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The Examination on Satisfaction and Behavioral Intention of Natural Science Majors Students Toward E-learning in Sichuan, China

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Abstract

Purpose: This paper mainly studies the factors impacting natural science majors' satisfaction and behavioral intention to adopt electronic learning (E-learning) at a public university in Sichuan, China. A conceptual framework was built upon the relationship between system quality, satisfaction, performance expectancy, effort expectancy, social influence, attitude, and behavioral intention. **Research design, data, and methodology:** The sample is 500 natural science major's undergraduates from a public university in Sichuan Province. Non-probability samplings include purposive sampling, quota sampling, and convenient sampling. The validity and reliability test were employed before the data collection, approved by the item-objective congruence (IOC) index Cronbach's Alpha coefficient values of the pilot test. The data were analyzed by Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM). **Results:** Research shows that all hypotheses were consistent with the research objectives. System quality, performance expectancy, effort expectancy, social influence, and attitude significantly impact behavioral intention. Satisfaction has the strongest impact on natural science major students' behavioral intention to use E-learning **Conclusions:** Based on the findings, higher education decision-makers and policymakers focus on enhancing student satisfaction with e-learning by strengthening the IT infrastructure and their ability to sustain remote learning services.

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

JEL Classification Code: E44, F31, F37, G15

1. Introduction

Electronic learning (E-learning) is a breakthrough technology applied globally and utilized extensively by educational institutions (Salloum & Shaalan, 2018). E-learning is an educational model with students as the primary participant. It gives students the freedom to learn whenever, wherever, and about anything they want, according to their learning goals. Gray and Tobin (2010) showed that online learning facilitates teaching strategies that are not possible with traditional textbooks and can reach many learners, overcoming time and space constraints without using up more resources. To aid students, an e-learning system is anticipated to strengthen and accomplish their purpose (Arkorful & Abaidoo, 2015; Kintu et al., 2017). Online instruction is an effort to encourage and facilitate genuine communication between students, professors, and resources (Dogbey et al., 2017).

According to a United Nations estimate, the most recent epidemic has wreaked havoc on almost every aspect of society, notably the education sector. COVID-19 has influenced 1.6 billion pupils in 190 countries worldwide, mostly children from low-income and lower-middle-income nations. The modern epidemic has significantly altered schooling with the rise of online learning. A method wherein lecturers teach remotely utilizing digital platforms (Li & Lalani, 2020). As exciting as it seems, many faculty members master online technologies and prepare notes and

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lectures for online delivery, yet several obstacles have developed. Switching from traditional learning to an online format is a chance to redesign the education sector. However, significant problems are associated with utilizing a new learning style and infrastructure support. Bacher-Hicks et al. (2020) presented that pupils and instructors in developing countries need more internet access and technical resources. Another significant problem is getting students to participate actively in online lectures (Adnan & Anwar, 2020).

The satisfaction and behavioral intention to use e-learning has been critical for higher education sector, determined the future of learning method in China. Hence, this paper mainly studies the factors impacting natural science majors' satisfaction and behavioral intention to adopt electronic learning (E-learning) at a public university in Sichuan, China. A conceptual framework was built upon the relationship between system quality, satisfaction, performance expectancy, effort expectancy, social influence, attitude, and behavioral intention.

2. Literature Review

2.1 System Quality

According to Guimaraes et al. (2009), system quality is the extent to which a system fulfills expectations. User-friendliness, availability, simplicity of learning, and reaction speed are features of an e-learning system that add to its quality. System quality refers to how users perceive the performance of online learning in terms of information retrieval and transmission. It evaluates the functionality of a system, including its navigability, accessibility, layout, visual appeal, and page load speed. Chen (2011) pointed out that information processing system quality is an assessment of the system itself. It depends upon the user's requirements established throughout the system's research and development. The technology acceptance model (TAM) suggests that, all else being equal, a user-friendly system is more likely to elicit a favorable attitude (Davis, 1989). It has been stated that SQ substantially affects users' satisfaction with using e-learning technology (Ramayah & Lee, 2012). Thus, the following hypothesis is drawn:

H1: System quality has a significant impact on satisfaction.

