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Antecedents of Higher Education Student Satisfaction With Online Learning in Chengdu, China

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Abstract

Purpose: This study explores the factors influencing higher education students' satisfaction with online learning in Chengdu, China. The examined variables include Effort Expectancy (EE), Information Quality (IQ), Performance Expectancy (PE), Course Structure (CS), Student-Student Interaction (SI), Student Engagement (SE), and Student Satisfaction (SS). **Research design, data and methodology:** This study employs quantitative methods, using a questionnaire survey to examine factors influencing student satisfaction with online learning in higher education. Non-probability sampling techniques, including judgment, stratified random, and convenience sampling, were used for sample selection. Prior to distribution, Item-Objective Consistency (IOC) analysis and a pilot test ensured reliability. Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) validated the conceptual framework and tested hypothesized relationships**. Results:** Statistical analysis revealed that the key antecedents of student satisfaction in online learning are effort expectancy, information quality, performance expectancy, and student engagement. Additionally, student engagement is influenced by student-student interaction. **Conclusions:** This study offers insights for higher education institutions to enhance student satisfaction with online learning. The findings suggest that ease of use, high-quality information, and effective student engagement are critical for satisfaction. Institutions can optimize LMS usability, foster interactive learning environments, and ensure content quality. These measures not only enhance student satisfaction but also support sustainable online learning and institutional competitiveness.

Keywords: Student Engagement, Student Satisfaction, Online Learning, Higher Education

JEL Classification Code: A20, I23, O30, P46

1. Introduction

Online learning, defined as education delivered synchronously or asynchronously via the internet, enables students to engage with instructors and peers from any location (Singh & Thurman, 2019). In recent years, it has grown rapidly due to technological advancements and the integration of Information Technology (IT) into educational curricula (Smart & Cappel, 2006), offering accessibility, affordability, and flexibility (Dhawan, 2020). While various definitions exist, online learning is generally characterized by the use of digital media to transmit diverse forms of information and knowledge to learners. For instance, Khlaisang and Likhitdamrongkiat (2015) emphasize digital media's role, while He (2002) highlights its capacity to enhance access to learning materials in China. This shift not only transforms teaching methodologies but also reshapes teacher-student interactions.

A significant extension of online learning is mobile learning, which enables learners to access educational resources without spatial or temporal limitations (Shim et al., 2011). Characterized by its flexibility, portability, and accessibility, mobile learning has become increasingly popular, driven by the widespread availability of smart devices and mobile applications (Davies et al., 2012). It also supports micro-learning, where complex topics are divided into manageable learning activities, enhancing information retention and learner engagement (Souza & Do Amaral, 2014). Furthermore, advances in mobile learning technology facilitate interactive learning experiences

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distinct from traditional classroom settings, enabling virtual classrooms and real-time collaboration (Wentzel et al., 2005).

In the context of China, online learning has emerged as a prominent educational model, fueled by a rapidly growing digital infrastructure. According to the 52nd Statistical Report on Internet Development in China, as of June 2023, the number of IPv6 addresses reached 68,055 pieces / 32, reflecting the expanding digital landscape (China Internet Network Information Center, 2023). These advancements underscore the significant potential for online education's growth and innovation.

Transitioning to the specific context of Chengdu, the rise of online education has been particularly notable, driven by improved digital connectivity and increasing student enrollment in online programs. In higher education, student satisfaction serves as a critical indicator of program quality and academic effectiveness (Kuo et al., 2013; Yekselturk & Yildirim, 2008). As virtual learning environments expand, identifying factors that enhance both satisfaction and educational outcomes becomes essential. While some research emphasizes positive engagement in online learning (Lim, 2001; Womble, 2007), others highlight challenges that online learners face (Martin et al., 2010). Effective participation in online education demands not only technical skills but also digital literacy and interaction capabilities (Shen et al., 2013). Student satisfaction in these environments is closely linked to academic success, with interaction playing a critical role in shaping the learning experience (Mandernach, 2005).

Therefore, the primary objective of this study is to examine the key factors influencing higher education students' satisfaction with online learning in Chengdu, Sichuan. Specifically, the research investigates the impact of Effort Expectancy (EE), Information Quality (IQ), Performance Expectancy (PE), Course Structure (CS), Student-Student Interaction (SI), and Student Engagement (SE) on Student Satisfaction (SS). Additionally, it aims to explore how these determinants can inform the optimization of Learning Management System (LMS) usability, the design of interactive learning environments, and the enhancement of content quality to improve student learning experiences. By analyzing these aspects, the study seeks to provide empirical insights for educators, administrators, and policymakers to optimize online learning strategies, thereby enhancing student engagement and satisfaction in Chengdu's higher education institutions.

