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Factors Impacting Sophomores' Satisfaction and Behavioral Intention to Use Online Learning: A Case Study of a Public University in Yunnan, China

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Abstract

Purpose: This study explores the factors impacting student satisfaction and behavioral intention to use online learning at a public university in Yunnan Province, China. The framework proposes causal relationships among service quality, instructor quality, task-technology fit, learning content quality, perceived usefulness, satisfaction, and behavioral intention. **Research Design, Data, and Methods:** Researchers used a quantitative method (n=500) to distribute questionnaires to sophomore students in four colleges from Yuxi Normal University in China. The researcher used purposive, stratified random, and convenience sampling to collect the data. Before data collection, the Item Objective Congruence (IOC) and Cronbach's alpha were used to ensure reliability and validity. Structural equation modeling (SEM) and confirmatory factor analysis (CFA) were used to analyze the data, including model fit, reliability, and validity tests. **Results:** The service quality, instructor quality, and task-technology fit significantly impact perceived usefulness. The learning content quality, perceived usefulness, and satisfaction significantly impact student behavioral intention. **Conclusion:** Seven hypotheses have been proven to meet the research objectives. Therefore, school administrators and teachers should maintain a good online learning environment, improve academic performance, increase teaching care, and establish a good image of the school to enhance students' satisfaction and behavioral intention about online learning.

Keywords : Service Quality, Task-Technology Fit, Content Quality, Satisfaction, Behavioral Intention

JEL Classification Code: E44, F31, F37, G15

1. Introduction

Since 2019, the COVID-19 pandemic has suspended face-to-face classes at all universities worldwide, severely challenging education and teaching. In response to the COVID-19 crisis, the government has taken action to issue public policies, including social distancing and isolation (Anderson et al., 2020). Human has experienced the most serious infectious disease pandemic. In response to the crisis, the Chinese government made a "Suspend classes without stopping teaching, suspend classes without stopping learning" decision. The teachers and students conducted an unprecedented large-scale online education practice, successfully responded to the outbreak crisis, and achieved the essence of online and classroom teaching equivalents. In 2020, education is important to inherit knowledge and culture and cultivate human wisdom and quality. It is also one of the crystallization ways for people to quickly master human wisdom, making people a faster channel for modern people. In this process, one of the important aspects is education to achieve this goal of education and teaching.

Online learning is the main channel for human beings to acquire knowledge regarding the future growth direction for teaching and education. Sener (2010) suggests that higher education institutions must develop online courses and education lessons if they wish to survive, and they must do it quickly from countries that have lived through these changes. Poorly prepared institutions will be affected in a crisis that

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requires e-learning, such as the COVID-19 pandemic (Wang et al., 2020). Creating an education that satisfies the people is the educational goal of China, and it is also the goal of running schools in China's higher education. Online education provides higher quality, fairer, more choice, more convenient, more open, more flexible education service, meets people's high quality, personalized learning needs, can achieve everyone can learn, everywhere can learn, always learn, help build a lifelong learning society and a learning country. Online learning is the proper meaning and only way for the high-quality development of education. As far as higher education is concerned, online learning creates new possibilities for the growth of higher education at a high level. Therefore, the educational goals in China include the satisfaction and behavioral Intention of online education in colleges and universities, which requires hard investment and research. China needs to invest in and study the satisfaction and behavioral Intention of online education in universities. So, researching the student's behavioral Intention of online learning in universities, especially at Yuxi Normal University, will help to increase education quality. However, research focusing on the behavioral Intention of online learning in universities, especially at Yuxi Normal University, has not been widely carried out and has not been comprehensive.

This study examined factors influencing students' behavioral intentions to utilize online learning by looking at those from four colleges at Yuxi University in Yunnan, China, who had used it for more than a year. The TAM, the unified theory of acceptance, and four theoretical frameworks from earlier studies were the foundation for the research conceptual framework. The framework included one dependent variablebehavioral Intention—two mediators—perceived usefulness and satisfaction—and four independent variables—service quality, teacher quality, task-technology fit, and learning content quality.

