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Factors Influencing Behavioral Intention Toward E-learning Among Film & Animation Undergraduates: An Empirical Study at a Public University in Chengdu, China

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Abstract

Purpose: This study analyzes online learning satisfaction and behavioral intents of undergraduate students in China, by examining system quality, service quality, perceived usefulness, effort expectancy, and performance expectancy. **Research design, data, and methodology:** In this study, a quantitative research methodology was used. A survey that included 500 undergraduate students with more than a year of experience in online learning was used to gather data. To guarantee the sample's representativeness, stratified random, convenience, and purposive sampling were used as sampling techniques. Prior to collecting data, a pilot test (n=50) and the Item-Objective Congruence (IOC) index were used to confirm the questionnaire's validity and reliability. The convergent and discriminant validity of the measurement model was then evaluated using confirmatory factor analysis (CFA). Ultimately, the correlations between the measured variables were tested using structural equation modeling. **Results:** The analysis results indicate that system and service quality significantly positively affect perceived usefulness and satisfaction. Perceived usefulness and effort expectancy significantly enhance students' satisfaction and behavioral intentions. Performance expectancy is an intermediary between system quality and satisfaction, with satisfaction being a key factor influencing behavioral intentions. **Conclusions:** Education administrators should focus on optimizing online learning platforms, emphasizing the enhancement of students' perceptions of usefulness and expectation management to improve overall learning outcomes.

Keywords: Behavioral Intentions, Satisfaction, System Quality, System Quality, Film and Animation

JEL Classification Code: E44, F31, F37, G15

1. Introduction

From the mid to late 1990s, campus networks emerged as the Internet became increasingly popular in universities. However, these campus networks need to catch up and learn, preventing them from realizing their full potential. Online education aims to complement traditional classroom teaching by utilizing its advantages while overcoming the time and space constraints of traditional classroom teaching. It is not intended to replace traditional classroom teaching. We can create a new and efficient teaching mode by utilizing the advantages of online learning. According to the opinions on Strengthening the Implementation and Management of Online Open Courses in Colleges and Universities, online open courses should be widely adopted. According to the specific standards and objectives of talent cultivation in colleges and universities, colleges and universities are encouraged to combine traditional classroom teaching, online teaching, and open courses. Creative ways are constantly being thought of to share materials and implement them inside and outside the classroom. As a result, the development of online and offline blended learning in higher education has accelerated due to the rapid expansion of online open courses (Yang et al., 2021).

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Online learning is an important part of teaching at Chengdu University in China. Nevertheless, there are still some special problems with current online education. Three main problems with teaching online are insufficient hardware and software resources, limited adaptability of educators and students to online learning methods, and teachers' lack of understanding of students' behavioral intentions and psychological needs. In addition, there are some irrationalities in the regulations of the relevant educational management departments for online learning.

This study resulted in a quantitative assessment of online learning for art majors. They also assessed undergraduate students' satisfaction and behavioral intentions in the School of Art and Design and the School of Film and Animation. The primary goal of this paper is to identify modifications and changes needed for future e-learning instructional strategies based on the learning technology assessment. Additionally, assessments and interpretations from survey respondents were included in this work. The results of the study will be useful to frontline teaching staff. Establish additional acceptable teaching strategies and reliable online learning platforms for undergraduate art students and verify that online education is an appropriate and trustworthy teaching structure. The results of this study will enhance instruction and learning and influence the development of online art major programs in China. The study's findings will benefit companies offering online learning platforms by providing insightful recommendations on how to improve the platforms' functionality, enrich the resource platforms' content, increase user stickiness, and ultimately help these companies capture a larger share of the educational services market.

2. Literature Review

2.1 System Quality

Analysis indicates that the quality of the online educational system includes elements like flexible interaction or optimal maintenance that positively affect users' assessments of the platform's effectiveness and life satisfaction (Rughoobur-Seetah & Hosanoo, 2021). It is believed that "system quality" refers to how well a system's features support instructors in carrying out their responsibilities and enhancing teaching and learning (Wang &Wang, 2009). Rughoobur-Seetah and Hosanoo (2021) claim that the system's quality positively affects the advantages that students gain from it.