2. Literature Review

2.1 Effort Expectancy

Effort expectancy refers to students' perceptions of the ease associated with using online learning platforms (Lwoga & Komba, 2015). Yadav et al. (2016) emphasized the importance of system ease of use in technology adoption, highlighting that perceived simplicity encourages engagement. During the developmental phase of online learning, effort expectancy significantly influences learners' willingness to adopt digital platforms (Samsudeen & Mohamed, 2019). Tarhini et al. (2017) further linked effort expectancy with perceived ease of use, suggesting that user-friendly e-learning services enhance satisfaction and performance expectations.

Research consistently affirms that when students perceive online platforms as easy to navigate, their satisfaction and learning outcomes improve (Koceska & Koceski, 2020; Venkatesh et al., 2003; Violaine & Hwang, 2019). However, existing studies largely focus on Western contexts or generalized online environments, with limited exploration of region-specific factors in Chinese higher education, particularly in Chengdu. Furthermore, the role of effort expectancy in relation to local digital infrastructure remains underexplored. This study addresses this gap by examining how effort expectancy influences student satisfaction within Chengdu's unique digital learning landscape, offering region-specific insights into technology adoption in Chinese universities. Based on this review, the following hypothesis has been formulated:

H1: Effort expectancy has a significant impact on student satisfaction.

2.2 Information Quality

Information quality in online learning refers to the degree to which educational content is accurate, relevant, complete, and timely, meeting students' learning needs (Koceska & Koceski, 2020). It includes attributes such as precision, reliability, and clarity (Swaid & Wigand, 2009). In digital learning environments, the quality of information is crucial for user acceptance and engagement, often outweighing the significance of system hardware or software capabilities (Bocchi et al., 2004; Lin & Lu, 2000).

Research consistently shows that high-quality content enhances student satisfaction and motivation, contributing to positive learning experiences (Eom et al., 2006; Mulhem, 2020; Pérez-Pérez et al., 2020; Roca et al., 2006). While existing studies affirm the importance of information quality, most focus on Western educational contexts or generalized online platforms, with limited exploration of its influence in Chinese higher education settings, particularly in Chengdu.

Moreover, the specific impact of information quality on student satisfaction within the localized digital infrastructure of Chengdu remains underexplored. This study addresses this gap by examining how the quality of digital content influences student satisfaction in Chengdu's universities, offering empirical insights into region-specific expectations and digital learning outcomes. Based on this review, the following hypothesis has been formulated:

H2: Information quality has a significant impact on student satisfaction.

2.3 Performance Expectancy

Performance expectancy refers to the degree to which individuals believe that using a technology will help them achieve specific goals (Venkatesh et al., 2003). In the context of online learning, students are more likely to express satisfaction when they perceive that digital platforms effectively support their learning objectives (Hayfaa, 2021). Research consistently indicates a positive relationship between performance expectancy and student satisfaction (Violaine & Hwang, 2019). Furthermore, studies by Almaiah et al. (2019), Song (2018), Wan et al. (2020), and Rahman et al. (2020) confirm that students report higher satisfaction levels with user-friendly and efficient online learning platforms.

Despite the established link between performance expectancy and satisfaction, current research predominantly focuses on general online learning environments, with limited analysis of how local technological infrastructure and digital literacy levels influence performance expectancy in Chinese higher education, particularly in Chengdu. This study addresses this gap by exploring the specific impact of performance expectancy on student satisfaction within Chengdu's universities, considering local platform design and student familiarity with digital learning tools. This region-specific perspective contributes to a deeper understanding of how performance expectations align with actual learning experiences in China's digital education landscape. Based on this review, the following hypothesis has been formulated:

H3: Performance expectancy has a significant impact on student satisfaction.

2.4 Course Structure

Course structure refers to the design of learning objectives, teaching strategies, and evaluation methods that shape the learning experience (Eom et al., 2006). A well-structured course provides clear objectives and organized content, enhancing students' understanding and navigation through online platforms (Jaggars & Xu, 2016; Peter, 1999). While structured learning pathways can compensate for limited interaction, their impact on student satisfaction remains a critical area of study.

