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Measuring Satisfaction and Behavioral Intention to Use Online Learning Among Junior Students in a Public University in Yunnan, China

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Abstract

Purpose: This study investigates factors impacting third-year student satisfaction and behavioral intention to use online learning in a public university in Yunnan, China. The research model is built upon service quality, teacher quality, task-technology fit, learning material quality, perceived usefulness, satisfaction, and behavioral intention all have causal linkages. **Research Design, Data, and Methods:** The researchers sent questionnaires to junior students at four colleges of Yuxi Normal University using a quantitative approach (n=500). The researcher utilized judgmental, quota and convenience sampling to collect the data. Before data collection, the Item Objective Congruence (IOC) and Cronbach's alpha were utilized to guarantee reliability and validity. The data were analyzed using confirmatory factor analysis and structural equation modeling, which included model fit, reliability, and validity assessments. **Results:** It has been demonstrated that seven hypotheses satisfy the study's goals. Task-technology fit, teacher quality, and service quality all greatly impact perceived usefulness. The educational content's quality, perceived value, and satisfaction highly influence student behavioral intention. **Conclusion:** To raise students' happiness and behavioral intention about online learning, school administrators and instructors should maintain a pleasant online learning environment, improve academic achievement, increase instructional care, and develop a favorable image of the school.

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

JEL Classification Code: E44, F31, F37, G15

1. Introduction

At the beginning of 2020, because of how COVID-19 has affected schools all around the country, all schools will delay the start of school, which will cause about 265 million students to switch from offline teaching to online courses, and also promote the full release of Chinese users' demand for online education in China. According to the data released by UNESCO in 2020, the COVID-19 epidemic has caused more than 1.7 billion students to be unable to attend classes. However, the help of information technology has led educational institutions to shift from offline course learning to online learning. All types of businesses are actively reacting to the enormous demand for online learning, and the sector is exhibiting spectacular growth. Data shows that during the pandemic, online education applications played an important role, with a considerable number of online education applications having millions of users every day, and in many cases, over 10 million people used the internet daily for schooling (Tadesse & Muluye, 2020).

Therefore, humankind needs to be aware of both the danger that COVID-19 poses and how the harm it does will accelerate the spread of human knowledge and culture. The teacher and students cannot concentrate on learning, face-to-face teaching, debate, and communication in normalizing global disease prevention and control. Therefore, humanity should consider how to transmit human knowledge and culture better (Kamalov et al., 2023). Contradiction is the source of power for human social development. The contradiction between the normalization of global epidemic

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prevention and control and the inheritance of human knowledge and culture must be reflected. How students learn intensively and interact with others in person will be significantly impacted by the normalization of global COVID-19 prevention and control. However, human education cannot stop, and the inheritance of human knowledge and culture will not stop. Human beings will be faced with the contradiction between whether to continue intensive learning and face-to-face communication and the standardization of epidemic control and prevention (Wang & Zhou, 2022).

The epidemic of COVID-19 has affected students' classroom teaching, which means that students' access to education has also been hindered. It will also cause social isolation, and education may continue to experience difficult times (Özüdoğru, 2021). Parents, students, and teachers are forced to pick the learning technique of online education since offline teaching institutions have been suspended, fulfilling the goal of education as the educational goals in China include the satisfaction and behavioral Intention of online education in colleges and universities, which requires hard investment and research (Wang & Zhou, 2022). China needs to invest in and study the satisfaction and behavioral Intention of online education in universities. At the same time, researching the students' 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 variable—behavioral 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

According to Parasuraman et al. (1985), service quality is typically described as how closely a service level given meets customer expectations. Service quality in the e-learning context can be considered the assistance provided by instructors and support service technicians (Ozkan & Koseler, 2009). However, the technical support services offered by online support service technicians are frequently the focus of quality measurement of personal services provided via the e-learning system. The instructor dimension of service quality is frequently regarded as the measure of instructor quality. It also showed that service quality substantially impacted customers' perceptions of playfulness in online purchasing. (Cheng, 2012). Gorla et al. (2010) believed that service quality, system quality, and information quality directly assess organizational effect from three elements. We shall discover that these three factors substantially impact the company. Service quality is crucial; the more satisfied people are with a service, the more likely they are to support and pick it. Online learning significantly impacts behavior intention, according to several studies that have examined the tangential relationship between service quality, perceived utility, and satisfaction, as demonstrated by the following hypothesis:

