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Factors Impacting on Satisfaction and Behavioral Intention of Social Science Majors Students Toward E-learning: A Case Study of a public university in Sichuan, China

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Abstract

Purpose: This research aims to examine the factors impacting social science majors' students' satisfaction and behavioral Intention to use electronic learning (E-learning) in a public university in Sichuan, China. The conceptual framework identifies the causal relationship between system quality, satisfaction, performance expectancy, effort expectancy, social influence, attitude, and behavioral intention. **Research design, data, and methodology:** Sample data was collected using the quantitative method and a questionnaire (N=500) as a tool. Item-Objective Congruence and pilot tests were adopted to test the content validity and reliability of the questionnaire before distribution. Data was analyzed by utilizing Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) to validate the model's goodness of fit and confirm the causal relationship among variables for hypothesis testing. **Results:** System quality, satisfaction, performance expectancy, effort expectancy, social influence, and attitude significantly impact behavioral intention. Furthermore, performance expectancy has the strongest impact on the behavioral intention of E-learning among social science majors' students. **Conclusions:** The creator of the course curriculum, the instructors, and the administration should guarantee the system's high quality. It is recommended that professors and university administration employ the active learning technique in online lectures to ensure maximum student participation and arouse their interest.

Keywords: E- learning, System Quality, Satisfaction, Behavioral Intention, Higher Education

JEL Classification Code: E44, F31, F37, G15

1. Introduction

Technology permeates many industries, encouraging educators and students to rethink their established approaches to teaching and learning (Kumar Basak et al., 2018). Electronic learning (E-learning) referred the utilization of the Internet and technology to offer educational materials and knowledge to individual students (Rosenberg, 2001).

Information technology, represented by computer technology and communication technology, has profoundly influenced people's lifestyles and education. With

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interconnected facilities, education is an ecosystem where instruction and learning can occur at any time and location (Van Hoa et al., 2020)—information technology and education combined since the beginning of the Internet in the late 1990s. China's e-learning industry has gradually become mature after continuous exploration. The process can be divided into three stages. In the 1990s, Internet education based on information and technology emerged. The development of online learning in this period had strong limitations, mainly due to the limitation of the external environment. With the enhancement of network broadband service performance, many Internet education firms have established enterprise models. Online education starts exploring and evolving continuously. Multimedia, new media, and we media have joined the online education industry, with products changing with each passing day and business models that are constantly updated. Entering the era of diversified online education with tools, platforms, and content, low-quality online education products are gradually falling behind, and the online education market is gradually becoming rational.

Higher education institutions were undergoing a technological revolution due to the rapid expansion of e-learning (Sihar et al., 2011). Information and communications technology (ICT) is critical to higher education institutions' fundamental functions, including teaching and learning in on-campus, online, and hybrid environments (Sun et al., 2008). Education in universities generally uses e-learning, which promotes improving students' information processing ability, autonomous learning ability, communication ability, and critical thinking ability. Thus, this research aims to examine the factors impacting social science majors' students' satisfaction and behavioral Intention to use electronic learning (E-learning) in a public university in Sichuan, China. The conceptual framework identifies the causal relationship between system quality, satisfaction, performance expectancy, effort expectancy, social influence, attitude, and behavioral intention.

2. Literature Review

2.1 System Quality

According to DeLone and McLean (2003), three different quality criteria were system quality, service quality, and information quality constructed in the most recent version of the Information Systems Success (ISS) model. Moreover, system quality indicates how well an information system operates regarding its precision, practicality, efficiency, adaptability, reliability, and responsiveness (Lee et al., 2009). Elevated system quality levels could produce a pleasant working environment for users, allowing them to quickly recognize the many functional groupings that the information system (IS) offers and explore the various resources that the IS made available (Huang & Duangekanong, 2022). This construct measures the quality of education features available through e-learning. Some elements included in this construct are utility, flexibility, discussion, forum, media, and other cooperative characteristics (Alksasbeh et al., 2019).

Ho et al. (2010) found that the system's quality can play an important role in defining learners' behaviors within an e-learning setting. The course content quality significantly impacted students' overall satisfaction with the system's quality (Lederer et al., 2000). DeLone and McLean (2003) suggested that system quality influenced user satisfaction positively. Thus, the following hypothesis is drawn:

H1: System quality has a significant impact on satisfaction.