Research underscores the importance of course structure in shaping student satisfaction. Kuo et al. (2013) identified student-content interaction as a key predictor of satisfaction, particularly in collaborative online settings. Similarly, Grandzol and Grandzol (2006) found that clear course design with effective navigational guides promotes student success. Although Eom et al. (2006) reported that course structure significantly influences satisfaction, its effect on perceived learning outcomes is less conclusive. According to Moore (1991), effective course structure enhances clarity and alignment with learning objectives, contributing to improved satisfaction in online learning.

Despite these findings, research on how course structure influences student satisfaction within Chinese higher education, specifically in Chengdu's digital learning environment, is limited. Existing studies tend to generalize course design principles without considering local curriculum requirements or platform design unique to Chinese universities. This study addresses this gap by investigating the role of course structure in enhancing student satisfaction within Chengdu's online education context, offering insights into culturally and regionally adapted learning designs. Based on this review, the following hypothesis has been formulated:

H4: Course structure has a significant impact on student satisfaction.

2.5 Student-Student Interaction

Student-student interaction refers to the social engagement among learners through discussions, collaborations, and idea exchanges, independent of instructor presence (Moore, 1989). This interaction, often facilitated by group projects and online discussions, enhances learning experiences by fostering open communication and peer support (Hayfaa, 2021; Kuo et al., 2014). Despite the structured nature of online learning, student-student interaction introduces informality that promotes engagement and community building.

Research consistently highlights the importance of peer interaction for student satisfaction and academic performance in online learning (Hayfaa, 2021; Jenny, 2021). Collaborative activities reinforce engagement, while quality peer interactions have been linked to improved learning outcomes (Alqurashi, 2019; Chen et al., 2020). During the COVID-19 pandemic, studies in China emphasized the critical role of student-student interaction in maintaining learning quality. Jaggars and Xu (2016) found that stronger peer interactions led to higher academic performance, while Borokhovski et al. (2012) revealed that peer engagement often surpasses student-instructor interaction in enhancing learning outcomes.

Despite these findings, limited research explores how student-student interaction influences engagement specifically within Chinese higher education settings, particularly in Chengdu's expanding digital learning landscape. Existing literature primarily focuses on Western contexts or general online learning environments, overlooking region-specific cultural and infrastructural influences. This study addresses this gap by examining how student-student interaction drives engagement among Chengdu's university students, offering localized insights into peer collaboration's impact on digital learning experiences. Based on this review, the following hypothesis has been formulated:

H5: Student-student interaction has a significant impact on student engagement.

2.6 Student Engagement

Student engagement refers to the time and effort students invest in educational activities, including attending lectures, participating actively, and demonstrating interest (Kuh, 2003; Trowler, 2010). Engaged students are more likely to achieve positive learning outcomes, as they dedicate substantial effort to academic tasks (ERIC Development Team, 2003). Effective engagement strategies, such as integrating technology into formative assessments, can enrich learning experiences and boost participation (Zweli & Gaylard, 2015).

Research consistently demonstrates a strong link between student engagement and academic success. Carini et al. (2006) found that increased engagement enhances critical thinking and performance, while Lei and Cui (2018) confirmed its positive correlation with academic achievement. Similarly, Gray and DiLoreto (2016) reported that higher engagement improves perceived learning and satisfaction. Online learning environments particularly benefit from peer collaboration and instructor interaction, both of which significantly influence student engagement (Lee et al., 2019).

Despite extensive research on engagement in online learning, existing studies primarily focus on Western educational contexts, with limited attention to engagement dynamics within Chinese higher education, especially in Chengdu. Moreover, there is a lack of empirical evidence on how region-specific factors, such as local teaching practices and digital infrastructure, shape student engagement. This study addresses this gap by examining student engagement within Chengdu's universities, offering insights into how local contextual factors impact digital learning engagement and satisfaction. Based on this review, the following hypothesis has been formulated:

H6: Student engagement has a significant impact on student satisfaction.

2.7 Student Satisfaction

Student satisfaction refers to learners' evaluations of university services and their experiences within educational programs (Wiers-Jenssen et al., 2002). It reflects the alignment between students' expectations and their actual learning experiences, serving as a crucial measure of program effectiveness (Koceska & Koceski, 2020; Kuo et al., 2014). In distance learning, satisfaction is a key determinant of educational quality, influencing both program success and student retention (Yekselturk & Yildirim, 2008).