Several researchers examined system quality since it is believed to directly influence user adoption and satisfaction (Rughoobur-Seetah & Hosanoo, 2021). According to preliminary studies, system quality may predict students' happiness in online learning environments (Samarasinghe, 2012). Users' inclination to use e-learning platforms and their degree of happiness with their educational experience are significantly influenced by the system's quality. Several academics have extensively discussed this point of view. According to Rui-Hsin and Lin (2018) study, system quality can improve users' opinions about the worth of e-learning, which will increase their degree of pleasure. Studies show that satisfaction and utilization are positively impacted by system quality (Aparicio et al., 2017). In e-learning, a system's fit for its intended purpose and users' requirements determine system quality (Freeze et al., 2019).

H1: System quality has a significant impact on satisfaction.

2.2 Service Quality

The effectiveness of the assistance given to instructors to make usage of such a system simpler is what is meant by "service quality" (Wang &Wang, 2009). Service quality is

This idea is primarily concerned with the consistency with which businesses deliver excellent service to users. Furthermore, it touches on the system's functionality, dependability, usability, and data quality (Rughoobur-Seetah & Hosanoo, 2021). The usefulness of multiple communication channels for quickly assisting consumers in addressing usage-related difficulties is a key component of service quality. It is defined as the level of satisfaction a user expresses with the overall quality of the services offered by an information system (Cheng, 2012).

The level of customer help provided determines the system's quality, just like it does for any other service (DeLone & McLean, 2003). In the meantime, based on a study done in 2021 by Rughoobur-Seetah and Hosanoo, service quality has a favorable influence on how valuable people believe their e-learning experience to be. This result was remarkably similar to Cheng's results from 2014, and the importance of service quality in determining perceived usefulness was amply confirmed. Online instruction context content and system aim are both significantly benefited by service quality (Mohammadi, 2015). Service quality was described by Petter and McLean (2009) as the assistance provided to users by the IS department, which is often judged by the organization's agility, dependability, and empathy. Service quality is determined by how well users are supported by the IT department or IT support personnel (Mtebe & Raphael, 2018).

H2: Service quality has a significant impact on satisfaction.

2.3 Perceived Usefulness

Perceived utility, according to Rughoobur-Seetah and Hosanoo (2021), is the degree to which an individual believes utilizing technology would enable them to complete a task more successfully. User pleasure is directly and significantly influenced by perceived usefulness. Users must also keep using the e-learning system and see its worth as another requirement for user satisfaction with using hybrid e-learning systems (Cheng, 2014). The degree to which instructors believe utilizing such systems may improve their capacity to teach is characterized by the perceived usefulness of technology (Wang &Wang, 2009).

Perceived usefulness directly affects the propensity to utilize. Further proof of the link between perceived usefulness, benefit, and continued usage was supplied by Rughoobur-Seetah and Hosanoo (2021), which asserted that perceived usefulness was positively associated with benefit. There was a favorable association between continuous usage and perceived usefulness. Perceived usefulness is a major factor in raising satisfaction levels among students and teachers. Evidence suggests that PU enhances both instructors' and students' e-learning engagement. Similarly, the user feels obliged to utilize the technology due to its perceived advantages (Ganesh Dash, 2023).

H3: Perceived usefulness has a significant impact on satisfaction.

2.4 Satisfaction

Learner satisfaction is the extent to which e-learning satisfies a learner's expectations as provided by an e-learning system. (Samarasinghe, 2012). According to Petter and McLean (2009), emotional state contentment denotes a strong reaction to utilizing technology. Acceptance or enjoyment of something as is, as well as output, is the definition of pleasure. The level of a user's happiness with a particular system's speed, variety, quality, and format is known as user appreciation. It also concerns a user's satisfaction with a system and their likelihood of using it again.

