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Key Drivers of E-learning Satisfaction and Behavioral Intention Among Art Major Undergraduates: Insights from a Public University in Sichuan, China

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Abstract

Purpose: This study aims to identify and examine the key factors influencing undergraduate art students' behavioral intentions and satisfaction with online learning at a public institution in Sichuan, including system quality, service quality, perceived usefulness, effort expectancy, and performance expectancy. **Research design, data, and methodology:** A quantitative research methodology was adopted through a survey administered to 500 undergraduate students with over one year of online learning experience. To ensure a representative sample, stratified random sampling, convenience sampling, and purposive sampling were employed. Before data collection, a pilot test (n = 50) and the Item-Objective Congruence (IOC) index were utilized to validate and ensure the reliability of the questionnaire. Convergent and discriminant validity of the measurement model were assessed using confirmatory factor analysis (CFA). Structural equation modeling (SEM) was then applied to examine the relationships between the variables. **Results:** The findings indicate that system quality and service quality significantly positively impact perceived usefulness and satisfaction. Both perceived usefulness and effort expectancy were found to positively influence students' satisfaction and behavioral intentions. Additionally, performance expectancy mediates the relationship between system quality and satisfaction, with satisfaction being a crucial determinant of behavioral intentions. **Conclusions:** The study highlights that improving system and service quality in online learning is a valuable strategy for enhancing the satisfaction and positive behavioral intentions of undergraduate art students.

Keywords: Perceived Usefulness, Satisfaction, Perceived Usefulness, System Quality, Art Students

JEL Classification Code: E44, F31, F37, G15

1. Introduction

The field of online education started to take shape with the arrival of the Internet era in the late 1990s. The online education sector has experienced tremendous transformation over the last 20 years, essentially falling into three phases: emerging, exploring, and maturing. Hu and Yu (2023) adopted a hypothesis-testing and sample-constructing approach in "A Study of the Mechanisms Influencing the Continuous Use of Online Learning Platforms by Chinese College Students." They investigated how three different expectations affect college students continued use of online learning environments. Ren (2021) examined the factors that influence online learners' continued willingness to learn from an ECM perspective in his article “A Study of Influencing Factors of Online Learners' Continued Willingness to Learn” and came up with the corresponding results.

In most art colleges today, undergraduate art students are taught and trained primarily using a fixed offline approach and other hybrid methods. Together, these components make up our primary art education and training program. It has remained constant over time, emphasizing "accuracy" in modeling. Students are taught the fundamentals of the Laws of Art using "similarity" as a benchmark. Undoubtedly, a

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unique pedagogical philosophy should be developed for each subject. Key factors include the type of teaching philosophy developed, who evaluates the value and importance of the philosophy, and whether the philosophy should be kept current.

The results of this study can help university instructional administrations make better decisions when allocating educational resources to art programs, create management systems that are better suited to the needs of online learning, and modify small investments in hardware, software, and other online learning resources. In addition, by developing new educational paradigms, creating online learning materials, designing blended-mode instructional strategies, utilizing information technology in this context, and constructing online instruction courses, the results of this study can increase faculty proficiency in teaching online, can help students better adapt to blended learning, and can help them recognize the differences between traditional modes of learning and how to apply such strategies for maximum Learning outcomes.

2. Literature Review

2.1 System Quality

According to the learners, the system enhanced their performance, education, and educational activities. The efficacy of e-learning services and systems significantly improves student performance, and student happiness is also positively impacted. (Thnayan & Husain, 2021). People's contentment with hybrid e-learning systems can be attributed to the significant influence that system quality has on perceived process and utility validation (Cheng, 2014). System quality refers to a system's functionality, including responsiveness, navigation, usability, and dependability (Gao & Bai, 2014).

These authors (DeLone & McLean, 2003) contend that the system's technological capabilities, usability, and utility are all factors that affect system quality. According to McKinney et al. (2002), it is acknowledged to impact a variety of factors, including performance traits, efficiency, and accessibility. These authors (DeLone & McLean, 2003) claim that Learners would believe that an e-learning system should meet their requirements for helpful features when it can provide them with more relevant and more advanced features to support their learning objectives. The technological capabilities, usability, and utility of the system are all quality factors. Their level of satisfaction with the solution and readiness to use it will significantly increase (Roca et al., 2006).