2.2 Satisfaction

Student satisfaction was defined as increased knowledge and abilities in e-learning (Reynolds, 2011). The learner's subjective impression of the learning procedure and outcomes is reflected in their level of learning satisfaction (Leong, 2011). According to Elliott and Shin (2002), student satisfaction is a state of happiness experienced when a person's needs and desires are met. In addition, students with a strong intention during the online learning procedure would have the desire, awareness, independence, self-confidence, and eagerness to obtain achievement satisfaction and influence friends (Patricia, 2020). System satisfaction is the overall satisfaction among students who used it and have come to appreciate its value as an e-learning tool.

Satisfaction refers to an individual's favorable attitude about utilizing a certain technology, product, or service, which may be a positive or negative emotion to future action (Jamal & Naser, 2003). High levels of learning pleasure might be anticipated if the learner's anticipated goal is achieved. The satisfaction experienced by students is seen as a decisive factor in determining whether they would continue to take advantage of online learning possibilities and whether or not they would recommend such chances to other individuals (Lu et al., 2019). As a result, the following hypothesis is proposed in the study:

H2: Satisfaction has a significant impact on behavioral intention.

2.3 Performance Expectancy

Acceptance and Use of Technology (UTAUT) divided the factors affecting user acceptance or use into dimensions (Venkatesh et al., 2003). Among them, Performance expectancy determined users' behavioral intention. Besides,

four control variables were introduced to adjust the influence of core variables. PE was equivalent to perceived usefulness in TAM and was regarded as the most critical core variable to illustrate the behavioral intention of information systems. Venkatesh et al. (2003) pointed out that PE was when a person believed that employing technique could raise his or her work performance. It was commonly assumed that this would result in enhanced efficiency. It referred to individuals who were certain that if they accepted certain systems, such systems would assist them in accomplishing a desired result. PE may be described as utility, convenience, time savings, and efficiency (Gupta & Sharma, 2016). Consequently, performance expectancy is a crucial determinant of ICT use intent. Existing research suggests that the less effort required to comprehend a technology, the greater the desire to embrace it (El-Masri & Tarhini, 2017). This study indicated that students would embrace e-learning when they felt it would improve academic success (Rudhumbu, 2020). According to this argument, the hypothesis stated below is offered:

H3: Performance expectancy has a significant impact on behavioral intention.

2.4 Effort expectancy

Effort expectation was a system's level of simplicity and usability (Venkatesh et al., 2003). Providing that any system that users become aware of is easy to use, there is likely a sense of benefits and an inclination to act in a particular manner (Thongsri et al., 2018). Numerous studies have stressed the significance of users' behavioral intentions regarding effort expectancy. The perceived difficulty level is proportional to the ease of operating the system. Students' perceptions of how simple or difficult it is to accept and make use of technologies are reflected in what is known as the effort expectancy construct. Empirical investigations have demonstrated that this phenomenon exists in learners' beliefs in the setting of e-learning (Lee et al., 2009). In this regard, learners who feel that a particular e-learning technology requires little effort to implement are more likely to anticipate that it would produce superior learning outcomes. Thus, a hypothesis is established based on this evidence:

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

2.5 Social Influence

Social influence is the manner that the views of influential individuals affect an individual's decision-making (Sun et al., 2008). Moreover, social influence refers to the social pressure individuals feel when accepting new technologies, such as recommendations from friends and advertisements in the media. SI is similar to the subjective norm addressed in the TPB, which means an individual was influenced by others, groups, subjective norms, and external factors (Venkatesh et al., 2003).

People frequently seek to consolidate others' ideas when uneasy about using technology (Ibukun et al., 2016). In the original UTAUT mod, SI significantly impacts customers' willingness to accept and use new technologies. It was discovered that people tend to discuss their technological acceptance with others (Thongsri et al., 2018). A peer-to-peer information exchange results in preconceived notions regarding the utility of e-learning technologies (Miller et al., 2003). It was decided that social influence was a key factor in how students decided to act on their plans to use e-learning to learn. Thus, this study suggests the following:

H5: Social influence has a significant impact on behavioral intention.