2. Literature Review

2.1 Service Quality

Service quality means the degree to which users perceive or experience the overall quality of services (Fan et al., 2021). It also refers to the various communication mechanisms or other aspects that can help users on time or solve other problems that arise during the use of IS (Cheng, 2012). Saeed et al. (2003) proposed that service quality was the effectiveness of the service provided by the higher education institute or technical assistance of LMS. Gaurav et al. (2019) stated that the study identified three dimensions of e-learning systems: service quality, system quality, and information quality. These three dimensions help to improve user satisfaction and net benefits. Islam (2012) listed four qualities connected to the system quality of e-learning systems: navigation, ease of use, accessibility, and dependability. Service quality is very important; the better the service quality, the more users like it, the more they will support and choose. Numerous research studies have looked at the tangential link between service quality, perceived usefulness, and satisfaction and have presented the idea that online learning greatly influences behavior intention as demonstrated by the following hypothesis:

H1: Service quality has a significant impact on perceived usefulness.

2.2 Instructor Quality

Cheng (2014) defined instructor quality as the degree to which they assist learners through electronic learning systems. Learners perceive teachers' attitudes as related to their timely response, teaching style, and quality. The quality of teachers is crucial, as they are a key figure in learners' behavior during the e-learning process (Zhou, 2011). Chien and Georgia (2012) thought interaction with learners is positively affected if the teacher's attitude is friendly, warm, sociable, and approachable. According to Cheng (2014), while assessing students' acceptance of e-learning, one alternative indicator of teacher quality in the process should be considered: instructors' attitudes toward e-learners. Because the attitude of teachers is related to factors such as their timely response, teaching style, and extending ECM to learners through electronic learning systems, they are all related to teaching style. They can profoundly affect learners' e-learning attitude, enthusiasm, and engagement. Suppose teachers can promptly respond to or address learners' needs during the learning process and use e-learning systems to handle learners' online learning. Learners' e-learning experience will be considered (Sun et al., 2008). Thus, this study hypothesizes that:

H2: Instructor quality has a significant impact on perceived usefulness

2.3 Task-Technology Fit

According to Teo and Men (2008), task-technology fit matching refers to the capacity of technical support tasks to match technological capabilities with work objectives. According to Ellyana Dwi et al. (2009), Task-Technology Fit Matching (TTF) describes the connection between a task's needs for completion, a person's aptitudes, and technological operations inside an organization's information system. According to Lu and Yang (2014), TTF relates to how successfully a technology aids users in completing tasks like work or schoolwork. When students utilize electronic learning systems, task characteristics, and technical features

can influence the fitting of task technology. This can influence how useful students perceive the technology and confirm the system's adoption (Lin & Wang, 2012). Tu et al. (2021) showed that task technology matching influences students' attitudes toward mobile learning. It is often used to clarify whether information technology functions are suitable for users' tasks, and it has been demonstrated that e-learning attitudes among students may be altered. Hence, a hypothesis is indicated:
H3: Task-technology fit has a significant impact on perceived usefulness.

2.4 Learning Content Quality

Jahmani et al. (2018) stated that the contextual component of knowledge quality is the degree to which knowledge is considered within the task's context and is related to relevance and added value. The availability of resources and Learning content quality refers to products and services directly related to student learning results (Cao et al., 2005; Uppal et al., 2018). In e-learning, information quality is the most often used metric of course content quality (Lee, 2006). This comprises both content richness and update frequency. Because of this, it is crucial to provide students with outstanding online courses through educational institutions' e-learning platforms. Cheng (2020) states that the best markers of an online course's quality are often its design and content. This study "demonstrates the relationship between course quality and students' intention to use cloud-based e-learning services in the future." The main factor is how well students think the subject is being taught, and they believe that there is a link between course quality and course design quality and their happiness with the PU, confirmation, and system. Therefore, a hypothesis is developed:
H4: Learning content quality has a significant impact on satisfaction.

2.5 Perceived Usefulness

The degree to which a student believed that utilizing an LMS would enhance his or her learning ability was perceived usefulness (Davis, 1989). According to Fokides (2017), PU measures how much a person thinks using a hybrid education system would increase their learning productivity. PU, according to Salimon et al. (2021), is a person's estimation of the advantages associated with utilizing a certain system. According to a study, how strongly individuals perceive innovations like ELPs affects their attitudes and behaviors toward them. The conception also indicates the level to which the university students who employed the e-earning system would accelerate their academic achievement (Vululleh, 2018). Users will typically have a more favorable perception of the services if they think cloud computing services are effective and beneficial (Cheng, 2020). According to Salimon et al. (2021), a prior study used experimental evaluation to determine the relevance of the relationship between PU and benefits. It revealed that PU influences learners' reported satisfaction, perceived usefulness, and system usage, resulting in more effective learning. Accordingly, a hypothesis is constructed:
H5: Perceived usefulness has a significant impact on satisfaction.