H1: System quality has a significant impact on satisfaction.

2.2 Service Quality

Effective service support in an e-learning system requires high service quality, which could be gauged by traits like adaptability, compassion, confidence, and confidentiality (DeLone & McLean, 2003). A company's excellent customer service primarily measures customer service consistency. Researchers are now reevaluating the value of high service standards as it has evolved to electronic quality of service due to technology (Rughoobur-Seetah & Hosanoo, 2021). According to Roca et al. (2006), service quality is a broad evaluation or perspective on an excellent offering. Service quality is the measure of how well customers are supported by the information system, including support and retraining (Mohammadi, 2015).

It is imperative to underscore the significance of service quality in shaping student happiness. (Rughoobur-Seetah & Hosanoo, 2021). Although the managed support options provided by different customer service specialists are frequently the focus of performance evaluation of personal services provided by the typical example, and the educator dimension of service quality is frequently thought of as the benchmark of instructor quality, service quality in the area of e can be thought of as the assistance offered by instructors and customer service specialists. (Cheng, 2012). The adaptive design, involvement, and reliability that online learning may offer were universally praised by respondents, as evidenced by their satisfaction and the system's usage (Aldholay et al., 2018).

H2: Service quality has a significant impact on satisfaction.

2.3 Perceived Usefulness

According to Mouakket and Bettayeb (2015), perceived usefulness refers to people's perception that employing information technologies will improve productivity at work. According to Davis, perceived usefulness is the arbitrary likelihood that a specific application system would improve a potential user's output or performance. The Technology Acceptance Model (TAM), which explains why users adopt a certain kind of technology, also includes this as one of its fundamental premises (Davis et al., 1989). According to Islam et al. (2017), "perceived usefulness" describes how students view the advantages of utilizing the internet through wireless devices. When a new technology is used to complete a task, how much improvement is added to the worker's productivity is referred to as perceived usefulness. It is always considered the main cause of embracing cutting-edge technology, particularly e-learning.

Previous research has shown that a user's opinion of how beneficial a system is affects how much they like using it and whether they plan to keep doing so (Mouakket & Bettayeb, 2015). Products may be included in the TAM framework

partly because of their usefulness. (Davis et al., 1989). Perceived usefulness was one of the key variables that, when combined with wireless internet technology, significantly influenced students' SAT performance, according to the TSM (Islam et al., 2017). Perceived usability has been demonstrated to be a good indicator of user behavior during both the early and post-adoption phases, according to a study by Gao and Bai (2014). However, as users gain more user experience, the impact of perceived usability gradually diminishes and becomes less significant. In both the early adoption and post-adoption phases, perceived usability has been proven to be a reliable predictor of user behavior (Gao & Bai, 2014).

H3: Perceived usefulness has a significant impact on satisfaction.

2.4 Satisfaction

The category of thoughts that a person has when using a service and feels good about it is called satisfaction (Mouakket & Bettayeb, 2015). Aldholay et al. (2018) claim that it also depends on how content online students are with their decision to utilize it and how effectively it meets their needs. In information systems, satisfaction has already been widely utilized as a measurement tool since it is one of the most significant indicators for assessing the success of new system adoption. The e-learning system's users are also encouraged to utilize it in the future based on their satisfaction. Consumers' general attitudes toward a service or good and emotional responses to it are important considerations. It may be summed up by gauging how much the interaction made them happier (Cheng, 2014).

Numerous research has revealed that students' decisions to stick with an online learning platform are influenced by their level of satisfaction (Samarasinghe, 2012). Total happiness is what we define as an affective state that results from an emotional response to the full Web site search process. This concept emphasizes the process assessment associated with the purchase activity more than the outcome-oriented approach, which emphasizes the buyer's cognitive state because of the consuming experience (McKinney et al., 2002). Using a learning management system as an example, it is believed that feeling fulfilled strongly predicts future willingness to use the system to enhance learning (Mouakket & Bettayeb, 2015).