It is based on personal experiences, which means that both good and bad things can affect contentment. When determining whether to continue using a system, users' perceptions of their happiness are crucial since they greatly impact how reliable the system is (Mtebe & Raphael, 2018). Positive behavioral intentions to use the technology are influenced by satisfaction. When the technology fits the user's needs or desires, her degree of enjoyment rises, and, as a result, her tendency to employ the product is positively impacted. According to several empirical studies, behavioral intention to use is positively impacted by customer happiness (Dash, 2023).

H4: Satisfaction has a significant impact on behavioral intention.

2.5 Effort Expectancy

An individual's effort expectation is their estimate of how simple it will be to learn and use the applicable application—the greater the utilization behavior, the less work is required (Avcı, 2022). Effort expectation is the degree of convenience provided by technologies that minimize an individual's effort (effort and time) while doing his duties. Rosmayanti et al. (2022) base their variable on three constructs: Perceived ease of use (PEOU) derived from the TAM model, perceived ease from the diffusion theory of development (IDT) model, and complexity of PC utilization (MPCU) model. Venkatesh et al. define effort expectancy (EE) as "the degree of ease associated with the use of the system" (2003).

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

2.6 Performance Expectancy

The anticipation that a user would gain anything from utilizing a technical application is known as performance expectancy. It conveys the teacher's viewpoint on the value of digital instructional technology to their pupils when they utilize these programs in the classroom. According to research done on instructors, Performance Expectancy (Avcı, 2022) was the behavioral intention variable on technology that was shown to be the most successful. Using characteristics from earlier study models, Rosmayanti et al. (2022) define performance expectation as a person's conviction that putting a system in place will enhance their work performance. Alamri, M.M. (2021) describes Performance Expectancy (PE) as "the extent to which an individual believes that using the system will assist him or her in attaining gains in job performance."

Several elements influence students' expected performance when they use technology to learn English, such as perceived value, extrinsic motivation, job fit, relative advantage, and outcome expectations. Students may believe that technology has improved their English proficiency because, according to Davis et al. (1989), perceived usefulness is the extent to which an individual believes that adopting a certain system will boost their performance. Previous research has revealed that performance expectation positively influences behavior intention to use technology in the UTAUT and UTAUT2 models. The performance expectation variable also included components from other studies on technological acceptance, such as perceived utility and relative benefit (Raman et al., 2022).

H6: Performance expectancy has a significant impact on behavioral intention.

2.7 Behavioral Intention

A person's inspiration or readiness to engage in an activity is known as behavioral intention. Many theories contend that intent is the most fundamental predictor of conduct, including the rational action model and the hypothesis of planned behavior (Avcı, 2022). Behavioral intention is a proxy factor for consumer willingness to use and accept a certain technology. This study aims to ascertain how high school students prefer and intend to use YouTube for instructional purposes. The UTAUT hypothesis states that BI is a potent indicator of actual technology adoption (Alamri, 2021). Ajzen (1991) states that behavioral intentions (Bl) are decisions to engage in a specific behavior. Through behavioral intentionality, this project aims to equip pre-service teachers for mobile learning. Intentions are affected by various factors, such as social influence (Asghar et al., 2021).

The issue that may be debated is whether technological advancements over the past two decades have caused a change in behavioral intentions. Or and Chapman (2021) propose that usability will first influence lecturers' perceptions of online assessment and, via lecturers' perceptions, will substantially affect lecturers' business intelligence. Although the idea that attitude plays a key role in mediating behavioral intentions is not brand-new, these dimensions have never been included before in the UTAUT paradigm. (Or & Chapman, 2021). The advantages of the online learning system feature on students' attitudes and behavioral intents toward utilizing the online learning system should be utilized by online administrators at Jordan's higher education institutions (Mizher et al., 2022).