2.6 Satisfaction

User satisfaction was described by Chopra et al. (2019) as the amount of learning that a user may reasonably expect from a particular e-learning system, as well as the user's openness to the skills that could be developed or knowledge that could be increased by using that system, and the researcher also stated that the three elements that make up an e-learning system: information quality, service quality, and system quality—increase consumer happiness and net benefits. Customers are likely to wish to keep utilizing cloud computing services if they find them to be gratifying, it may be anticipated. According to studies on cloud-based contexts, contentment is a good indicator of continuing intention (Tan & Kim, 2015; Xu et al., 2017). The study's conclusions show that student happiness is more relevant than e-learning quality in influencing students' propensity to use online learning (Theresiawati et al., 2020). Consequently, this research proposes a hypothesis:
H6: Satisfaction has a significant impact on behavioral intention.

2.7 Behavioural Intention

Theresiawati et al. (2020) proposed that behavioral intention refers to users' plans to utilize online learning indefinitely to support courses, suggest it to other users, and accept its benefits. Samsudeen and Mohamed (2019) stated that the indicator of users' preparedness to engage in a certain action is signaled by behavioral intention, which is seen as a prelude to use behavior. Abbas (2016) asserts that Individuals' BI to adopt a particular technology is influenced by subjective norms, with perceived utility (PU) and perceived usability acting as mediating factors. According to Chang (2013), a person's BI refers to the extent to which they have made deliberate decisions about whether or not to carry out a particular future activity. It may be summed up as the individual's propensity to engage in problematic conduct. According to Cheng (2020), an improved ECM incorporating interaction and CQ factors is required to understand why students are happy and want to keep utilizing a cloud-based e-learning platform.

3. Research Methods and Materials

3.1 Research Framework

The conceptual framework was created by research on earlier research frameworks. It is four theoretical models that have been modified. The first theoretical framework was conducted by Kao and Lin (2018). It was demonstrated that the success of police viewed e-learning to be positively impacted by subjective criteria, job relevance, system and service quality, and convenience of use. System and service quality positively impacted police perceptions of the value of e-learning. The second theoretical framework was conducted by Cheng (2014). The results suggest that instructor quality significantly affects students' flow experiences, which causes them to increase immersion in instructor-student interactions through the e-learning system. The third theoretical framework was conducted by Cheng (2021). The findings show that the perceived TTF of medical professionals indirectly affects their happiness and desire to continue using the cloud-based e-learning system, first through confirmation and secondarily through PU and flow experience. The fourth theoretical framework was conducted by Theresiawati et al. (2020), who stated that the effectiveness of the learning materials has a significant impact on the e-learning system's service level.

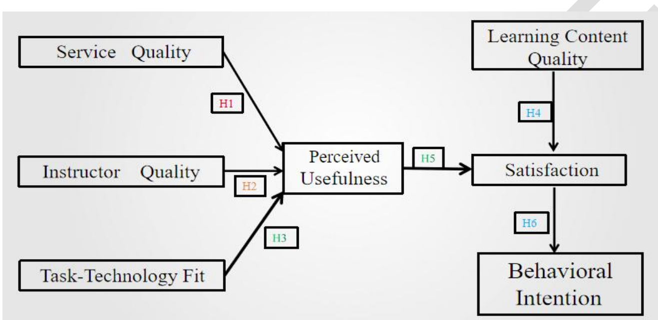

Figure 1: Conceptual Framework

H1: Service quality has a significant impact on perceived usefulness.
H2: Instructor quality has a significant impact on perceived usefulness.
H3: Task-technology fit has a significant impact on perceived usefulness.
H4: Learning content quality has a significant impact on satisfaction.
H5: Perceived usefulness has a significant impact on satisfaction.
H6: Satisfaction has a significant impact on behavior intention.

3.2 Research Methodology

The researcher will be able to investigate variables influencing sophomore students' behavioral intention to use online learning in a public university in Yunnan, China. Introduction of research methodologies and tools, including selection of sampling units, sample size, and target demographic. The target population was surveyed, and this study collected data using a quantitative methodology. The method for data collection and its statistical analysis are both described. The index of item-objective congruence (IOC) and Cronbach's Alpha were used to verify the content before data collection. In this research, the researcher sought IOC ratings from three experts within the study's field. It is worth highlighting that all variables meet the minimum inter-item correlation (IOC) threshold of 0.6. Adhering to the reliability guidelines, it is important to note that, as suggested by Straub (1989), a Cronbach's alpha value exceeding 0.7 was achieved, meeting the established criterion for acceptability. The best strategy, according to experts, structural equation modeling (SEM), was employed to validate the structural relationship between variables after data collection.

