solid evidence of the measurement model's excellent fit.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	3.286
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.854
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.823
NFI	≥ 0.80 (Wu & Wang, 2006)	0.838
CFI	≥ 0.80 (Bentler, 1990)	0.880
TLI	≥ 0.80 (Sharma et al., 2005)	0.865
RMSEA	< 0.08 (Pedroso et al., 2016)	0.068
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.

Discriminant validity is a concept in psychometrics and statistical analysis that assesses the extent to which a particular construct or variable is distinct from other constructs. It ensures that the variables or constructs being measured are not only related to what they are intended to assess but also that they are not too closely related to other variables that they should theoretically differ from.

Table 5: Discriminant Validity

	FC	PE	EE	SI	SF	BI	UB
FC	**0.744**						
PE	0.062	**0.771**					
EE	-0.237	-0.051	**0.758**				
SI	0.028	-0.080	0.070	**0.765**			
SF	-0.072	0.171	-0.276	-0.154	**0.766**		
BI	0.069	-0.110	-0.069	-0.068	-0.236	**0.801**	
UB	-0.165	-0.376	0.112	-0.102	-0.087	-0.038	**0.725**

Note: The diagonally listed value is the AVE square roots of the variables
Source: Created by the author.

4.3 Structural Equation Model (SEM)

Structural equation modeling (SEM) refers to covariance structural analysis and correlation structural analysis (Cheung, 2015). According to Byrne (2010), SEM is a statistical method that utilizes confirmatory methods to measure the correlation of structural equations while putting the hypothesized model to the test in the analysis. The goodness of fit indices for structural equation modeling (SEM) are shown in Table 6. Awang (2012) and Al-Mamary and Shamsuddin (2015) suggested that the acceptable value for the ratio of the chi-square coefficient to the degrees of freedom should be set at five or lower and that the GFI and CFI should be higher than 0.8. They calculate the SEM and adapt the model using SPSS AMOS version 29. The results of the fit indices showed good fit, i.e., CMIN/DF = 3.095, GFI = 0.866, AGFI = 0.840, NFI = 0.845, CFI = 0.889, TLI = 0.876, and RMSEA = 0.065.

Table 6: Goodness of Fit for Structural Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	3.095
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.866
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.840
NFI	≥ 0.80 (Wu & Wang, 2006)	0.845
CFI	≥ 0.80 (Bentler, 1990)	0.889
TLI	≥ 0.80 (Sharma et al., 2005)	0.876
RMSEA	< 0.08 (Pedroso et al., 2016)	0.065
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.

4.4 Research Hypothesis Testing Result

The degree of correlation between the independent and dependent variables proposed in the hypotheses was measured through regression coefficients or standardized path coefficients. As shown in Table 7, eight proposed hypotheses were supported. Satisfaction with online learning is strongly influenced by effort performance, followed by satisfaction with behavioral intention and performance expectations. Facilitating conditions have a significant effect on the behavior of using online learning.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: FC→SF	-0.308	-4.050*	Supported
H2: PE→SF	0.299	4.850*	Supported
H3: EE→SF	-0.347	-7.036*	Supported
H4: PE→BI	-0.141	-2.224*	Supported
H5: EE→BI	-0.146	-2.685*	Supported
H6: SI→BI	-0.115	-2.063*	Supported
H7: SF→BI	-0.278	-4.936*	Supported
H8: FC→UB	-0.355	-4.329*	Supported
H9: BI→UB	0.029	0.561	Not Supported

Note: * $p<0.05$
Source: Created by the author

The result from Table 7 can be refined as follows: the standardized path coefficient of facilitating conditions and satisfaction in H1 is -0.308 with a t-value of -4.050, proving that facilitating conditions significantly affect satisfaction. Through research, Lee (2010) found that online learning is easy for students to use if they can get support in online registration, course selection, online technical guidance, and timely tutor feedback. In H2, the standardized path coefficient is 0.299, and the t-value is 4.850, which shows that performance expectancy significantly affects satisfaction. Martirosyan et al. (2015) also pointed out that when students are satisfied, their academic performance and outcomes will be improved. In H3, the standardized path coefficient of effort expectancy and satisfaction is -0.347, with a t-value of -7.036. This shows that effort expectancy has the greatest effect on satisfaction. In H4, the standardized path coefficient of performance expectancy on behavioral intention is -0.141, and the t-value is -2.224. This finding is consistent with the previous study of (Sung et al., 2015), who concluded that performance expectancy is an important predictor of college students' persistent behavioral intention to use technology in online learning and also proves that performance expectancy can have some influence on behavioral intention. In H5, the standardized path coefficient of effort expectancy on behavioral intention is -0.146, with a t-value of -2.685. A situation where students have increased effort expectancy and are aware of the ease of use of online learning proves that effort expectancy can positively impact behavioral intentions. In H6, the standardized path coefficient of social influence on behavioral intention is -0.115, with a t-value -2.063. In the context of online learning technology, students' decision to adopt and accept online learning is usually influenced by pressure from other students, teachers, and family members (Cheung & Vogel, 2013; Chu & Chen, 2016; Lin et al., 2013; Marchewka et al., 2014). A significant effect of satisfaction on behavioral intention was demonstrated in H7 with a standardized path coefficient of -0.278 and a t-value of -4.936. This is in line with the findings of Alraimi et al. (2015) that the higher the student's level of satisfaction with online learning, the higher the student's behavioral intention. The standardized path coefficient of facilitating condition on use behavior in H8 is -0.355, and the t-value is -4.329. Facilitating conditions are "observers' identification with objective factors in the environment that make the behavior easier to accomplish." This view is consistent with that proposed by (Chiu & Wang, 2008; Taiwo & Downe, 2013; Venkatesh et al., 2003; Wang & Shih, 2009). With a standardized path of 0.029 and a t-value of 0.561, use behavior was not influenced by behavioral intention, and thus H9 was not supported. This result is consistent with the findings of Yunus et al. (2021) that students may not develop use behaviors even when predisposed to behavioral intentions.