2.2 Satisfaction

The extent to which an experience, in one's opinion, elicits pleasant sensations is known as satisfaction (Rust & Oliver, 1994). The degree to which users perceive that information systems (IS) satisfy their demands has been defined as user satisfaction, which is a widely used IS success (ISS) metric (Davis, 1993). Researchers have a long history of utilizing user satisfaction as a proxy for success (Guimaraes et al., 2006). According to Arif and Ilyas (2013), student satisfaction is the emotion felt by someone who has experienced performance and evaluated the degree to which their expectations were met. Satisfaction is a psychological or subjective state from a cognitive evaluation of the expected performance gap (Bhattacherjee, 2001). Students' satisfaction with the e-learning platform is measured by validating system-related expectations (Lee, 2010). Individuals' appraisal and emotional reaction to the total experience with a product or service is called satisfaction (Oliver, 1980). The ISS model is one of the key elements in this study's analysis of the effectiveness of e-learning systems (DeLone & McLean, 1992). Student satisfaction is used in this study to gauge how well the e-learning system and its learners interacted (Min et al., 2022). As a result, the following assertion is made:

H2: Satisfaction has a significant impact on behavioral intention.

2.3 Performance Expectancy

The unified theory of acceptance and use of technology (UTUAT) model was created by combining elements (Venkatesh et al., 2003). The first aspect of UTAUT is performance expectation, defined as the extent to which an individual feels that he or she can benefit from a certain technology. The significance of performance expectancy in the users' behavioral intention to accept technology has been extensively studied (Rudhumbu, 2022). Researcher Amparo (2021) discovered a strong correlation between students' performance expectations and behavioral intentions to adopt blended learning. Performance expectancy is the amount to which students believe that e-learning will improve their academic achievement. Consistently, it has been established that beliefs about the utility of e-learning technologies are important predictors of the behavioral intention to start or continue using a certain tool (Chang & Tung, 2008). The intention to employ learning technologies has been predicted using the performance expectation model (Gunasinghe et al., 2020). Thus, a hypothesis is formed:

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

2.4 Effort expectancy

Effort expectancy was people's estimates of how easy technology is (Rahi et al., 2019), which derives from users' views that technology use requires less mental work. EE is

the second component in UTAUT, which refers to an individual's perception of the ease and convenience of technology use. Prior studies show that students' behavioral intentions are strongly predicted by their effort expectations (Jaradat & Banikhaled, 2013). Effort expectancy derives from users' views that technology use requires less mental work. It describes how simple it is to operate a system like e-learning tools. Prior research indicates that learners' perceptions of the effort required on their part have a substantial effect on their propensity to use e-learning technologies. Cognitive dissonance theory also identifies this phenomenon, in which individuals tend to devalue an activity if they feel incapable of performing it or if it involves significant effort. Hence, it is proposed that the following:
H4: Effort expectancy has a significant impact on behavioral intention.

2.5 Social Influence

Social influence is a psychological definition that presupposes a specific person's and other people's shared interests (Goldsmith, 2015). In internet-based learning, it is stated that a learner's attitudes regarding technology are influenced by the opinions of a community of other learners (Sun et al., 2008). It was discovered that people tend to discuss their technological acceptance with others (Thongsri et al., 2018). Social influence covers learners' impressions of the acceptance of their usage of e-learning resources by others. It is acknowledged that social circle members' experiences or views may impact one's perceptions of the merits of a certain e-learning medium (Hars & Ou, 2002). As favorable word-of-mouth from referent peers has an impact, SI substantially influences the desire to accept technology in developing countries with a high degree of collectivism (Tarhini et al., 2016). SI is a significant determinant of BI to use of a technique or technology as a proposed hypothesis:
H5: Social influence has a significant impact on behavioral intention.

2.6 Attitude

A person's thinking, feeling, and doing may be described as attitude (Bhuvaneswari & Dharanipriya, 2020). Lee et al. (2013) displays that attitude substantially affects behavioral intention in a certain way. Attitude has been established as a crucial element for predicting the acceptance and utilization of information technology in the IS sector. It refers to the emotional response to a given behavior and is believed to influence the inclination to utilize information technology (Davis, 1989). Yu and Yu (2010) found that attitude substantially impacts the behavioral intention to use online learning systems. Users who had a favorable attitude toward technology, as found by Luan et al. (2005), were more likely to make use of that technology. According to some research, educational institutions must study and report students' perceptions regarding online learning (Zhu et al., 2020). Universities can create student-friendly online learning models by understanding student attitudes and viewpoints. The following theory is put out considering the discussion above:
H6: Attitude has a significant impact on behavioral intention.

2.7 Behavioral intention

Behavioral intention was the extent to which people were eager to use effort to achieve an action (Ajzen, 1991). A person's intention to follow through with behavior is their behavioral intention, which can be measured (Fishbein & Ajzen, 1975). El-Masri and Tarhini (2017) have defined BI as the eagerness of individuals to engage in specific behaviors. The UTAUT hypothesized that both EE and PE are predictors of behavioral intention (Venkatesh et al., 2003). Online education success has been associated with behavioral intentions for some time (Rudhumbu, 2020).