3.3 Population and Sample Size

The target group of this paper is undergraduates who have studied at the Yuxi Normal University of China and have more than one year of study experience. Yuxi City is in the southwest of China. The target demographic data are Sophomore undergraduates of Yuxi Normal University, China.

Freshman, juniors, and senior undergraduates are outside the target group because researchers want to ensure that respondents are familiar with the university study and do not affect the questionnaire survey's interaction, authenticity, and seriousness. After all, they are busy looking for a job after graduation. At the same time, based on probabilistic and non-probabilistic sampling, further samples are selected from the target group. Sampling procedures will be outlined in the next section. There are sophomores in Yuxi Normal University, China. The optimal sample size was, therefore, chosen by the researchers. Using past studies as a foundation, researchers collected 500 samples from Yuxi Normal University.

3.4 Sampling Technique

Judgmental sampling was employed by selecting sophomores in Yuxi Normal University, China. Quota sampling was conducted as in Table 1. The dissemination and gathering of data may be completed more quickly and effectively using this form of data collection through Internet channels, which offers several advantages over previous approaches. While doing so, the online distribution collection is the most effective and quick technique to finish the data collection to reach the target number of respondents set by each college. For convenience sampling, respondents may complete the data gathering and collation by comparing their responses to the online WeChat WPS documents on their mobile phones.

Table 1: Sample Units and Sample Size

College Name	Population Size	Proportional Sample Size
College of Teacher Education	264	160
College of Foreign Language	114	69
College of Mathematics and Information Technology	262	159
College of Physical Education	183	112
Total	**823**	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

Table 2 provides demographic information for the sample of the target group, which consists of 500 people. 46.2% of respondents were female, while 53.8% were male. The sample's oldest age group, which comprises 66.4% of respondents, is between 20 and 22 years old. This group is followed by respondents between 18 and 20 years old (20.2%), those between 22 and 24 years old (13.0%), and those between 24 and 26 years old (0.40%). The sample's largest category in frequency per week is 1-3 times, which accounts for 33.8% of responses. This is followed by 3-7 times, which accounts for 33.6%; more than seven times, which accounts for 31.6%; and 0 times, which accounts for 1%. Mobile phones make up the largest preference category in the sample, accounting for 60.2% of respondents, followed by PCs and laptops with 22.8%, tablets with 12.2%, and miscellaneous items with 4.8%.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Female	231	46.20%
	Male	269	53.80%
Age	18-20 years old	101	20.20%
	20-22 years old	332	66.40%
	22-24 years old	65	13.00%
	24-26 years old	2	0.40%
Per week	0 times	5	1.00%
	1-3 times	169	33.80%
	3-7times	168	33.60%
	more than 7 times	158	31.60%
Preference	Mobile Phone	301	60.20%
	Tablet	61	12.20%
	PC/laptop	114	22.80%
	other	24	4.80%

Source: Constructed by author

4.2 Confirmatory Factor Analysis (CFA)

In this investigation, confirmatory factor analysis (CFA) was used. The significant items for each variable show the factor load to assess the convergent validity. Hair et al. underlined Factor loading as crucial for each project in 2003. It is necessary for the factor loading to be 0.5 and for the P-value coefficient to be less than 0.05. Additionally, the cut-off points with CR greater than 0.7 and AVE greater than 0.5, according to Fornell and Larcker (1981).

The reliability test known as Cronbach's alpha was also applied, and all constructs passed with values greater than 0.70 (Nunnally, 1978). Table 3 shows that CA values are above 0.7, factors loading are all above 0.5, CR values are above 0.7, and AVE was greater than 0.4, at a range of 0.442 to 0.719. It demonstrates that the CFA test results are good and that the conclusions drawn from the data analysis are sound.