H4: Satisfaction has a significant impact on behavioral intention.

2.5 Effort Expectancy

According to Asghar et al. (2021), Effort Expectancy (EE) is the simplicity of usage. From the previous study, the ease of use in TAM and complexity in MPCU are connected to effort expectations. Technology must have an interface that is simple to use. The concept of effort expectancy (EE), according to Venkatesh et al. (2012), is "the degree of ease associated with the use of the system." One of the direct predictors of BI, according to UTAUT, is EE. According to several research, EE significantly influences BI (Bardakci, 2019). "The degree of ease with which the system is to be used" is the definition of effort expectancy (EE). According to UTAUT, EE is one of the key indicators of BI. Numerous studies have found that EE greatly impacts BI (Bardakci, 2019). Mtebe and Raisamo (2014) define effort expectation as "the degree of ease connected with system usage."

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

2.6 Performance Expectancy

Performance Expectancy (PE), according to Asghar et al. (2021), is the extent to which a person believes in employing technology. Both positive and negative results can be evaluated using the PE factor. The user's gender and age impact their Performance Expectancy (PE), defined as "the extent to which an individual believes that using the system will help him or her to attain gains in job performance." UTAUT proposed PE as one of the factors directly influencing whether people want to utilize technology. According to Mtebe and Raisamo (2014), performance expectation is "the extent to which an individual expects that using the system will help the individual to attain gains in job performance."

Performance expectations were developed based on the students' opinions regarding the possible advantages of utilizing YouTube for educational purposes. The hypothesis behind this study was that students would be more inclined to utilize YouTube if they thought it would be helpful and raise the standard of their education. This assumption was by past studies on UTAUT. According to Mtebe and Raisamo (2014), performance expectancy is the best indicator of behavioral intention to use various technologies in voluntary and involuntary situations. It assesses students' perceptions of how much mobile learning would improve their academic performance and yield superior results (Xu et al., 2014). According to Mtebe and Raisamo (2014), performance expectancy is the best indicator of behavioral intention to use various technologies in voluntary and involuntary situations.

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

2.7 Behavioral Intention

As stated by Bardakci (2019), "Intentions are assumed to capture the motivational factors that influence a behavior; they are indications of how hard people are willing to try and

of how much of the effort they are going to put forth to achieve the behavior." BI is used as a proxy measure of user acceptability and technological utilization.BI monitors the interests and plans of high school students using YouTube for educational purposes. The technology acceptance model was created by Mizher et al. (2022) to forecast user adoption of new technologies before they are launched. The behavioral objectives of the user may predict how they will use new technology.

Carlson and O'Cass (2010) claim that due to the internet environment, perceptions of e-service quality may all be elevated, which might improve e-commerce online competitive advantages regarding customer stickiness, purchase intent, and favorable word-of-mouth referral behaviors. To predict behavioral intention to utilize OER in teaching, much work must be put into expanding the UTAUT model with new elements. According to Bardakci (2019), a few variables are attitude, information quality, and awareness. The explained variance of BI did not perform any better than the initial UTAUT model put out by Or (2023), despite efforts to look at additional direct links between the variables in Model 2. 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.

3. Research Methods and Materials

3.1 Research Framework

This study aimed to find the conceptual framework that affects undergraduate art students' behavioral intention and satisfaction with online learning. The survey disclosed every study variable: three main ideas and earlier theoretical frameworks were the foundation for developing the research framework. The conceptual framework of this study is based on theories such as ISSM, TAM, UTAUT model, and D & M IS model. The researcher concluded this investigation after making various connections. Abbad (2021) firstly presented the framework of previous research which includes the study of Performance expectancy, effort expectancy, social influence, and facilitating factors. In Figure 1, the study framework is displayed.