2.6 Attitude

Ajzen (1991) introduced that the Theory of Planned Behavior (TPB) goal is applied to foretell and explicate customer behavioral intention. TPB was introduced initially by (Ajzen, 1985) and developed by Ajzen (1991) as well. The TPB defined attitude toward the activity as positive or negative sentiments about the performance of an action. Attitude played an important part in describing the model and comprehending consumer technology use (Upadhyay et al., 2022). It is associated with how customers judge the behavior, resulting in a favorable or unfavorable opinion (Ajzen, 1991).

Literature demonstrated that attitude substantially affected Information System usage and acceptability (Lee et al., 2011; Liao et al., 2009). People acted according to their behavioral intentions, which were highly susceptible to attitudinal, subjective, and controlling influences (Ajzen, 1991). People were more likely to keep using a new system or piece of technology if they liked it and thought it would help them. Therefore, it was assumed that when people had a favorable opinion of an e-learning application, they would be more inclined to use it (Lee et al., 2011). Moreover, this study discovered that attitudes about use greatly influenced students' behavioral intention to utilize e-learning. In light of this argument, the following hypothesis is proposed:

H6: Attitude has a significant impact on behavioral intention.

2.7 Behavioral intention

BI was the individual's willingness and effort to accomplish the underlying behavior. Scholars contended that intentions might encompass a variety of motivating elements that impact an individual's behavior (Upadhyay et al., 2022). The background showed that users' willingness to embrace e-learning systems was determined by behavioral intention

(Salloum et al., 2019). Kwok and Gao (2005) said that individuals were likelier to engage in a certain behavior if they had a favorable attitude toward that behavior, and vice versa. The individual's perceived likelihood was that he or she would engage in the conduct in issue and arrange to utilize certain technology (Davis, 1989).

3. Research Methods and Materials

3.1 Research Framework

This paper's conceptual framework is primarily made up of four different earlier theoretical frameworks. Chao (2019) researched Satisfaction (SA) in the first framework. Tan (2013) provided research on Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Behavioral Intention (BI) in the second framework. Boateng et al. (2016) researched Attitude (AT) in the third frame. Cidral et al. (2020) provided research on System Quality (SQ) in the fourth framework. To sum up, there were seven variables in the conceptual framework of this study. These variables may be classified into three groups: independent variables (IV), intermediate variables (MV), and dependent variables (DV). The suggested conceptual framework for the study is shown in Figure 1.

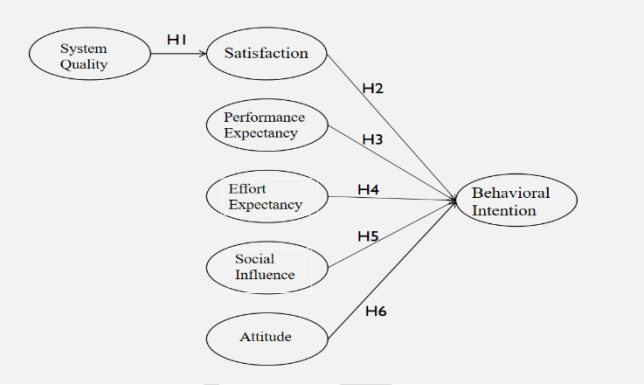

Figure 1: Conceptual Framework

H1: System quality has a significant impact on satisfaction.
H2: Satisfaction has a significant impact on behavioral intention.
H3: Performance expectancy has a significant impact on behavioral intention.
H4: Effort expectancy has a significant impact on behavioral intention.
H5: Social influence has a significant impact on behavioral intention.
H6: Attitude has a significant impact on behavioral intention.

3.2 Research Methodology

The quantitative method was conducted, and online questionnaires were distributed to the social science major students of four grades at Panzhihua University in Sichuan, China. The components of the questionnaire are screening questions, measuring variables with the five-point Likert scale from strongly disagree (1) to agree (5), and demographic information strongly. Before the data collection, the item-objective congruence (IOC) index was initially examined. Three experts scored on each scale item, resulting in all items being approved at a score of 0.66 or above. Afterward, a pilot test of 30 respondents was carried out. Cronbach's Alpha coefficient values were approved and ensured all constructs' reliability. SPSS and SPSS AMOS analyzed the data. Confirmatory factor analysis (CFA) was used to test the validity and reliability of the results, and the structural equation model (SEM) was used to verify the causal relationship between variables.