3. Research Methods and Materials

3.1 Research Framework

Four theoretical frameworks constitute the conceptual framework of this study. Firstly, Chao (2019) mainly discussed the causal relationship between satisfaction and behavioral intention. Secondly, Tan (2013) concluded that PE, EE, and SI impact BI. Finally, Boateng et al. (2016) discussed the relationship between system quality and satisfaction. The fourth theoretical framework conducted by Cidral et al. (2020) mainly discussed the relationship between attitude and BI. Accordingly, the conceptual framework of this paper is shown in Figure 1.

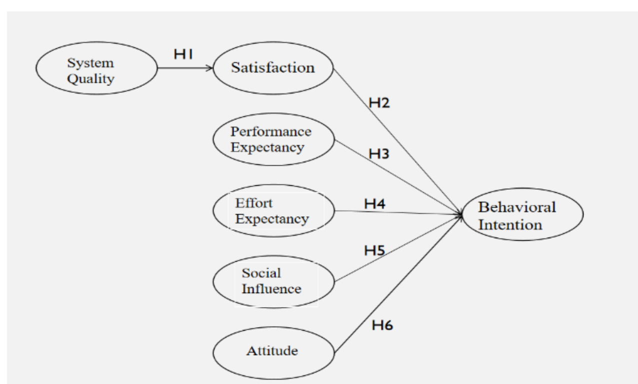

Figure 1: Conceptual Framework

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

This quantitative study distributed online questionnaires to 500 natural science majors' undergraduates from Panzhihua University in Sichuan, China, who have at least one semester of e-learning experience. Three sections are composed of a screening questions questionnaire, a five-point Likert scale of measuring items, and demographic profiles.

The pre-analysis of data is the test of validity and reliability. The item-objective congruence (IOC) index involved three experts, resulting in all items being approved at a score of 0.66 or above. Later, Cronbach's Alpha was used to test the validity of constructs in the pilot test of 30 participants, resulting in all internal consistency of all constructs being acceptable at a score of 0.872 or above. The final questionnaire was distributed to 500 students. The data were analyzed by SPSS and SPSS Amos to detect the relationship between variables, applying confirmatory factor analysis (CFA) and structural equation model (SEM).

3.3 Population and Sample Size

The target population is natural science majors' undergraduates at Panzhihua University, China. The minimum sample size of complex models was 500 cases (Hair et al., 2010). Therefore, the researcher decided to collect 500 samples at an appropriate.

3.4 Sampling Technique

Nonprobability sampling was accounted for with purposive, quota, and convenience samplings. Firstly, purposive sampling was employed by selecting science major's undergraduates for at least one semester of e-learning experience from Panzhihua University in Sichuan China. Quota sampling was used to calculate the sample size of each year of study, as shown in Table 1. Thirdly, convenient sampling was the data collection via online survey methods, such as questionnaire star software. The data were collected in January 2023.

Table 1: Sample Units and Sample Size

Four Grades	Population	Proportional Sample Size
Freshman	2,642	139
Sophomore	2,405	126
Junior	2,436	128
Senior	2,035	107
Total	**9518**	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

Questionnaires were distributed and collected among 500 students at Panzhihua University. According to Table 2, the majority is male, with 73.4% (367), whereas the female is 26.6% (133). The age profile shows that most respondents were 22-23, with 42% (210) of the total respondents. Most respondents' current year of study was first-year students, with 27.8% (139). Most participants adopt Mooc, accounting for 33.8%, and 13.8% utilize other systems. 40.2% and 33.8% of students use e-learning more than seven times and 3-7 times per week.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	367	73.4
	Female	133	26.6
Age	Less than 20	62	12.4
	20-21 years old	160	32
	22-23 years old	210	42
	24-25 years old	32	6.4
	25 years old and above	36	7.2
Year of Study	Freshman	139	27.8
	Sophomore	126	25.2
	Junior	128	25.6
	Senior	107	21.4
Types of E-learning system	MOOC	169	33.8
	Zhihui Shu	157	31.4
	Super Star	105	21
	Other	69	13.8
Frequency of E-learning in a week	1 time	10	2
	2-3 time	120	24
	3-7 time	169	33.8
	More than 7 times	201	40.2

Source: Constructed by author

4.2 Confirmatory Factor Analysis (CFA)

According to Brown (2006), CFA is a structural equation model focusing on measurement models to examine the correlation between observed and potential variables. 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). In addition, Cronbach's Alpha results were approved at a score of 0.70 or above (Sekaran, 1992). It can be seen from Table 3 that all results meet the conditions.