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

2.2 Instructor Quality

Daultani et al. (2021) stated that the ability of a teacher to assist the use of the learning system through timely responses, technical proficiency, and effective teaching methods is known as instructor quality. Instructor quality is an instructor's response timeliness, technical competence, and teaching style to facilitate using the learning system. The degree to which instructors support students through electronic learning technologies is what Cheng (2014) characterized as an instructor's quality. The quality of an instructor is measured by how much students think the instructor cares about them and how they are treated while using an online learning system. Instructor quality is determined by the instructors' expertise, responsiveness, preparation, and capacity to create an integrated learning environment. Instructors are the primary players in delivering a technology-mediated learning environment; according to Daultani et al. (2021), these subfactors encourage student interaction and long-term interests. Cheng (2012) found that the factors of teacher quality and teachers' attitudes towards e-learners have been found to have a significant impact. At the same time, these findings from the study show how important teachers are to students' online learning. This will help students understand the value of e-learning, spark their innate interest in it, and further motivate them to keep studying using electronic learning systems. It will also help students recognize the efficacy of e-learning. Accordingly, a hypothesis is indicated:

H2: Instructor quality has a significant impact on perceived usefulness

2.3 Task-Technology Fit

Task-technology fit assumes that technology adoption depends on the new technology's fit for a particular work (Goodhue & Thompson, 1995). According to Ellyana Dwi et al. (2009), Task-Technology Fit (TTF) describes the connection between a task's needs for completion, a person's aptitudes, and technological operations inside an organization's information system. Task-Technology Fit (TTF) measures how well a person can use technology to carry out activities related to their financial portfolio. Technology is viewed as a tool used by persons in their jobs (Goodhue & Thompson, 1995), and jobs are generally described as activities made by individuals to change inputs into outputs. 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). In this study, one facet of TTF pertains to the technology issue, and technology attributes are represented as affordance, which is how ESM's capabilities allow people to achieve particular goals (Fu et al., 2020). Thus, a hypothesis is concluded:

H3: Task-technology fit has a significant impact on perceived usefulness.

2.4 Learning Content Quality

The availability of resources and services that are directly connected to student learning outcomes is referred to as learning content quality (Cao et al., 2005; Uppal et al., 2018). According to Cheng's (2021) proposal, the caliber of the learning materials produced by the e-learning system constitutes the course content. The terms "content richness" and "update regularity" refer to two different aspects of content quality. "Content richness" is the first of them, and it has a beneficial impact on students' happiness with the course (Arbaugh, 2000; Burns et al., 1990). The effectiveness of the learning contents has a significant impact on the e-learning system's service level. Creating learning content can enhance learning optimization and increase students' motivation to study. The quality of the instructional content significantly influences the efficiency of the e-learning system. Through the creation of learning materials, the optimization of learning may raise student interest in learning. As a result, the quality of e-learning content affects the effectiveness and satisfaction of e-learning services. As a result, e-learning services' quality and satisfaction are influenced by the quality of the content they provide (Theresiawati et al., 2020). Subsequently, a hypothesis is concluded:

H4: Learning content quality has a significant impact on satisfaction.

2.5 Perceived Usefulness

Perceived usefulness, according to Davis (1989), is the extent to which a student thought using an LMS would improve his or her learning capacity. According to Cheng (2012), perceived usefulness is "the extent to which a person believes that using a particular system would be free of physical and mental effort." Perceived usefulness, which relates to users' views of the anticipated benefits of IS/IT usage, is one of the essential presumptions for understanding user adoption of a particular type of system in the technological acceptance paradigm, according to Cheng (2020). Perceived usefulness was defined by Cheng (2014) as "the degree to which a person believes that using a particular system would enhance his/her job performance." Lee (2006) regarded that despite the substantial impacts of material quality on perceived utility, this study discovered that subjective norms strongly affected perceived usefulness in both scenarios. Thanks to technical advancement and high-quality content, PU and perceived ease of use significantly influenced perceived ease of use, affecting e-learning intention (Feng et al., 2022; Salimon et al., 2021). Accordingly, a hypothesis is indicated:

H5: Perceived usefulness has a significant impact on satisfaction.