Studies have demonstrated that high-quality system design and information delivery are critical to student satisfaction. Koceska and Koceski (2020) applied an integrated model combining the Technology Acceptance Model (TAM) and the Information System Success (ISS) Model to analyze online education platforms, revealing that system usability and information quality enhance engagement and satisfaction. Furthermore, Hayfaa (2021) found that the accuracy, comprehensiveness, and relevance of information positively impact satisfaction levels in online learning. Teacher attitudes also play a significant role, with Bashir and Ganai (2019) identifying a link between student satisfaction and institutional commitment.

Although existing studies confirm the importance of system quality, information relevance, and instructor attitudes, there is limited research on how these factors specifically influence student satisfaction in the context of Chengdu's higher education institutions. Most studies generalize findings from Western contexts or broader Chinese regions, overlooking localized digital learning environments. This study addresses this gap by examining the determinants of student satisfaction in Chengdu's universities, offering insights into region-specific drivers of satisfaction in online learning.

3. Research Methods and Materials

3.1 Research Framework

Clark and Ivankova (2016) noted that a conceptual framework is grounded in previous theories and models and closely linked to theoretical frameworks. This study incorporates three theoretical frameworks: (1) effort expectancy, information quality, and performance expectancy, (2) student-student interaction, student engagement, and student satisfaction, and (3) course structure. Independent variables include effort expectancy, information quality, performance expectancy, student-student interaction, and course structure, while student satisfaction serves as the dependent variable. Student engagement acts as a mediating variable.

The research is based on the UTAUT and ISS models, integrating external variables from UTAUT to identify key factors influencing mobile learning acceptance and student satisfaction. The study proposes six hypotheses, examining the causal relationships among variables. The conceptual framework, built on ISS and UTAUT, aims to identify the key determinants of student satisfaction with online learning in higher education in Sichuan, China.

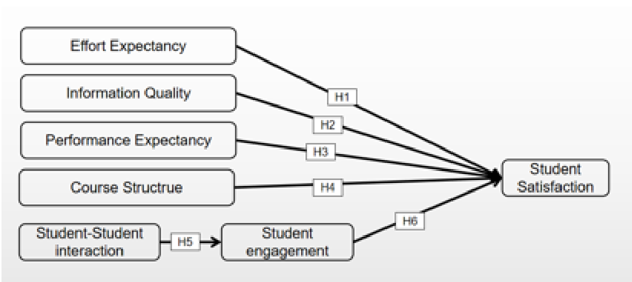

Figure 1: Research Conceptual Framework

3.2 Research Methodology

This study employs empirical analysis and quantitative methods, utilizing a questionnaire survey to examine factors influencing student satisfaction with online learning systems in higher education. The questionnaire was developed using the WeChat mini-program Wenjuanxing, an online survey platform that facilitated efficient data distribution and collection. The target population comprised undergraduate, master's, and doctoral students from four universities in Chengdu, with a calculated sample size of 515 participants. Prior to data collection, the questionnaire underwent rigorous testing to ensure reliability and validity, employing Item-Objective Consistency (IOC) to measure content validity. A pilot test was conducted with 50 participants to assess the survey's effectiveness before full-scale distribution. The final survey was administered online, gathering responses from students across the four universities.

Following data collection, SPSS and AMOS statistical tools were used for analysis. Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) were applied to validate the conceptual framework and test the hypothesized relationships between variables. Adhering to the standards of empirical research, this study follows a structured approach, including the introduction, theoretical foundation and literature review, theoretical model construction and hypothesis formulation, questionnaire design and data collection, empirical analysis, results discussion and interpretation, conclusion, and future research directions.

This study adhered to ethical research principles, ensuring participant consent, anonymity, and data protection. All participants were informed of the research objectives and voluntarily provided consent before participating. Personal information was anonymized to maintain confidentiality, and data were securely stored and handled in accordance with institutional guidelines to protect participant privacy. Additionally, survey responses were used strictly for academic research purposes, ensuring compliance with ethical standards in social science research.

3.3 Population and Sample Size

In this study, the target population comprises undergraduate, graduate, and doctoral students from four higher education institutions in Chengdu, Sichuan Province, China. All participants have at least one year of online learning experience, ensuring familiarity with online education and interactive engagement.

According to the A-priori Sample Size Calculator for Structural Equation Modeling (SEM) developed by Soper (2006), the recommended minimum sample size for a model with seven latent variables and 23 observed variables at a 0.05 probability level is 425. To meet this requirement, questionnaires were distributed and screened, yielding 515 valid responses.