3. Research Methods and Materials

3.1 Research Framework

This research aimed to determine the conceptual framework that influences undergraduate art students' satisfaction and behavioral intention to learn online. The survey revealed all research variables. The study framework was developed based on three basic hypotheses and previous theoretical frameworks. Theories like the ISSM, TAM, UTAUT model, and D & M IS model provide the basis of this study's conceptual framework. The researcher concluded this investigation after making various connections. The framework of earlier research, which encompasses the examination of performance expectancy, effort expectancy, social impact, and enabling factors, was initially given by Abbad (2021). In Figure 1, the study framework is displayed.

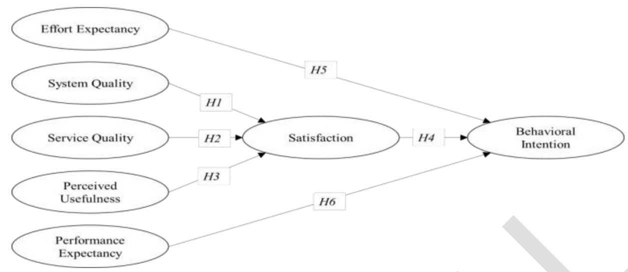

Figure 1: Conceptual Framework

H1: System quality has a significant impact on satisfaction.
H2: Service quality has a significant impact on satisfaction.
H3: Perceived usefulness has a significant impact on satisfaction.
H4: Satisfaction has a significant impact on behavioral intention.
H5: Effort expectancy has a significant impact on behavioral intention.
H6: Performance expectancy has a significant impact on behavioral intention.

3.2 Research Methodology

Art majors were the study's target audience at a public undergraduate institution in Chengdu, China. Undergraduate students with at least a year of experience in online courses were given questionnaires. According to the study's ethical guidelines, no personal data was used, and respondents had to give their approval for the data to be used. Three components comprised the questionnaire: questions for screening, measurement variables, and demographics. The variables were measured using a five-point Likert scale.

Furthermore, the researcher evaluated content validity using the Item Objective Consistency Index (IOC) before administering the questionnaire. To ensure the questionnaire's reliability, Cronbach's alpha test was conducted on 50 target populations. The researchers then distributed the questionnaire to 600 students and obtained 500 usable responses. Lastly, AMOS and SPSS were used to perform Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM).

3.3 Population and Sample Size

According to Malhotra and Segars (2005), the target population is a collection of elements containing information about the study design. According to Cooper and Schindler (2014), the target population is a group of individuals with values and traits similar to those of the study. According to Clark-Carter (2010), the target population consists of people who act in comparable ways toward specific objects. Additionally, the target population for the study includes individuals, records, or events, according to Cooper and Schindler (2011). Zikmund et al. (2013) view the target population as a group with common characteristics. This is corroborated by the assertion made by Malhotra and Birks (2007) that the target population is a group of people in whom the researcher is interested. Since a larger percentage of the general population is being measured, the larger the dataset, the greater the precision (Larson & Larson, 1987). Taherdoost (2017) asserts that the sample size is the key component of any empirical study aimed at concluding a sample population. In this investigation, the proper sample size was determined using a calculator; a minimum sample size of 425 was advised. However, according to Hair et al. (2010), the density of the model measurements determines the right sample size. As a result, the target demographic received 600 questionnaires, of which 500 were deemed valid.

3.4 Sampling Technique

Quantitative methods were used for data collection and subsequent analysis. The researcher employed both probability and non-probability sampling as sample strategies. Furthermore, this study's sample procedure was broken down into three phases: purposive sampling, stratified random sampling, and convenience sampling. First, we randomly sampled undergraduate students majoring in art and design at a public undergraduate institution in Chengdu, China, who had completed more than a year of online coursework. Data were then gathered proportionately using stratified random sampling, as indicated in Table 1. With consent from the participating schools and students, the researcher used an easy sample approach to send online questionnaires to participants via WeChat, social media, and email.