2.6 Satisfaction

According to Bokhari (2001), user satisfaction may be used to gauge how well an e-learning system meets users' wants and demands, promoting greater satisfaction. User satisfaction was defined by Kim and Malhotra (2005) as the anticipated level of knowledge gained through a certain e-learning platform. According to Shneiderman (2010), user satisfaction refers to how receptive a user is to the skills or knowledge growth of a certain e-learning system. According to Cheng (2021), satisfaction is a psychological or subjective condition related to a cognitive assessment of the expectation-performance gap's findings. The joy consumers feel when their demands are met is known as satisfaction. It also refers to the link between the client's prior anticipation of a product or service and their experience after using it. If students are happy with the e-learning system, they may continue using it (Larsen et al., 2009). It is important to understand the so-called IS acceptance-discontinuance anomaly phenomenon, which occurs when users stop using the system after initially accepting it (Bhattacherjee, 2001), because the findings suggest that satisfaction is crucial to determining cloud-based e-learning continuance intention, despite having favorable perceptions of other predictors. Accordingly, a hypothesis is indicated:

H6: Satisfaction has a significant impact on behavioral intention.

2.7 Behavioural Intention

Personal intention is crucial in deciding whether to carry out a certain action. Hence, forecasting personal intention would be the best approach to evaluate the specific action (Ajzen, 1991). According to Udo et al. (2011), behavioral intention refers to users' intentions to use, recommend, and be open to utilizing e-learning continually to accompany lectures. According to Samsudeen and Mohamed (2019), among the exogenous elements evaluated for their impacts on BI and use behavior were performance expectations, effort expectations, work-life quality, hedonistic incentives, online experience, and enabling conditions. In addition, perceived utility, user contentment, and switching cost greatly and negatively impact switching intention. However, switching intention and habit can admirably predict switching behavior (Xu et al., 2017). Cheng (2020) defined behavioral intention as the intention. BI refers to the transition of individuals from existing learning methods to future intentions to use them, and it is a pioneer of use behavior. It indicates that the user is prepared to perform a particular behavior. Individuals use everything from existing learning methods to future e-learning systems (Samsudeen & Mohamed, 2019).

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). To support and construct a conceptual framework, the researcher used four key theoretical frameworks, two major theories-TAM and UTAUT-and two significant theories. The conceptual foundation for this study is based on four significant prior relevant theoretical frameworks and two fundamental hypotheses. Combining research theories and previous relevant literature, a conceptual framework for examining users' behavioral intentions in using online learning in higher education is constructed. The link between online learning and behavioral intention among students was investigated using the conceptual framework.

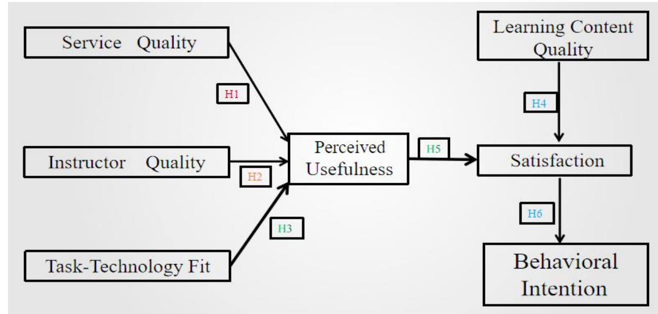

Figure 1: Conceptual Framework

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 can investigate variables influencing behavioral intention to use online learning in public universities in Yunnan, China; research methods and instruments were introduced, including the choice of sampling units, sample size, and target demographic. This study employed a quantitative approach, and the target group's questionnaire and data were gathered through a survey. The procedure for gathering data and the statistical analysis of that data is presented. The content was validated with item IOC and Cronbach's Alpha before collecting data. 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.

Following data collection, structural equation modeling (SEM), which researchers consider the best method, was used to confirm the structural link between variables. The eight components that comprise the research methodology are the research method, respondents and sampling strategy, research instruments or questionnaires, validity and internal consistency reliability of the research instruments, data collection/gathering procedures, CFA, and goodness of fits or model fits. Finally, SEM examines the effect of variables.