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
Service Quality (SQ)	Cheng (2014)	3	0.813	0.750 - 0.803	0.813	0.592
Instructor Quality (IQ)	Cheng (2014)	3	0.813	0.659 - 0.842	0.815	0.597
Task-technology Fit (TTF)	Cheng (2021)	4	0.754	0.594 - 0.752	0.759	0.442
Learning Content Quality (LCQ)	Lee (2006)	3	0.775	0.701 - 0.785	0.776	0.536
Perceived Usefulness (PU)	Lee (2006)	4	0.783	0.599 - 0.744	0.790	0.486
Satisfaction (ST)	Cheng (2021)	4	0.814	0.696 - 0.763	0.825	0.525
Behavioral Intention (BI)	Anderson et al. (2020)	3	0.885	0.817 - 0.883	0.884	0.719

When doing CFA testing, model fitting indicators such as CMIN/DF, GFI, AGFI, NFI, CFI, TLI, and RMSEA are utilized. The number attained in this research is higher than the permitted value, demonstrating the model's effectiveness at providing a good match. The measurement outcomes of these models also confirm the efficacy of later structural model estimations and cement the discriminating efficiency, according to Table 4.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	≤ 5.0 (Wheaton et al., 1997)	1.611
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.943
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.925
RMSEA	≤ 0.10 (Hopwood & Donnellan, 2010)	0.930
CFI	≥ 0.80 (Bentler, 1990)	0.972
NFI	≥ 0.80 (Wu & Wang, 2006)	0.967
TLI	≥ 0.80 (Sharma et al., 2005)	0.035
Model Summary		**In harmony with empirical data**

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, RMSEA = Root mean square error of approximation, CFI = Comparative fit index, NFI = Normed fit index and TLI = Tucker-Lewis index

The discriminant validity of the model is quite excellent, as seen in Table 5 below, where the square root of the AVE of each variable is bigger than its correlation coefficient with other variables. This is known as the Tucker-Lewis index.

Table 5: Discriminant Validity

	SQ	IQ	TTF	LCQ	PU	ST	BI
SQ	**0.769**						
IQ	0.473	**0.772**					
TTF	0.345	0.396	**0.664**				
LCQ	0.111	0.184	0.109	**0.732**			
PU	0.594	0.485	0.419	0.189	**0.697**		
ST	0.322	0.293	0.324	0.062	0.459	**0.724**	
BI	0.478	0.648	0.424	0.262	0.533	0.255	**0.847**

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

4.3 Structural Equation Model (SEM)

As a generalization of the regression model, the structural equation model (SEM) offers many benefits that the regression model does not, including the ability to handle multiple independent and dependent variables concurrently, which satisfies the ever-increasing complexity requirements of theoretical models in social science research. SEM is a crucial statistical approach in social science research (Wang et al., 2020).

As shown in Table 6, the Structural Equation Model's (SEM) goodness of fit indices is calculated. The findings of the fit index were shown as a satisfactory fit after the SEM calculation and model adjustment using SPSS AMOS, which is 3.931 CMIN/DF, 0.852 GFI, 0.819 AGFI, 0.077 RMSEA, 0.819 NFI, 0.858 CFI, and 0.840 TLI. The acceptable values are mentioned in Table 6.

Table 6: Goodness of Fit for Structural Model

Index	Acceptable	Statistical Values
CMIN/DF	≤ 5.0 (Wheaton et al., 1997)	3.931
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.852
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.819
RMSEA	≤ 0.10 (Hopwood & Donnellan, 2010)	0.077
CFI	≥ 0.80 (Bentler, 1990)	0.858
NFI	≥ 0.80 (Wu & Wang, 2006)	0.819
TLI	≥ 0.80 (Sharma et al., 2005)	0.840
Model Summary		**In harmony with Empirical data**

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, RMSEA = Root mean square error of approximation, CFI = Comparative fit index, NFI = Normed fit index and TLI = Tucker-Lewis index

4.4 Research Hypothesis Testing Result

The research model determines the explanatory power of the independent variable to the dependent variable according to standardized path coefficient and t-values to evaluate the significance of the regression path coefficient according to its t-value. The strongest impact of service quality support on perceived usefulness was measured at 0.599, compared to instructor quality support at 0.296, task-technology fit at 0.312, learning content quality support satisfaction at 0.560, and satisfaction support behavioral intention at 0.373. Table 7 shows that while all other hypotheses are supported at the significance level of 0.05, only H4 is not.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-Value	Result
H1: SQ → PU	0.599	8.789*	Supported
H2: IQ → PU	0.296	5.733*	Supported
H3: TTF → PU	0.312	5.578*	Supported
H4: LCQ → ST	-0.015	-0.294	Not Supported
H5: PU → ST	0.560	8.057*	Supported
H6: ST → BI	0.373	6.919*	Supported

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

This is how the results in Table 7 are interpreted:

H1 demonstrated that service quality considerably influences students' perceived usefulness; the structure path's standardized coefficient value is 0.599. The outcome of **H2** demonstrated that instructors' quality considerably influences pupils' perceived usefulness; the structure path's standardized coefficient value is 0.296. **H3** demonstrated that task-technology fit strongly affects students' perceived usefulness; the structural path's standardized coefficient value is 0.312. The learning content quality did not significantly influence students' satisfaction, according to the standardized coefficient value of **H4** of -0.015. **H5** has a standardized coefficient of 0.560. In other words, perceived usefulness strongly affects students' satisfaction.