3.4 Sampling Technique

This study employed non-probability sampling techniques, including judgment sampling, quota random sampling, and convenience sampling, to conduct scope analysis and sample selection. Non-probability sampling was chosen for its practicality and efficiency in targeting specific student groups within selected universities in Chengdu, Sichuan, China. Given logistical constraints and the dispersed nature of the student population, these methods enabled effective data collection from key institutions that represent diverse online learning experiences.

The sampling process began with judgment sampling, where four major higher education institutions were selected based on their prominence and established digital learning infrastructures. These universities included Sichuan University of Media and Communications, Chengdu University of Information Technology, Chengdu University of Technology, and the University of Electronic Science and Technology of China.

Next, quota random sampling was applied to determine proportional representation from each institution, ensuring that the sample reflects the distribution of students across these universities. The proportional sample sizes for each institution are displayed in Table 1, demonstrating the calculated representation based on total population size.

Finally, convenience sampling was employed to distribute the online questionnaire through the Wenjuanxing platform, leveraging digital accessibility for efficient data collection. This approach facilitated the gathering of 515 responses from students across the four universities.

Table 1: Sample Size of Students

University Name	Population Size	Proportional Sample Size
Sichuan University of Media and Communications	23,000	91
Chengdu University of Information Technology	25,000	98
Chengdu University of Technology	38,000	149
University Of Electronic Science and Technology Of China	45,000	177
Total	**131,000**	**515**

4. Results and Discussion

4.1 Demographic Information

Demographic data included academic discipline and years of study. A total of 515 students from four higher education institutions participated, comprising 200 undergraduates (38.8%), 249 postgraduates (48.3%), and 66 doctoral students (12.9%). By discipline, 220 students (42.7%) were from science and engineering, 103 (20.0%) from arts and sports, 171 (33.2%) from literature and history, and 21 (4.1%) from other fields. For daily online learning duration, 90 students (17.4%) spent less than one hour, 145 (28.2%) spent one to two hours, 193 (37.5%) spent two to three hours, 64 (12.4%) spent three to four hours, and 23 (4.5%) spent more than four hours.

Table 2: Demographic Information

Demographic and General Data (N=515)		Frequency	Percentage
Year of Study	Undergraduate students	200	38.8
	Postgraduate students	249	48.3
	PhD students	66	12.9
Academic Disciplines	Science and Engineering	220	42.7
	Arts and Sports	103	20.0
	Literature and History	171	33.2
	Other fields	21	4.1
Daily Online Learning	Less than one hour	90	17.4
	One to two hours	145	28.2
	Two to three hours	193	37.5
	Three to four hours	64	12.4
	more than four hours	23	4.5

4.2 Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis (CFA) is a crucial component of Structural Equation Modeling (SEM) and a fundamental step in the process (Hair et al., 2010). As an integral part of SEM, CFA examines the relationships between observed and latent variables (Arbuckle, 2008). CFA also assesses convergent and discriminant validity, ensuring the robustness of the measurement model. The analysis result for convergent validity is presented in Table 3. The validity is proven from the values of construct reliabilities above 0.70, factor loading and average variances extracted greater than 0.50. The study employed various model fit indices in the Confirmatory Factor Analysis (CFA), including GFI, AGFI, NFI, CFI, TLI, and RMSEA, to ensure the measurement model's adequacy.

Table 3: Confirmatory Factor Analysis (CFA), Composite Reliability (CR), and Average Variance Extracted (AVE) Results

Variable	Source of Questionnaire (Measurement Indicator)	No. of Item	Cronbach's Alpha	Factor Loading	CR	AVE
Effort Expectancy (EE)	Hayfaa (2021)	3	0.826	0.762-0.794	0.8266	0.6138
Information Quality (IQ)	Hayfaa (2021)	3	0.809	0.752-0.782	0.8093	0.5859
Performance Expectancy (PE)	Hayfaa (2021)	4	0.860	0.751-0.807	0.8598	0.6054
Course Structure (CS)	Nashaat et al. (2021)	4	0.838	0.557-0.913	0.8347	0.5700
Student-Student Interaction (SI)	Kim and Kim (2021)	3	0.830	0.749-0.825	0.8310	0.6214
Student Engagement (SE)	Kim and Kim (2021)	3	0.813	0.747-0.795	0.8136	0.5928
Student Satisfaction (SS)	Hayfaa (2021)	3	0.828	0.779-0.796	0.8291	0.6178

Note: CR = Composite Reliability, AVE = Average Variance Extracted

Table 4 presents the square roots of the extracted variance differences, demonstrating that the correlations among the study variables are suitable. Collectively, these measures confirm the validity of the structural model estimated in this research.