After gathering quantitative data, the researcher used statistical software such as SPSS and AMOS to examine the sample data. Researchers empirically examined the conceptual framework they had created as the potential link between the variablEM, and the results were evaluated using CFA and SEM.

3.3 Population and Sample Size

There are undergraduate students in the population from Yuxi Normal University, China. According to various studies, the sample size of 50 instances was insufficient; nevertheless, the sample sizes of 100-500 were all found to be good, very good, and the perfect sizes for factor analysis, respectively (Comrey & Lee, 2013). So, the researchers selected the best sample size. Using past studies as a foundation, researchers collected 500 samples from Yuxi Normal University to get better statistical results. At the same time, after the researchers screened the respondents, they distributed the questionnaire to 500 students and returned 500 questionnaires.

3.4 Sampling Technique

Judgmental sampling was employed by selecting juniors in Yuxi Normal University, China. Quota sampling was conducted as in Table 1. To ensure the quickness and efficiency of the questionnaire dissemination as well as the seriousness and veracity of the responses from the students, the researchers distributed the answers to the students through the counselor and the class teacher during the class meeting or class time. This method of collecting data through online channels has many advantages over other methods and can complete data distribution and collection faster and more efficiently. While doing so, to complete the number of respondents defined by each college, the online distribution collection is the most efficient and fastest way to complete the data collection. For convenience sampling, respondents can complete the data collection and collation by checking the answers through the mobile phone WeChat WPS online documents.

Table 1: Sample Units and Sample Size

College Name	Population Size	Proportional Sample Size
College of Teacher Education	259	158
College of Foreign Language	120	73
College of Mathematics and Information Technology	270	165
College of Physical Education	171	104
Total	**820**	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

The demographic information for the sample of the target population, which consists of 500 people, is provided in Table 2. Men comprised 54.6% of the respondents, while women comprised 45.4%. The sample's oldest age group, including 49.4% of respondents, is between 22 and 24 years old, followed by 18 to 20 years old (13% of respondents), 20 to 22 years old (32.60%), and 24-26 years old (5% of respondents). The biggest category in the sample, in terms of times per week, is 3–7 times, which accounts for 40.8% of the responses, followed by 1-3 times, which accounts for 29.40%, more than seven times, which accounts for 29.2%, and 0 times, which accounts for 0.60%. In terms of preference of the devices used, the group with the biggest share of responses in the sample is Mobile Phone (55.60%), followed by PC/laptop (28.10%), Tablet (9.20%), and other (7.00%).

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Female	227	45.40%
	Male	273	54.60%
Age	18-20 years old	65	13.00%
	20-22 years old	163	32.60%
	22-24 years old	247	49.40%
	24-26 years old	25	5.00%
Per week	0 times	3	0.60%
	1-3 times	147	29.40%
	3-7times	204	40.80%
	more than 7 times	146	29.20%
Preference	Mobile Phone	278	55.60%
	Tablet	46	9.20%
	PC/laptop	141	28.20%
	other	35	7.00%

Source: Constructed by author

4.2 Confirmatory Factor Analysis (CFA)

This research employed confirmatory factor analysis (CFA). 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 & Bernstein, 1994).

Table 3 shows that CA values are above 0.7, factors loading are above 0.5, CR values above 0.7, and AVE values above 0.5. 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	0.825	0.762-0.810	0.825	0.612
Instructor Quality (IQ)	Cheng (2014)	3	0.843	0.730-0.847	0.844	0.644
Task-technology Fit (TTF)	Cheng (2021)	4	0.855	0.597-0.895	0.864	0.619
Learning Content Quality (LCQ)	Lee (2006)	3	0.762	0.674-0.755	0.763	0.518
Perceived Usefulness (PU)	Lee (2006)	4	0.830	0.675-0.802	0.833	0.555
Satisfaction (ST)	Cheng (2021)	4	0.831	0.697-0.801	0.832	0.554
Behavioral Intention (BI)	Anderson et al. (2020)	3	0.897	0.836-0.889	0.898	0.746