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	0.911	0.784-0.946	0.909	0.716
Satisfaction (SA)	Chao (2019)	5	0.934	0.776-0.841	0.900	0.644
Performance Expectancy (PE)	Venkatesh et al. (2003)	3	0.891	0.741-0.930	0.856	0.667
Effort Expectancy (EE)	Venkatesh et al. (2003)	3	0.910	0.793-0.868	0.879	0.708
Social Influence (SI)	Venkatesh et al. (2003)	4	0.920	0.806-0.886	0.908	0.712
Attitude (ATT)	Buabeng-Andoh (2018)	3	0.872	0.773-0.821	0.840	0.637
Behavioral Intention (BI)	Hsiao and Tang (2014)	4	0.896	0.585-0.924	0.829	0.556

This investigation evaluated the measurement model's goodness of fit using CMIN/DF, GFI, CFI, NFI, AGFI, TLI, and RMSEA. As of Table 4, all 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)	2.049
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.912
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.889
NFI	≥ 0.80 (Wu & Wang, 2006)	0.919
CFI	≥ 0.80 (Bentler, 1990)	0.957
TLI	≥ 0.80 (Sharma et al., 2005)	0.949
RMSEA	< 0.08 (Pedroso et al., 2016)	0.050
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 is crucial for researchers since it involves possible variables whose structure is represented by several indicators (Hamid et al., 2017). As shown in Table 5, convergent and discriminant validities were adequate.

Table 5: Discriminant Validity

	SQ	SA	PE	EE	SI	ATT	BI
SQ	**0.846**						
SA	0.310	**0.802**					
PE	0.265	0.473	**0.817**				
EE	0.289	0.556	0.473	**0.841**			
SI	0.250	0.539	0.504	0.532	**0.844**		
ATT	0.376	0.388	0.412	0.402	0.380	**0.798**	
BI	0.429	0.654	0.617	0.603	0.587	0.549	**0.746**

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

4.3 Structural Equation Model (SEM)

Baumgartner and Hombur (1996) stated that SEM has mostly been utilized to validate a structural model and its significance level in a structural route. Table 6 shows the acceptable criteria for each fit index in SEM. The results were CMIN/DF=3.107, GFI=0.852, AGFI=0.823, NFI=0.871, CFI=0.908, TLI=0.898 and RMSEA=0.071, showing that the model meets the goodness of fit.

Table 6: Goodness of Fit for Structural Model

Index	Acceptable Criteria	Statistical Values
CMIN/df	< 5.00 (Al-Mamary et al., 2015; Awang, 2012)	3.107
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.852
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.823
NFI	≥ 0.80 (Wu & Wang, 2006)	0.871
CFI	≥ 0.80 (Bentler, 1990)	0.908
TLI	≥ 0.80 (Sharma et al., 2005)	0.898
RMSEA	< 0.08 (Pedroso et al., 2016)	0.071
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

The results of six hypotheses are explicated with standardized path coefficients (β) and $p<0.05$, as shown in Table 7.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-Value	Result
H1: SQ→SA	0.186	3.540*	Supported
H2: SA→BI	0.380	7.828*	Supported
H3: PE→BI	0.301	6.244*	Supported
H4: EE→BI	0.183	3.870*	Supported
H5: SI→BI	0.164	3.528*	Supported
H6: ATT→BI	0.276	5.549*	Supported

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

The results in Table 7 can be elaborated as follows:

H1 shows that system quality has a significant impact on satisfaction with β = 0.186 and t-value = 3.540, as aligned with many studies that system quality has a significant impact on learner's level of willingness with the system as well as their desire to use the system in the future (Almaiah & Alismaiel, 2019; Mohammadi, 2015).

H2 confirms that satisfaction has the strongest impact on BI with β = 0.380 and t-value = 7.828. Many kinds of literature discovered that the level of satisfaction experienced by users has a considerable influence on their BI to keep using internet services and systems (Roca et al., 2006).

H3 reveals that performance expectancy is an antecedent of behavioral intention with β = 0.301 and t-value = 6.244. Many scholars agree with this result that students with higher performance expectancy were more inclined to utilize e-learning systems (Lwoga & Komba, 2015).