3.3 Population and Sample Size

The main target population of this paper is social science major students with at least one semester of e-learning experience from Panzhihua University in Sichuan, China. According to Hair et al. (2010), the sample size was recommended to be 500. By setting the relevant factor parameters and the number of variables (Soper, n.d.) through calculation, the minimum sample size was 425. In order to enhance effective measures, the researcher selects 500 as the sample size to achieve the research objectives.

3.4 Sampling Technique

Non-probability sampling was used as a sampling technique. Firstly, judgment sampling was to select social science major students with at least one semester of e-learning experience at Panzhihua University. Secondly, quota sampling used a population of 1,970 divided into four subgroups of 120, 113, 151, and 116, as shown in Table 1. Lastly, convenient sampling was executed by distributing the questionnaire online method. Data was collected in January 2023.

Table 1: Sample Units and Sample Size

Four Grades	Population	Proportional Sample Size
Freshman	474	120
Sophomore	444	113
Junior	596	151
Senior	456	116
Total	**1,970**	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

The respondents are 266 females and 234 males, representing 53.2%, and 46.8%, respectively. Freshman accounts for 24%, sophomore accounts for 22.6%, junior accounts for 30.2%, and senior accounts for 23.2 %. Most undergraduates were 20-21 (42.2%); the smallest group was 25 years old and above 1.8%. Most participants adopt the Zhihui Shu system, accounting for 37.8%, and only 8.6% utilize other systems. 39.6% and 30% of students use e-learning 3-7 times and 2-3 times per week. Table 2 displays the demographic findings for 500 individuals.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	266	53.2
	Female	234	46.8
Age	Less than 20	79	15.8
	20-21 years old	211	42.2
	22-23 years old	190	38
	24-25 years old	11	2.2
	25 years old and above	9	1.8
Year of Study	Freshman	120	24
	Sophomore	113	22.6
	Junior	151	30.2
	Senior	116	23.2
Types of E-learning system	MOOC	156	31.2
	Zhihui Shu	189	37.8
	Super Star	112	22.4
	Other	43	8.6
Frequency of E-learning in a week	1 time	50	10
	2-3 time	150	30
	3-7 time	198	39.6
	More than 7 times	102	20.4

Source: Constructed by author

4.2 Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis (CFA) was conducted in this study. Allen et al. (2009) pointed out that CFA was a process of identifying variance and covariance between indicator sets. In the results of Table 3, Cronbach's alpha was a method used to assess the construct's internal consistency of the elements (Killingsworth et al., 2016). Cronbach's Alpha results were approved at a score of 0.70 or above (Sekaran, 1992). Furthermore, the factor loading should be higher than 0.5, and the p-value should be lower than 0.05 (Fornell & Larcker, 1981). The extracted variance extracted (AVE) value should exceed 0.5 to meet the convergent validity (Henseler et al., 2009). However, composite reliability or CR values are over 0.6, which can approve AVE at lower than 0.4.

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 (SQ)	DeLone and McLean (2003)	4	0.901	0.802-0.926	0.902	0.699
Satisfaction (SA)	Chao (2019)	5	0.810	0.601-0.850	0.815	0.472
Performance Expectancy (PE)	Venkatesh et al. (2003)	3	0.842	0.763-0.860	0.842	0.641
Effort Expectancy (EE)	Venkatesh et al. (2003)	3	0.780	0.721-0.752	0.781	0.543
Social Influence (SI)	Venkatesh et al. (2003)	4	0.901	0.780-0.962	0.904	0.705
Attitude (ATT)	Buabeng-Andoh (2018)	3	0.926	0.857-0.939	0.927	0.809
Behavioral Intention (BI)	Hsiao and Tang (2014)	4	0.856	0.661-0.919	0.862	0.613

Indices employed for measurement included CMIN/DF, GFI, AGFI, NFI, CFI, TLI, and RMSEA, all whose statistical values from CFA were greater than acceptable levels. They demonstrated the measurement model's goodness of fit. According to Table 4, all models for measuring results were acceptable

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/df	< 5.00 (Al-Mamary et al., 2015; Awang, 2012)	1.657
GFI	≥0.85 (Sica & Ghisi, 2007)	0.936
AGFI	≥0.80 (Sica & Ghisi, 2007)	0.919
NFI	≥ 0.80 (Wu & Wang, 2006)	0.941
CFI	≥ 0.80 (Bentler, 1990)	0.976
TLI	≥ 0.80 (Sharma et al., 2005)	0.976
RMSEA	< 0.08 (Pedroso et al., 2016)	0.036
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, NFI = Normed fit index, CFI = Comparative fit index, TLI = Tucker–Lewis index, and RMSEA = Root mean square error of approximation.