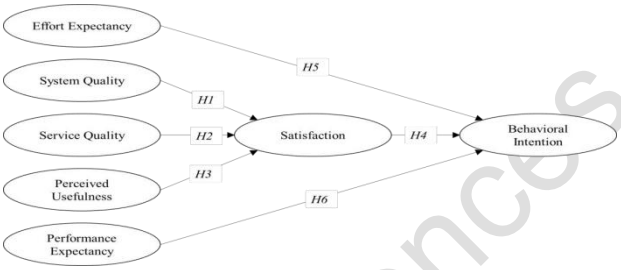

Figure 1: Conceptual Framework

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

The study's target audience was the art majors at a public undergraduate university in Chengdu, China. Undergraduate students who had completed at least one year of online school 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. Likert scales with five points were used to measure the variables.

Furthermore, the researcher evaluated content validity using the Item Objective Consistency Index (IOC) before administering the questionnaire. Fifty target group members underwent a Cronbach's alpha test to confirm the questionnaire's reliability. The results of IOC were passed at above 0.6. In addition, Cronbach's alpha results for pilot test were acceptable at 0.7 and over. 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

Malhotra and Segars (2005) describe the target population as a set of elements that provide essential information about the study's design. Cooper and Schindler (2014) define the target population as a group of individuals sharing similar characteristics and values related to the study. Clark-Carter (2010) suggests that the target population

consists of individuals who exhibit comparable behavior toward specific items. Additionally, Cooper and Schindler (2011) explain that the target population may consist of individuals, records, or events. Zikmund et al. (2013) state that the target population comprises individuals with common traits, a notion supported by Malhotra and Birks (2007), who argue that the researcher's interest lies in this group. Larson and Larson (1987) adds that measuring a larger percentage of the population increases dataset precision. According to Taherdoost (2017), the sample size is a critical element in empirical research aimed at making inferences about a population. For this study, the appropriate sample size was calculated, recommending a minimum of 425 participants. However, Hair et al. (2010) suggest that the model's measurement density should guide sample size determination. Therefore, 600 questionnaires were distributed, with 500 being valid for analysis.

3.4 Sampling Technique

Quantitative methods were employed for both data collection and analysis. The researcher utilized a combination of probability and non-probability sampling techniques. The sampling process was conducted in three stages: convenience sampling, stratified random sampling, and purposive sampling. Initially, undergraduate students majoring in cinema and animation at a public institution in Chengdu, China, who had completed over a year of online learning, were selected using purposive sampling. Data were then collected proportionally through stratified random sampling, as shown in Table 2. To distribute the online questionnaires, the researcher used convenience sampling, sending them via WeChat, social media, and email with the necessary permissions from both the schools and students.

Table 1: Sample Units and Sample Size

Target Institution	Subjects	Population	Sample Units and Sub-Sample Size
School of Fine Arts and Design	Visual Communication Design	487	224
	Environmental art design	301	138
	Product design	301	138
Total		**1089**	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

Table 2 shows that 382 (76.44%) of the 500 respondents were female, and 118 (23.56.05%) were male. There were 224 (44.8%) students studying visual communication design. Environmental Art and Design students totaled 138 (27.6%). Product Design students totaled 138, or 27.6%. They are all public university undergraduates with more than a year of online learning experience between them.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	118	23.56%
	Female	382	76.44%
Major	Visual Communication Design	224	44.8%
	Environmental art design	138	27.6%
	Product design	138	27.6%

4.2 Confirmatory Factor Analysis (CFA)

To assess the convergent validity of the conceptual model, this study used factor loading, average variance extracted (AVE), and composite reliability (CR) as standard measures (Hair et al., 2013). The reliability of the questionnaire was evaluated using Cronbach's alpha, with all constructs in the study found to be reliable, as each group's alpha coefficient exceeded 0.7. Convergent and discriminant validity of the measurement model were initially examined through confirmatory factor analysis (CFA), a method developed by Jöreskog (1969). Byrne (2010) also highlighted two key validity methods: convergent and divergent validity. Alkhadim et al. (2019) considered CFA a crucial technique for analyzing all expected variables in a structural model. All variables in the study had factor loading values greater than 0.5 and p-values below 0.05, deemed acceptable (Hair et al., 2013). Furthermore, every variable had an AVE value exceeding 0.5 and a CR value above 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	0.855	0.546-0.923	0.858	0.558
Service Quality (SEQ)	Samarasinghe (2012)	3	0.823	0.658-0.866	0.830	0.622
Perceived Usefulness (PU)	Rughoobur-Seetah and Hosanoo (2021)	3	0.860	0.799-0.834	0.860	0.672
Effort Expectancy (EE)	Mtebe and Raisamo (2014)	4	0.891	0.694-0.933	0.892	0.677
Performance Expectancy (PE)	Mtebe and Raisamo (2014)	4	0.871	0.599-0.939	0.872	0.637
Satisfaction (SAT)	Samarasinghe (2012)	3	0.820	0.744-0.810	0.822	0.607
Behavioral Intention (BI)	Alamri (2021)	3	0.818	0.740-0.843	0.820	0.604