Table 1: Sample Units and Sample Size

Target Institution	Subjects	Population	Sample Units and Sub-Sample Size
School of Film and Animation	Animation	421	255
	Radio and TV Director	140	145
	Digital media Technology	165	100
Total		**726**	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

According to Table 2, out of 500 respondents, 126(25.2%) were male and 374(74.8%) were female. Animation students totaled 255 (51%). Radio and TV Director students totaled 145 (29%). Radio and TV Director students totaled 100 or 20%. All of them are public university undergraduate students with more than one year of online learning experience.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	126	25.2%
	Female	374	74.8%
Major	Animation	255	51%
	Radio and TV Director	145	29%
	Digital media Technology	100	20%

4.2 Confirmatory Factor Analysis (CFA)

In order to evaluate the convergent validity of the conceptual model, factor loading, mean-variance extraction (AVE), and complete reliability (CR) were commonly used in this work (Hair et al., 2013). Cronbach's alpha was employed to assess the questionnaire's reliability. Every construct in this study was deemed credible, and each group's alpha coefficient was above 0.7. An early evaluation of the measurement model's convergent and discriminant validity was conducted using validated factor analysis (CFA), created by Jöreskog (1969). Additionally, Byrne (2010) noted that two conceptual validity methodologies can be utilized for validation: divergent and convergent. According to Alkhadim et al. (2019), CFA is a crucial technique for examining each predicted variable in a structural model. Hair et al. (2013) state that factor loading values for all variables were greater than 0.5 and that p-values less than 0.05 were considered acceptable. Every variable had an AVE value of more than 0.5 and a CR value of more than 0.7.

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
System Quality (SYQ)	Cheng (2012)	5	0.904	0.649-0.929	0.904	0.657
Service Quality (SEQ)	Samarasinghe (2012)	3	0.848	0.851-0.870	0.850	0.655
Perceived Usefulness (PU)	Rughoobur-Seetah and Hosanoo (2021)	3	0.856	0.730-0.899	0.860	0.673
Effort Expectancy (EE)	Mtebe and Raisamo (2014)	4	0.886	0.731-0.908	0.887	0.663
Performance Expectancy (PE)	Mtebe and Raisamo (2014)	4	0.896	0.701-0.938	0.901	0.697
Satisfaction (SAT)	Samarasinghe (2012)	3	0.815	0.694-0.839	0.818	0.601
Behavioral Intention (BI)	Alamri (2021)	3	0.761	0.661-0.776	0.768	0.526

According to Brown (2015), one way to ascertain whether the measurement model between observed and latent variables in a model is compatible with the observed data is through confirmatory factor analysis (CFA). Ainur et al. (2017) Good-of-Fit (GOF) is a metric that can quantify the model's degree of fit. The GOF values from Table 4 are as follows: GFI = 0.919, AGFI = 0.895, NFI = 0.917, CFI = 0.960, TLI = 0.952, RMSEA = 0.048, and CMIN/DF = 510.842/250or 2.043.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 3.00 (Hair et al., 2006)	510.842/250or 2.043
GFI	≥ 0.90 (Hair et al., 2006)	0.919
AGFI	≥ 0.85 (Schermelleh-Engel et al., 2003)	0.895
NFI	≥ 0.90 (Hair et al., 2006)	0.917
CFI	≥ 0.90 (Hair et al., 2006)	0.960
TLI	≥ 0.90 (Hair et al., 2006)	0.952
RMSEA	< 0.05 (Hu & Bentler, 1999)	0.048
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 = normalized fit index, CFI = comparative fit index, TLI = Tucker Lewis index and RMSEA = root mean square error of approximation

According to Fornell and Larcker (1981), discriminant validity is confirmed when the AVE's square root is greater than any relevant construct coefficient. As shown in Table 5, the measurement model in this study was acceptable for discriminant validity because all AVE values were flat.