Discriminant validity appeared satisfactory in Table 5. All variables were significant from the higher value of AVE square roots compared to the factor correlations. Table 5 includes indicators of good fit that were evaluated.

Table 5: Discriminant Validity

	SQ	SA	PE	EE	SI	ATT	BI
SQ	**0.836**						
SA	0.173	**0.687**					
PE	0.288	0.167	**0.801**				
EE	0.240	0.218	0.438	**0.737**			
SI	0.441	0.311	0.283	0.295	**0.804**		
ATT	0.322	0.252	0.275	0.190	0.408	**0.899**	
BI	0.360	0.338	0.456	0.404	0.458	0.374	**0.783**

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

4.3 Structural Equation Model (SEM)

Combining the multivariant analysis principle, the SEM analysis was a technique to find the reasons and relationships. SEM is more precise than regression analysis since it detects errors when examining linear relationships between variables. SEM could test the causal relationship among variables (Gonzalez et al., 2008). SEM is a set of statistical methods that can determine how observable and latent variables are related (Beran & Violato, 2010). All values from fit indices exceeded the permitted values, so validating the model's fitness in Table 6.

Table 6: Goodness of Fit for Structural Model

Index	Acceptable Criteria	Statistical Values
CMIN/df	< 5.00 (Al-Mamary et al., 2015; Awang, 2012)	3.219
GFI	≥0.85 (Sica & Ghisi, 2007)	0.860
AGFI	≥0.80 (Sica & Ghisi, 2007)	0.833
NFI	≥ 0.80 (Wu & Wang, 2006)	0.879
CFI	≥ 0.80 (Bentler, 1990)	0.913
TLI	≥ 0.80 (Sharma et al., 2005)	0.904
RMSEA	< 0.08 (Pedroso et al., 2016)	0.066
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, NFI = Normed fit index, CFI = Comparative fit index, TLI = Tucker–Lewis index, and RMSEA = Root mean square error of approximation.

4.4 Research Hypothesis Testing Result

Regression coefficients or standard path coefficients quantify the magnitude of the correlation between independent and dependent variables. As shown in Table 7, all hypotheses were considered significant at $p<0.05$. All hypotheses are significant.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-Value	Result
H1: SQ→SA	0.207	4.131*	Supported
H2: SA→BI	0.235	5.072*	Supported
H3: PE→BI	0.306	6.524*	Supported
H4: EE→BI	0.212	4.350*	Supported
H5: SI→BI	0.256	5.919*	Supported
H6: ATT→BI	0.196	4.498*	Supported

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

According to Table 7, the discussions are as follows:

H1 shows that system quality significantly impacts satisfaction with $\beta = 0.207$ and t-value = 4.131. System quality positively affects the satisfaction of service students in an e-learning context (Alksasbeh et al., 2019).

H2 confirms that satisfaction is an antecedent of behavioral intention with $\beta = 0.235$ and t-value = 5.072. Bhattacherjee (2001) revealed that early pleasure with an information system has a beneficial impact on the intention to continue using it.

H3 reveals that performance expectancy is an antecedent of behavioral intention with a standardized coefficient value of 0.306. Venkatesh et al. (2003) believed that if users can improve their productivity by using new technology, they would have a stronger intention to continue using it.

H4 affirms that the impact of effort expectancy upon behavioral intention is significant with $\beta = 0.212$ and t-value = 4.350. Effort expectancy was identified as the direct, decisive factor of behavioral intention. It referred to how easily users expect to learn new technologies, and users' efforts would affect the acceptance and use of technologies (Alharbi & Drew, 2014).

H5 presents that social influence's impact on behavioral intention is significant with $\beta = 0.256$ and t-value = 5.919. In the present research, university students will create a behavioral intention to utilize e-learning if they perceive that their friends, professors, classmates, or parents believe they should use it in their studies (Rudhumbu, 2020).