H4 affirms that the relationship between effort expectancy and behavioral intention is supported with β = 0.183 and t-value = 3.870. The result was the same with earlier studies that effort expectancy was interpreted to suggest that college students who assumed that adopting blended learning would be effortless would create a behavioral intention to adopt it (Rudhumbu, 2022).

H5 confirms the significant impact of SI on BI with β = 0.164 and t-value = 3.528. Many scholars have a consensus with this result. The information offered by close friends and family members helps increase knowledge and intentions toward technological advancements (Alalwan et al., 2016).

H6 The relationship between attitude and BI was supported with β = 0.276 and t-value = 5.549. Existing research suggested that one's utilization of digital technology was influenced by his or her positive attitude, regardless of how advanced the technology was (Dwivedi et al., 2011).

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

This research accomplishes to determine the factors impacting nature science major university students' satisfaction and behavioral intention at Panzhihua University in Sichuan, China. This study extended the UTAUT to investigate the acceptance of e-learning. The proposed model produced favorable outcomes. A conceptual framework shows that system quality, satisfaction, PE, EE, SI, and attitude significantly impact BI. Furthermore, system quality has an impact on student satisfaction.

The results show that satisfaction has the strongest impact on student BI, followed by performance expectancy, attitude, system quality, effort expectancy, and social influence. The findings revealed that satisfaction critically enhances student behavioral intention because 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).

Performance expectancy pertains to the degree to which he or she believes a system would enhance job performance (Venkatesh et al., 2003), which can determine a user's behavioral intention. The attitude was a response to life's technological adaptation. It might refer to a person's perspective, thinking, or beliefs on the services, directly affecting their behavioral intention. Moreover, researchers discovered that attitude was a critical factor that could affect a person's utilization of e-learning. The result suggested that when students found system quality adaptable, user-friendly, and simple to operate, their satisfaction increased. It would raise student satisfaction by enhancing the system's effectiveness for them. Therefore, students' satisfaction with system quality was crucial in an educational environment.

Effort expectancy and social influence are crucial bodies of behavioral intention. Effort expectancy has been experimentally examined and proven to be a strong predictor of behavior in previous research conducted in various countries. When students use a network learning platform to learn, if they pay less effort in the process of learning operation, the easier it would be to master the operation process, and the more it could maximize the motivation of students to use the learning system. These findings implied that students who believed e-learning was simple to employ in their coursework acquired behavioral intentions to embrace it. When individuals feel insecure about technology usage, they seek out others' consolidations (Ibukun et al., 2016).

5.2 Recommendation

This study designed and evaluated a research model that examined the impacts of social science students e- learning behavioral intention. It was based on well-established theory and empirical research. The report urges policymakers to pay close attention to students' contact with e-learning systems to ensure their willingness to adopt e-learning. It would benefit university administrators to allocate resources appropriately to improve educational services, comprising support facilities and services. Higher education decision-makers and policymakers focus on enhancing student satisfaction with e-learning by strengthening the IT infrastructure and their ability to sustain remote learning services.

There is a need to encourage information literacy among students, instructors, and school officials. In essence, educators and system management should prioritize organizing trial services for students and educating them about the advantages of using an e-learning platform. Instructors must provide study instructions and use more adaptable training and assessment techniques in each topic to assist undergraduates in embracing the new method and increasing their using intentions. How a person thinks that e-learning would improve their academic achievement is a significant predictor of their BI to use e-learning. Instructors should also guide students to reliable websites and e-libraries for subject-specific materials, enhancing students' comprehension of the benefits of e-learning, such as saving time and being easy to operate. To achieve a high level of user acceptance and the success of an e-learning service, it is advised for suppliers that prior to the construction of an e-learning system, the characteristics of the intended students and the course content should be thoroughly evaluated.

5.3 Limitation and Further Study

There are areas for improvement in this study that must be addressed. As for the demographic profile, the only sample group in this study is nature science undergraduates in one public university in Sichuan, China. The survey scope is relatively small, and there may be deviations in the data collected. Therefore, it is advised that the researchers gather information from a bigger sample size across several China cities.

Secondly, the findings may not generalize to nations with different education cultures. In order to increase the research's external validity and generalizability, it is advised that the model be examined in other cultural and geographical situations.

Thirdly, according to the conceptual framework, this study verifies six factors that impact student satisfaction and behavioral intention, but this paper needs to cover whether there are other influencing factors.

Finally, this study only examined the quantitative method, which should be to further explored in qualitative for better implications of results. Future researchers can also observe or interview students about their online learning experiences and preferences for a more real-world, qualitative approach.

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