Table 5: Discriminant Validity

	SYQ	SEQ	PU	EE	PE	SAT	BI
SYQ	**0.811**						
SEQ	0.135	**0.809**					
PU	0.017	0.021	**0.820**				
EE	0.065	0.118	0.031	**0.814**			
PE	-0.029	0.187	0.002	-0.051	**0.835**		
SAT	0.289	0.15	0.101	0.014	0.054	**0.775**	
BI	0.046	0.195	0.012	0.131	0.517	0.401	**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)

Collier (1995) regarded SEM as a statistical technique for examining the relationship between variables using the covariance matrix of variables. Table 6 displays the appropriate indications. The statistical values are CMIN/DF = 556.558/265 or 2.100, GFI = 0.913, AGFI = 0.893, NFI = 0.918, CFI = 0.955, TLI = 0.949, and RMSEA = 0.049. To summarize, the above values can determine the fit of the structural model.

Table 6: Goodness of Fit for Structural Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 3.00 (Hair et al., 2006)	556.558/265 or 2.100
GFI	≥ 0.90 (Hair et al., 2006)	0.913
AGFI	≥ 0.85 (Schermelleh-Engel et al., 2003)	0.893
NFI	≥ 0.90 (Hair et al., 2006)	0.918
CFI	≥ 0.90 (Hair et al., 2006)	0.955
TLI	≥ 0.90 (Hair et al., 2006)	0.949
RMSEA	< 0.05 (Hu & Bentler, 1999)	0.049
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 = normalized fit index, CFI = comparative fit index, TLI = Tucker Lewis index and RMSEA = root mean square error of approximation

4.4 Research Hypothesis Testing Result

According to Lefcheck (2021), structural equation modeling can distinguish between measurement and structural models. In structural equation modeling, latent and unobserved structures are set up to integrate the path analysis framework with the measurement structure found in factor analysis. The observed variables of the measurement conceptualization originate from the former. The latter constructs relationships between constructs and incorporates mediating paths into the structural model. In the meantime, the structural equation model's route coefficients quantify the relationship between the exterior and internal potential variables. The results of hypothesis testing support H1, H2, H3, H4, H5, and H6, as shown in Table 7.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: SQY→SAT	0.258	4.985*	Supported
H2: SEQ→SAT	0.146	2.731*	Supported
H3: PU→SAT	0.111	2.102*	Supported
H4: SAT→BI	0.472	8.559*	Supported
H5: EE→BI	0.189	4.215*	Supported
H6: PE→BI	0.565	10.060*	Supported

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

H1: System quality significantly affects satisfaction with a standardized path coefficient of 0.258 and a t-value of 4.985*. According to the empirical study by da Silva (2014), system quality affects the use and satisfaction of online education. Samarasinghe (2012) proposed that user happiness increased with the technological quality of e-learning systems and supported this hypothesis with actual data. The Information Systems Success Model (Wang &Wang, 2009) suggests that system quality has a significant impact on user satisfaction. An earlier study by Rai et al. (2002) shows a favorable link between system quality and personal well-being. System quality is significantly influenced by user happiness (Almazán et al., 2017).

H2: Service quality significantly affects satisfaction with a standardized path coefficient of 0.146 and a t-value of 2.731*. Studies have shown that service quality significantly and positively affects online learning satisfaction (Xu et al., 2014). These first-class support services may produce professional participant acceptance rates and satisfaction with the web-based learning experience (Cidral et al., 2017). Ofori et al. (2018) claimed that high service quality improves the factors affecting customer well-being. According to an important study by Aparicio et al. (2017), the well-being of web-based learners is affected by the efficiency of e-education services. Tam (2000) also clearly stated that the level of service quality has a significant effect on customer satisfaction.