During the CFA testing, various model fitting indicators such as CMIN/DF, GFI, AGFI, NFI, CFI, TLI, and RMSEA are typically used. In this study, the obtained values for these indicators exceeded the acceptable thresholds, indicating that the model provided a good fit. The measurement results from these models further validate the effectiveness of subsequent estimations in the structural model and reinforce its discriminative efficiency, as shown in Table 4.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	≤ 5.0 (Wheaton et al., 1997)	1.479
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.947
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.932
RMSEA	≤ 0.10 (Hopwood & Donnellan, 2010)	0.031
CFI	≥ 0.80 (Bentler, 1990)	0.981
NFI	≥ 0.80 (Wu & Wang, 2006)	0.977
TLI	≥ 0.80 (Sharma et al., 2005)	0.944
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

Table 5 below shows that the model's discriminant validity is good, with the square root of each variable's AVE being greater than its correlation coefficient with other variables. The Tucker-Lewis index is used to measure this.

Table 5: Discriminant Validity

	SQ	IQ	TTF	LCQ	PU	ST	BI
SQ	**0.782**						
IQ	0.460	**0.802**					
TTF	0.141	0.129	**0.786**				
LCQ	0.264	0.326	0.062	**0.719**			
PU	0.510	0.426	0.279	0.292	**0.719**		
ST	0.319	0.308	0.090	0.299	0.393	**0.744**	
BI	0.441	0.610	0.142	0.330	0.454	0.244	**0.744**

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

4.3 Structural Equation Model (SEM)

The structural equation model (SEM), as an extension of the regression model, provides several advantages that the regression model alone does not offer. One such advantage is the ability to simultaneously handle multiple independent and dependent variables, which meets the growing complexity demands of theoretical models in social science research. SEM is considered a vital statistical approach in the field of social science research, as highlighted by Wang et al. (2020).

The goodness of fit indicators for the Structural Equation Model (SEM) are calculated, as seen in Table 6. After using SPSS AMOS to calculate the SEM and adapt the model, the fit index results—which are 3.307 CMIN/DF, 0.875 GFI, 0.848 AGFI, 0.068 RMSEA, 0.903 CFI, 0.867 NFI, and 0.891 TLI—were proven to be satisfactorily fit. Table 6 lists the allowable values following such values.

Table 6: Goodness of Fit for Structural Model

Index	Acceptable	Statistical Values
CMIN/DF	≤ 5.0 (Wheaton et al., 1997)	3.307
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.875
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.848
RMSEA	≤ 0.10 (Hopwood & Donnellan, 2010)	0.068
CFI	≥ 0.80 (Bentler, 1990)	0.903
NFI	≥ 0.80 (Wu & Wang, 2006)	0.867
TLI	≥ 0.80 (Sharma et al., 2005)	0.891
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 evaluates the significance of the standardized path coefficient according to its t-value and calculates the explanatory ability of the independent variable to the dependent variable. Table 7 reports that at the level of significance p=0.05, all hypotheses are supported.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-Value	Result
H1: SQ → PU	0.498	8.716*	Supported
H2: IQ → PU	0.300	6.046*	Supported
H3: TTF → PU	0.236	5.082*	Supported
H4: LCQ → ST	0.254	4.674*	Supported
H5: PU → ST	0.421	7.452*	Supported
H6: ST → BI	0.326	6.275*	Supported

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

The results in Table 7 are interpreted as follows:

H1 showed that service quality significantly impacts students' perceptions of the utility of service; the standardized coefficient value for the structural path is 0.498.

Since the structure path's standardized coefficient value is 0.300, the result of **H2** showed that instructors' quality significantly impacts how students view usefulness.

The structural path's standardized coefficient value for **H3** is 0.236, demonstrating how the task-technology fit significantly impacts students' perceptions of usefulness.

The standardized coefficient value of **H4** was 0.254, indicating a significant impact of the learning material quality on student happiness.

The standardized coefficient for **H5** is 0.421, indicating that perceived usefulness significantly impacts students' pleasure.

Finally, the standardized coefficient value for **H6** of 0.326 shows that students' degree of satisfaction significantly impacts their intentions.