According to Brown (2015), confirmatory factor analysis (CFA) is utilized to assess the compatibility of the measurement model between observed and latent variables with the observed data. Ainur et al. (2017) noted that the Goodness-of-Fit (GOF) index serves as a measure of how well the model aligns with the data. The GOF values presented in Table 4 are as follows: GFI = 0.918, AGFI = 0.894, NFI = 0.917, CFI = 0.954, TLI = 0.946, RMSEA = 0.049, and CMIN/DF = 529.705/253, which simplifies to 2.094.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 3.00 (Hair et al., 2006)	529.705/253or 2.094
GFI	≥ 0.90 (Hair et al., 2006)	0.918
AGFI	≥ 0.85 (Schermelleh-Engel et al., 2003)	0.894
NFI	≥ 0.90 (Hair et al., 2006)	0.917
CFI	≥ 0.90 (Hair et al., 2006)	0.954
TLI	≥ 0.90 (Hair et al., 2006)	0.946
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

Fornell and Larcker (1981) assert that discriminant validity is established when the square root of the average variance extracted (AVE) exceeds any associated construct coefficient. As demonstrated in Table 5, this study's measurement model was deemed acceptable for discriminant validity since all AVE values were satisfactory.

Table 5: Discriminant Validity

	SYQ	SEQ	PU	EE	PE	SAT	BI
SYQ	**0.747**						
SEQ	0.287	**0.789**					
PU	0.058	-0.067	**0.820**				
EE	0.035	0.068	-0.032	**0.823**			
PE	0.184	0.138	0.006	0.071	**0.798**		
SAT	0.179	0.118	0.369	-0.032	0.128	**0.779**	
BI	0.11	0.013	0.086	0.119	0.261	0.430	**0.777**

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

4.3 Structural Equation Model (SEM)

Using the covariance matrix of the data, Collier (1995) employed structural equation modeling (SEM) as a statistical technique to investigate the relationships among variables. Table 6 presents the fitting indicators: CMIN/DF = 515.842/266, or 1.939; GFI = 0.920; AGFI = 0.902; NFI = 0.919; CFI = 0.959; TLI = 0.954; and RMSEA = 0.045. In summary, these statistics can be used to evaluate the adequacy of the structural model fit.

Table 6: Goodness of Fit for Structural Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 3.00 (Hair et al., 2006)	515.842/266 or 1.939
GFI	≥ 0.90 (Hair et al., 2006)	0.920
AGFI	≥ 0.85 (Schermelleh-Engel et al., 2003)	0.902
NFI	≥ 0.90 (Hair et al., 2006)	0.919
CFI	≥ 0.90 (Hair et al., 2006)	0.959
TLI	≥ 0.90 (Hair et al., 2006)	0.954
RMSEA	< 0.05 (Hu & Bentler, 1999)	0.045
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. By establishing latent and unobserved structures, structural equation modeling integrates the route analysis framework with the measurement structure found in factor analysis. The former is where the measurement conceptualization's observed variables come from. In the latter, mediating routes are incorporated into the structural model and construct linkages between constructs. In the meantime, the structural equation model's route coefficients quantify the relationship between the exterior and internal potential variables. As seen in Table 7, the results of hypothesis testing support H1, H2, H3, H4, H5, and H6.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: SQY→SAT	0.143	2.861*	Supported
H2: SEQ→SAT	0.103	2.030*	Supported
H3: PU→SAT	0.425	7.751*	Supported
H4: SAT→BI	0.475	8.235*	Supported
H5: EE→BI	0.103	2.180*	Supported
H6: PE→BI	0.229	4.523*	Supported

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

H1: System quality significantly affects satisfaction with a standardized path coefficient of 0.143 and a t-value of 2.861*. This means that system quality leads to learners' satisfaction with e-learning. According to Hossain (2016), the platform's quality significantly impacts user satisfaction. According to the empirical study by Machado da Silva in 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.