H3: Perceived usefulness significantly affects satisfaction with a standardized path coefficient of 0.111 and a t-value of 2.102*. Perceived usefulness is one of the elements influencing user satisfaction with e-learning services offered by certain worldwide United Nations agencies, according to Roca et al. (2006). Users of the New Zealand online banking system reported similar results (Lee et al., 2014), which is consistent with Wang and Wang (2009) assertion that perceived usefulness significantly influences customer satisfaction and willingness to continue using online banking services. In addition, previous research suggests that perceived usefulness may significantly impact satisfaction in online education (Joo et al., 2017). Similar findings were made by Lee et al. (2014) about the relationship between student satisfaction, perceived utility, and willingness to continue using educational programs.

H4: Satisfaction significantly affects behavioral intention with a standardized path coefficient of 0.472 and a t-value of 8.559*. Some scholars have argued that positive and negative outcomes of behavioral intentions are associated with negative emotions, and they have viewed satisfaction as an empathy survey (Babin & Babin, 2001). Despite this, emotional arousal has a stronger impact on behavioral intention than their dissatisfied disposition (Clemes et al., 2008). According to Munadi et al. (2022), satisfaction with online learning is a key indicator of people's behavioral intentions.

H5: Effort Expectation significantly affects Behavioral Intention with a standardized path coefficient of 0.189 and a t-value of 4.215*. According to previous studies, there is a significant association between effort expectancy and behavioral intention. Percy and Van Belle (2012) found that effort expectancy significantly affects behavioral intention (Keats, 2003). Students' expectations of how easy and effortless it is to adopt m-learning are reflected in their effort expectations (Mtebe & Raisamo, 2014). Effort expectations are reflected in the ease of innovation, the level of social impact, and the extent to which customers consider the opinions of friends and family on how to use modern technology, as well as effort expectations (Raman et al., 2022).

H6: Performance expectations significantly affect behavioral intention with a standardized path coefficient of 0.565 and a t-value of 10.060*. Raman et al. (2022) performance expectations are based on students' perceptions of the potential benefits of behavioral intentions. Samsudeen and Mohamed (2019), in their care study, also proposed that performance expectations and behavioral intentions impact students. In this case, performance expectations are the main factor influencing whether a professor will use an e-learning platform. According to Abbad (2021), performance expectations and affective expressions significantly affect the physical health of students who use online courses. Performance expectations are the main determinant of how behavioral intentions are used. Kuadey et al. (2021) results showed superiority over other traditional algorithms in predicting behavioral intentions through performance expectations.

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

This research examines the factors influencing undergraduates majoring in art enrolled in online courses in the Sichuan region and their behavioral goals. Three basic theories and pre-existing theoretical frameworks are the foundation for its conceptual framework. The framework encompasses system quality, service quality, perceived usefulness, effort expectancy, performance expectancy, satisfaction, and behavioral intentions. Researchers formulated six hypotheses centered around the research topic. They conducted preliminary testing on 50 questionnaires, using the Index of Item-Objective Congruence (IOC) and Cronbach's alpha to validate the questionnaire's validity and reliability. Data collection employed probability and non-probability sampling techniques, obtaining data from 500 participants in Chengdu. The convergent and discriminant validity of the measurement model was then assessed using confirmatory factor analysis (CFA), and the influences between the variables were examined using structural equation modeling (SEM) to get the research conclusions.

The following summary of the study's findings: Firstly, performance expectancy has the largest impact on behavioral intentions, indicating it is the most significant influencing factor. Numerous studies have shown that performance expectancy is a critical component when examining technology acceptance, substantially influencing behavioral intentions. According to Mikalef et al. (2016), performance expectancy dramatically increased behavioral intentions. According to Tarhini et al. (2016), performance expectancy is the most important latent variable among others and considerably impacts learners' behavioral intentions to utilize e-learning systems. The second influencing factor identified in this study is satisfaction. Behavioral intentions' positive or negative outcomes are associated with negative emotions, and satisfaction is viewed as an empathy survey (Babin & Babin, 2001). While emotional arousal has a greater impact on behavioral intentions than adverse reactions to satisfaction (Clemes et al., 2008), according to the research by Munadi et al. (2022), satisfaction with online learning is a key indicator of behavioral intentions. Next, system quality, service quality, and perceived usefulness significantly impact satisfaction, as demonstrated in this study. Samarasinghe (2012) proposed and supported with empirical data the hypothesis that user well-being improves with the technical quality of e-learning systems. The Information Systems Success Model (Wang & Wang, 2009) posits that system quality significantly impacts user satisfaction. Studies have indicated that online learning satisfaction is positively influenced by service quality (Xu et al., 2014). This high-level support service may increase professional participant acceptance rates and satisfaction with the web-based learning experience (Cidral et al., 2017). According to Roca et al. (2006), perceived usefulness is one of the factors affecting user satisfaction with e-learning services provided by several global institutions.