5. Conclusion and Recommendation

5.1 Conclusion

This research paper focuses on the use of online learning by college students in Sichuan, China. It examines the factors influencing college students' behavioral intentions and behavior using online learning. Hypotheses are proposed as a conceptual framework to investigate how facilitating conditions, performance expectancy, effort expectancy, social influence, and satisfaction affect behavioral intentions and use behavior. Questionnaires were developed for students with one year of online learning experience in five higher education institutions in Chengdu, Sichuan Province, China. The data analysis aimed to explore the influences on behavioral intention and use behavior that affect college students' online learning. Confirmatory factor analysis (CFA) was conducted on the conceptual model to ensure and test its validity and reliability. Therefore, Structural Equation Modeling (SEM) was applied to analyze the factors influencing behavioral intention and use behaviors that affect college students' online learning.

The results of the study are as follows. First, facilitating conditions, performance expectancy and effort expectancy can positively influence satisfaction, and satisfaction can positively influence behavioral intention. Teo and Wong's (2013) pre-documentary study confirms college students' acceptance of English e-learning websites, and their results support the claim that students' behavioral intention to use online learning websites depends on students' facilitating conditions, performance expectancy, effort expectancy, and satisfaction claims. Secondly, performance expectancy, effort expectancy, and social influence can positively influence behavioral intention. Chao C-M (2019) explored the behavioral intention to use online learning from the perspective of consumers, and the results of the study showed that performance expectancy, effort expectancy, and social influence have a significant positive effect on behavioral intention; finally, facilitating condition can positively influence the use behavior, which is consistent with Tan (2013) proposed that if students are given more facilitating conditions to use online learning sites, students will use these online learning sites more frequently. In conclusion, the goal of this study has been achieved, which is that facilitating conditions, performance expectancy, effort expectancy, social influence, and satisfaction are the factors that affect college students' behavioral intention and use behavior in online learning.

5.2 Recommendation

Based on the findings of this study, several key recommendations can be made. First, educational institutions and e-learning platforms should focus on enhancing facilitating conditions, performance expectancy, and effort expectancy, as these factors positively influence student satisfaction, which in turn enhances their behavioral intention to use online learning platforms. This is supported by Teo and Wong's (2013) study, which highlights that college students' acceptance of English e-learning websites is driven by these factors, alongside satisfaction.

Second, efforts should be made to improve performance expectancy, effort expectancy, and social influence, as these elements directly and positively impact students' behavioral intention to engage with online learning platforms. Chao C-M's (2019) research confirms the significant role of these factors from the perspective of consumers' behavioral intentions.

Lastly, educational institutions should invest in improving facilitating conditions, as this positively affects students' actual usage behavior. Consistent with Tan (2013) findings, providing students with more opportunities and resources to access online learning platforms can lead to increased usage frequency.

In conclusion, this study reaffirms that facilitating conditions, performance expectancy, effort expectancy, social influence, and satisfaction are critical factors influencing college students' behavioral intention and usage of online learning platforms. Institutions should prioritize these factors to foster greater engagement and success in e-learning.

5.3 Limitation and Further Study

The limitation of this study is that the population and sample were limited to students with one year of online learning experience in five equal institutions in Chengdu, Sichuan, China. Different analyses may be produced when investigating schools in different provinces, sizes, and levels in China. Further research could be conducted on other behavioral intentions and usage behaviors that affect students' online learning, such as perceived ease of use, usefulness, and attitudes toward use. Certainly, the results of this study have the potential to help educators and researchers understand the key factors of online learning as well as the antecedents and consequences, including how these factors interact to explain students' behavioral intentions and use behaviors toward online learning, with far-reaching implications for teachers as well as students' online learning, as in the era of prevalent AI, it is expected that the use of online learning in future teaching and learning will become increasingly convenient and frequent.

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