H6 reveals that attitude significantly impacts behavioral intention with $\beta = 0.196$ and t-value = 4.498. Attitude has been determined to be a key influential factor in determining intent to utilize technique (Yuen & Ma, 2008).

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

This study attempts to determine the origins of social science major university students' satisfaction and behavioral intention at Panzhihua University in Sichuan, China. The results established that system quality,

satisfaction, PE, EE, SI, and attitude significantly impact BI. The findings can be implied theoretically and practically. This outcome is consistent with both the original UTAUT theory and earlier research.

Performance expectancy is a crucial determinant of ICT use intent. It has effectively influenced university students' mobile learning behavior (Chao, 2019). It was probable that males would place a higher significance on performance expectancy, which emphasized getting the job done. In contrast, women would place a higher significance on effort expectancy (Wang, 2016). In this study, e-learning as a teaching medium, students easily received positive or negative comments from social media and friends around them. Suppose the people around had a positive attitude towards the learning system, which would encourage or promote user acceptance. Women tended to be more sensitive to the opinions of others. As a result, they discovered that peer influence was more relevant to women regarding their desire to utilize technology (Venkatesh et al., 2000).

Numerous studies have repeatedly proved that customers' satisfaction was favorably associated with their intent to continue using it (Chiu et al., 2005). With the rising global reliance on technology, particularly in the educational sphere, one of the ways to raise student satisfaction was to promote the system's quality. In addition, researchers discovered that attitude was the single most critical factor in determining a person's desire to use mobile learning. Attitude was the majority factor in the intention to use (Buabeng-Andoh, 2018).

5.2 Recommendation

As e-learning systems in higher education continue to rise, a greater grasp of effectively employing such tools will always be desired. The study seeks to identify the characteristics that can boost online education's acceptability in China. The study's conclusions made important aspects that might affect student e-learning satisfaction and behavioral intention stand out for educators and researchers. As indicated in the study, system quality, satisfaction, PE, EE, SI, and attitude play key roles in the acceptability of students e- learning. As a result, the findings support the UTUAT paradigm when applied to China university students.

PE is a statistically significant predictor of BI to use of e-learning regarding determinants of this variable. According to Ngai et al. (2007), some users may be unwilling to devote time, particularly if the medium's value needs better validation. This means students should believe that using instructional technology would improve their learning outcomes and performance. To see the e-learning system's value, students must believe its learning materials are sufficient and comprehensive.

Thus, the creator of the course curriculum, the instructors, and the administration should guarantee the system's high quality. It is recommended that professors and university administration employ the active learning technique in online lectures to ensure maximum student participation and arouse their interest. Higher educational institutions should place a premium on ensuring students' technological needs are met. As individuals start using e-learning, they might influence their friends and classmates to do the same. This may indicate that educational institutions can increase the acceptance of e-learning by users with a high level of willingness, which can result in other users' adoption of the technology (Wang & Wang, 2010). Institutions must invest more in different equipment and technologies to serve a diverse student body. This can also help students understand the importance of technology devices in other areas, such as smart cards, code-scanning apps, and face recognition. This modification can bolster the attitude. Gradually, employing technology in universities can become routine, allowing students to maximize their talents while saving time and effort.

5.3 Limitation and Further Study

There are areas for improvement in this study that must be addressed.First, this study investigated undergraduates from a single public university in the province of Sichuan. Hence, future research should expand its scope to include other universities or different types, such as private universities. Also, researchers might investigate students in various places.

Next, this study mainly addressed the six influential elements of social science major students' satisfaction and behavioral intention in the conceptual framework. Future research should focus more on online courses' service quality and learning outcomes.

Future studies may broaden the research object to increase the conclusions' generalizability and representativeness. In addition to students, researchers can study professors and administrators to gain insight into the digital transformation of education. As a result, more analysis and comparison can be made in greater detail, and recommendations and specific findings can be made for each unique object.

In conclusion, quantitative research can contribute to statistical significance. Thus, qualitative research should be included to compare outcomes and generate superior conclusions and recommendations. Future researchers can also observe or interview students about their e-learning experience and preference for a more real-world qualitative approach.

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