Last but not least, **H6's** standardized coefficient value of 0.373 indicates that their level of satisfaction highly impacts students' behavioral intentions.

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

This study examines the elements that affect university sophomore students in Yunnan Province, China, online learning satisfaction, and behavioral intention. Six assumptions and seven variables make up the model. Sophomore students from four colleges of Yuxi Normal University in Yuxi City, Yunnan Province, were selected as the questionnaire respondents. The data analysis aims to investigate the variables that influence behavioral intentions and student satisfaction. Confirmatory factor analysis (CFA) is performed to assess conceptual models' reliability and validity. The impact link suggested by the hypothesis was examined using a structural equation model (SEM).

First, in this research, perceived usefulness is the strongest predictor of both attitudes toward using and behavioral intention to use online learning. Hence, Government and school management should vigorously develop and promote the above key factors, promoting the perceived usefulness of online learning must be emphasized. This means that undergraduates are willing to use online learning if they think that online learning is a useful way to improve their academic performance. The curriculum developers, teachers, and the top administrators of higher education institutions should ensure the service quality of online learning, the quality of the instructors, and the attributes of task-technology fit. Second, the features provided by online learning should be rapid responsiveness, flexibility, accuracy, and relevance to student studies. It also includes high-quality back office technical assistance, and sufficient training should be conducted to improve the service level of back office and service managers to help learners learn online courses more effectively to improve learners' willingness to accept online learning. Once the online learning quality features are ensured, the online learning of operation procedures, task technology, and other service quality supports should be promoted to the students, such as training or media communications, to increase their online learning awareness and recognition. These can stimulate or increase the positive satisfaction of student attitudes and the likelihood of selecting online learning in their learning process. Customers will likely keep utilizing cloud computing services if they find them gratifying. It may be anticipated that contentment is a good indicator of continuing intention, according to studies on cloud-based contexts (Tan & Kim, 2015; Xu et al., 2017). Third, it is consistent with the expected results that the more satisfied students are, the higher their behavioral intention will be. Samsudeen and Mohamed (2019) stated that the indicator of users' preparedness to engage in a certain action is signaled by behavioral intention, which is seen as a prelude to use behavior. The study's findings confirmed that perceived advantages and learner satisfaction are correlated, with learner satisfaction being a strong predictor of student benefits (Rughoobur-Seetah, 2021). This study also proved that student satisfaction significantly impacts student behavioral intention.

5.2 Recommendation

Through a survey of factors impacting online learning satisfaction and behavioral intention among Yuxi Normal University sophomore students in Yunnan province, the researchers found that the key factors affecting students' satisfaction and behavioral intention are perceived usefulness, service quality, instructor quality, and task technology fit. Therefore, this means undergraduates are willing to use online learning if they think it is useful to improve their academic performance. The curriculum developers, teachers, and the top administrators of higher education institutions should ensure the service quality of online learning, the quality of the instructors, and the attributes of task-technology fit, which will help improve students' satisfaction. Student satisfaction assesses education, services, and facilities during their studies (Elliot & Shin, 2002). At the same time, seeing the significant influence relationship between the perceived usefulness and task-technology fit, by starting from the perceived usefulness, improves the task-technology fit and enhances students' satisfaction.

Finally, through the research, it is found that satisfaction has a significant impact on behavioral intention. When students' satisfaction is improved, behavioral intention will also be improved accordingly.

5.3 Limitation and Further Study

It is important to be aware of the study's shortcomings, which include its narrow emphasis on higher education and the small sample size (data was only gathered from a few colleges at Yuxi Normal University in Yunan). The study on college students' perceived usefulness of online learning and behavioral intention still must develop in light of the higher education landscape in China as it stands today. The scope of the examination and the level of theoretical research still has numerous flaws. The integration of theory and practice must be tighter, and the model's building of student satisfaction and perceived usefulness is more inventive and referential. As a result, there is still much room for study and value in college students' satisfaction and perceived usefulness, which requires additional investigation by scholars.

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