Similarly, effort expectancy also significantly influences behavioral intentions. Previous studies have shown a significant correlation between effort expectancy and behavioral intentions. Percy and Van Belle (2012) found that effort expectancy significantly impacts behavioral intentions (Keats, 2003). Students' expectations of the ease and effortlessness of adopting mobile learning are reflected in their effort expectancy (Mtebe & Raisamo, 2014).

In conclusion, the behavioral intentions of online learning satisfaction are determined by system quality, service quality, perceived usefulness, effort expectancy, and performance expectancy. Furthermore, satisfaction is a key predictor of behavioral intentions.

5.2 Recommendation

Researchers designed a survey focused on seven dimensions: system quality, service quality, perceived usefulness, effort expectancy, performance expectancy, satisfaction, and behavioral intentions. The goal was to understand how these factors influence the online learning satisfaction and behavioral intentions of art major undergraduates at public universities in Sichuan.

The study's conclusions can be summarized as follows: Among the variables of system quality, service quality, perceived usefulness, effort expectancy, performance expectancy, satisfaction, and behavioral intentions, performance expectancy emerged as the strongest predictor. This indicates that students' expectations regarding the performance of online learning systems greatly impact their overall behavioral intentions toward online learning. Satisfaction was the second most influential factor, demonstrating that students' contentment with their online learning experience significantly affects their intentions to use these platforms. Furthermore, while performance expectancy and satisfaction dominate in predicting behavioral intentions, other variables like system quality, service quality, perceived usefulness, and effort expectancy contribute to the overall model. High-quality systems and services can enhance perceived usefulness and satisfaction, influencing behavioral intentions. Similarly, ease of use (effort expectancy) and the practical benefits of the system (perceived usefulness) help foster positive behavioral intentions. These variables collectively highlight the key factors affecting art major undergraduates' online learning satisfaction and behavioral intentions.

In summary, the results indicate that improving the system performance and user experience of online learning platforms, providing practical and relevant course content, enhancing technical support and learning guidance to improve service quality, simplifying operations to reduce the difficulty of use, and regularly collecting feedback for continuous improvement are important steps. Additionally, incorporating cultural and social contexts and providing motivational support, such as reward mechanisms and achievement displays, can effectively increase student satisfaction and behavioral intentions, promoting a more efficient online learning experience.

5.3 Limitation and Further Study

Although this research offers insightful information about the online learning satisfaction and behavioral intentions of art major undergraduates in Sichuan, it has several limitations. Firstly, the research sample is limited to a specific region and discipline, affecting the results' applicability. Therefore, future studies should expand the sample to include more regions and disciplines to enhance external validity. Additionally, the study primarily relies on self-reported data, which may introduce subjective bias; thus, combining more objective data sources is recommended to enhance the reliability of the study.

Further research should also consider other potential influencing factors, such as motivation, learning styles, and cultural factors, which may significantly impact the results but were not included in the current study. Employing a longitudinal research design could help capture long-term trends and dynamic changes, thereby providing a deeper understanding of the complex mechanisms of online learning. By addressing these limitations, future research can reveal deeper influencing mechanisms and validate the applicability of the findings in other contexts.

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