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

This study investigated the factors influencing behavioral intention and satisfaction with online learning among third-year university students in Yunnan Province, China. The model consisted of seven variables and six assumptions. The participants were selected from four colleges at Yuxi Normal University in Yuxi City. The data analysis examined the variables influencing behavioral intentions and student satisfaction. Confirmatory factor analysis (CFA) was used to assess the validity and reliability of the conceptual models, while a structural equation model (SEM) was employed to analyze the proposed hypothesis.

The study's first finding revealed that perceived usefulness is the strongest predictor of attitude towards and behavioral intention to use online learning. This suggests that perceived usefulness significantly impacts satisfaction and the intention to utilize online learning. Additionally, service quality, instructor quality, and task-technology fit were found to have a significant influence on perceived usefulness, while learning content quality significantly impacted satisfaction. These findings indicate that students attach increasing importance to online learning content as they progress in their academic journey. The study also highlighted that students' perceptions of service quality, learning content quality, instructor quality, and task-technology fit are crucial in shaping their perceived usefulness, affirmation, satisfaction, and desire to continue using online learning.

The second finding emphasizes the importance of incorporating characteristics such as responsiveness, adaptability, accuracy, and relevance to students' studies in online learning. Additionally, providing top-notch technical support and adequate training for back-office and service managers can enhance students' online learning experience and increase their adoption of online learning. It is recommended that educational institutions and administrators prioritize task-technology fit, learning content quality, instructor quality, and service quality in online learning to encourage students to make the most of its advantages.

The third finding supports the hypothesis that behavioral intentions increase with higher satisfaction levels. Previous research has shown that behavioral intention is a precursor to actual use behavior and indicates a user's readiness to engage in a specific action. The study confirmed the relationship between perceived benefits and learner satisfaction, with learner satisfaction being a strong predictor of student benefits. Furthermore, the study demonstrated the significant impact of student satisfaction on behavioral intention.

In conclusion, this study underscores the importance of perceived usefulness, service quality, learning content quality, instructor quality, and task-technology fit in influencing behavioral intention and satisfaction with online learning among university students. It highlights the need for educational institutions and policymakers to prioritize these factors and enhance students' online learning experience to promote their adoption of online learning.

5.2 Recommendation

Online learning is one of the information technology advancements that makes it easy for people to study on their own terms, organize the learning process around students' requirements, and reduce the cost of learning. Learning achievement might, therefore, improve. The key factors affecting students' satisfaction and behavioral intention are perceived usefulness, service quality, instructor quality, task-technology fit, and learning content quality, according to a survey of factors influencing online learning satisfaction and behavioral intention among Yuxi Normal University junior students in Yunnan province. Therefore, if undergraduates believe online learning will help them enhance their academic performance, they are eager to use it. The quality of online learning, the caliber of the instructors, the task-technology fit characteristics, and the learning content quality should all be ensured by curriculum developers, teachers, and top administrators of higher education institutions. Seeing the strong correlation between perceived usefulness and task-technology fit, one may increase task-technology fit by starting with perceived usefulness and raising students' satisfaction levels. The study's findings confirmed that perceived usefulness and learner satisfaction are correlated, with learner satisfaction being a strong predictor of student benefits Rughoobur-Seetah, 2021). Finally, through the research, it is found that satisfaction has a significant impact on behavioral intention. According to Cheng (2021), satisfaction is a psychological or subjective condition related to a cognitive assessment of the expectation-performance gap's findings. The level of behavior intention will rise directly to student satisfaction.

5.3 Limitation and Further Study

Although a specific scale and a comprehensive index system have been established from the survey and actual actions of college student's satisfaction, the study on their satisfaction and behavioral intentions still must be mature, given the state of higher education in China today. The scope and depth of theoretical study both continue to have significant shortcomings. The study on college students' perceived usefulness of online learning and behavioral intention still must develop considering the higher education landscape in China as it stands today. At the same time, 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). There are still many issues with the study's breadth and quality of theoretical investigation. The model's construction of student satisfaction and perceived usefulness is more creative and referential, and theory and practice integration must be tighter. Therefore, there is still a lot of value and potential for research on college students' pleasure and perceived usefulness, which calls for more academic research.

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