H2: Service quality significantly affects satisfaction with a standardized path coefficient of 0.103 and a t-value of 2.030*. Previous studies have shown that service quality affects customer satisfaction (Chang & King, 2005). According to Isik (2008), quality and customer happiness are related. Previous studies have shown that customer satisfaction is related to service quality (Chang & King, 2005). The quality of service affects learners' satisfaction with the education system (Rughoobur-Seetah & Hosanoo, 2021). 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 0.425 and a t-value of 7.751*. A reliable predictor of user satisfaction with an e-learning platform is how useful they perceive it to be (Roca et al., 2006). According to an earlier study by Jafari Navimipour and Zareie (2015), confirmation and perceived utility influence consumer happiness with e-learning. The perceived utility of an online education platform is a key determinant of user satisfaction (Cheng, 2019). According to earlier research, users' satisfaction with an information system and their determination to continue using it is positively influenced by their perceptions of its utility (Mouakket & Bettayeb, 2015).

H4: Satisfaction significantly affects behavioral intention with a standardized path coefficient of 0.475 and a t-value of 8.235*. Athiyaman (1997) suggests a link between satisfaction and subsequent behavioral intention among college students. Many studies on behavioral intentions and satisfaction have shown a link between these variables and participants' well-being (Machleit & Mantel, 2001). According to Munadi et al. (2022), satisfaction with online learning is a key indicator of people's behavioral intentions. Some scholars have argued that positive and negative outcomes of behavioral intentions are associated with negative emotions, and they view satisfaction as an empathy survey (Babin & Babin, 2001).

H5: Effort expectancy significantly affects behavioral intention with a standardized path coefficient of 0.103 and a t-value of 2.180*. Samsudeen and Mohamed (2019) According to this study, effort expectancy has the greatest effect on behavioral intention in the use of an e-learning system. Gunasinghe et al. (2020). had similar findings on key predictors of academicians. In a previous study, behavioral intention was found to be a highly reliable predictor. This independent variable was a key factor influencing learners' use of e-relevant learning systems and an important and critical factor influencing learners' use of online systems (Gunasinghe et al., 2020).

H6: Performance Expectation significantly affects Behavioral Intention with a standardized path coefficient of 0.229 and a t-value of 4.523*. Many studies have shown that performance expectation is a key component to be considered when examining technology acceptance, and it has a considerable effect on behavioral intention. Mikalef et al. (2016) found that performance expectation significantly increased behavioral intention. Tarhini et al. (2016) found that performance expectation significantly affects learners' behavioral intention to use the e-learning system. It has the highest estimated value and is the most influential potential variable among other variables.

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

This study aims to examine the variables that influence the happiness and behavioral intentions of art undergraduates learning online in the Sichuan region. The conceptual framework is built upon three foundational concepts and previous theoretical models, incorporating variables such as system quality, service quality, perceived usefulness, effort expectancy, performance expectancy, satisfaction, and behavioral intentions. Based on the research questions, the researchers formulated six hypotheses and conducted a preliminary test with fifty respondents. The validity and reliability of the questionnaire were assessed using Cronbach's alpha and the Index of Item-Objective Congruence (IOC). Data collection utilized both probability and non-probability sampling methods to gather responses from 500 participants in Chengdu, China. Confirmatory factor analysis (CFA) was employed to evaluate the convergent and discriminant validity of the measurement model, while structural equation modeling (SEM) was used to analyze the impacts of the various variables and draw research conclusions.

The findings of the study are summarized as follows: First, satisfaction emerged as the most significant factor influencing behavioral intentions, aligning with existing research. Behavioral intentions were associated with negative emotions, with satisfaction perceived as a reflection of empathy (Babin & Babin, 2001). While emotional arousal was found to impact behavioral intentions more than

negative satisfaction (Clemes et al., 2008), Munadi et al. (2022) highlighted that satisfaction with online learning is a crucial indicator of behavioral intentions.

Second, perceived usefulness was found to have a significant effect on satisfaction. Prior studies indicate that perceived usefulness positively influences satisfaction in online education (Joo et al., 2017). Lee et al. (2014) also reported similar findings regarding the relationship between learner satisfaction and the intention to continue using courses based on perceived usefulness.

Next, system quality positively impacted satisfaction. Hossain (2016) noted that platform quality plays a significant role in user satisfaction, supported by Machado da Silva's (2014) empirical study, which found that system quality affects both usage and satisfaction in online education. The results further validated that service quality positively influences satisfaction, with Isik (2008) demonstrating a relationship between service quality and customer well-being, while Chang and King (2005) emphasized its importance in customer satisfaction. Rughoobur-Seetah and Hosanoo (2021) also found that service quality in educational systems affects learner satisfaction.

Additionally, effort expectancy significantly impacted behavioral intentions. Percy and Van Belle (2012) identified a strong relationship between effort expectancy and behavioral intentions (Keats, 2003). Performance expectancy also significantly influenced behavioral intentions. Abbad (2021) noted that performance expectancy and emotional expression substantially affect the physical health of students engaged in online courses, positioning performance expectancy as a key determinant of behavioral intentions. Kuadey et al. (2021) found that performance expectancy is superior in predicting behavioral intentions compared to traditional algorithms.

In conclusion, behavioral intentions in online learning satisfaction are shaped by system quality, service quality, perceived usefulness, effort expectancy, and performance expectancy, with satisfaction serving as a key predictor of these intentions.

5.2 Recommendation

The researchers crafted their study around seven dimensions: system quality, service quality, perceived usefulness, effort expectancy, performance expectancy, satisfaction, and behavioral intentions. These dimensions were used to understand the influence of these factors on the satisfaction and behavioral intentions of art major undergraduates' online learning in public universities in the Sichuan region.

All key factors need to be developed and promoted to enhance students' satisfaction with online courses. The study found that satisfaction is the strongest predictor, having a direct and significant impact on students' online learning behavioral intentions. Therefore, increasing satisfaction should be a primary goal for any product or service provider. Perceived usefulness was identified as the second strongest predictor. When users see a system or service as practical and effective, their intention to use it significantly increases. Hence, ensuring that users perceive a product or service as valuable and useful can effectively drive their behavioral intentions. Improving user satisfaction and perceived usefulness is crucial for enhancing users' continued usage and behavioral intentions.

Meanwhile, the indirect effects of system quality, service quality, effort expectancy, and performance expectancy should be considered, as they may indirectly affect users' behavioral intentions by influencing satisfaction and perceived usefulness. High-quality systems typically enhance user experience, increasing satisfaction and perceived usefulness. Excellent service can enhance user satisfaction and positively influence users' perceptions of the system or service. Lower usage difficulty (effort expectancy) may also enhance satisfaction and perceived usefulness. Systems that meet or exceed users' expected performance standards increase perceived usefulness and satisfaction.

In summary, the researchers outlined the factors influencing art major undergraduates' satisfaction and behavioral intentions in online learning. This provides a reference for curriculum developers and decision-makers in higher education, allowing them to reasonably utilize these research findings to demonstrate and enhance the effectiveness of higher education programs in subsequent stages.

5.3 Limitation and Further Study

This study has several limitations, even though it offers insightful information about the behavioral intents and level of satisfaction of undergraduate art majors in Sichuan region public universities regarding their online learning experiences. The restricted geographical and disciplinary scope of the research sample impacts the overall applicability of the findings. Future studies should use a longitudinal approach and increase the sample size to capture long-term patterns. Additionally, reliance on self-reported data may introduce bias, so it is recommended to include objective data to enhance reliability. Other potential variables, such as motivation, learning styles, and cultural factors, which might influence the results, should have been included and considered in subsequent studies. By addressing these limitations, further research can uncover deeper mechanisms affecting online learning experiences and verify the universal applicability of the results.

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