Table 4: Discriminant Validity

Variable	Factor Correlations						
	EE	IQ	PE	CS	SI	SE	SS
EE	**0.783**						
IQ	0.178	**0.765**					
PE	0.296	0.126	**0.778**				
CS	0.176	0.101	0.124	**0.755**			
SI	0.383	0.202	0.312	0.205	**0.788**		
SE	0.263	0.285	0.205	0.224	0.307	**0.770**	
SS	0.466	0.302	0.381	0.19	0.379	0.441	**0.786**

Note: The diagonally listed value is the AVE square roots of the variables

4.3 Structural Equation Model (SEM)

In this study, Structural Equation Modeling (SEM) was employed to analyze the collected data, offering several advantages. It facilitates the exploration of dependent relationships (Hair et al., 2010) and examines causal relationships between latent and observed variables. By accounting for random error in observed variables, SEM enhances measurement accuracy and improves the reliability of results. The method also incorporates multiple indicators to measure latent variables, providing a more comprehensive assessment. Additionally, SEM allows for hypothesis testing at both the construct and item levels, making it a robust tool for data analysis (Hoyle, 2011).

The goodness of fit for the structural model was assessed and is presented in Table 5. The statistical values were CMIN/DF = 3.018, GFI = 0.896, AGFI = 0.872, NFI = 0.878, CFI = 0.915, TLI = 0.904, and RMSEA = 0.063. As all fit indices exceeded the acceptable thresholds, the model's overall fit was confirmed.

Table 5: Goodness of Fit for Structural Model

Index	Criterion	Statistical Value
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	3.018
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.896
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.872
NFI	≥ 0.80 (Wu & Wang, 2006)	0.878
CFI	≥ 0.80 (Bentler, 1990)	0.915
TLI	≥ 0.80 (Sharma et al., 2005)	0.904
RMSEA	< 0.08 (Sica & Ghisi, 2007)	0.063

Note: 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

The strength of the correlation between independent and dependent variables in the proposed hypotheses is assessed using regression coefficients or standardized path coefficients.

The hypothesis testing results reveal that five out of the six proposed hypotheses are supported, indicating significant relationships between the identified independent variables and student satisfaction or engagement. Effort Expectancy (EE), Information Quality (IQ), Performance Expectancy (PE), Student-Student Interaction (SI), and Student Engagement (SE) demonstrated positive and significant impacts. In contrast, Course Structure (CS) did not show a statistically significant effect on student satisfaction. These findings are summarized in Table 6 and further illustrated in Figure 2.

Table 6: Hypothesis Testing Result

Hypothesis	Standardized path coefficients (β)	t-value	Test Result
H1: EE → SS	0.392	7.590*	Supported
H2: IQ → SS	0.187	3.898*	Supported
H3: PE → SS	0.279	5.849*	Supported
H4: CS → SS	0.064	1.434	Not Supported
H5: SI → SE	0.377	6.932*	Supported
H6: SE → SS	0.380	7.425*	Supported

Note: *=p-value<0.05

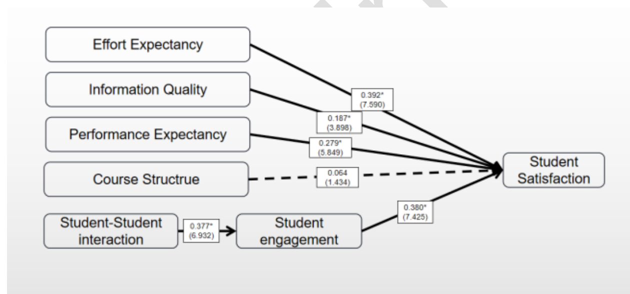

Figure 2: Path Diagram Result
Note: Solid line reports the Standardized Coefficient with as p<0.05, and t-value in Parentheses; Dash line reports Not Significant

H1: Effort expectancy has the strongest impact on student satisfaction. The path relationship between effort expectancy and student satisfaction has a standardized path coefficient of 0.392 and a t-value of 7.590. This result supports previous studies by Hayfaa (2021), Violaine and Hwang (2019), and Koceska and Koceski (2020). Students are more satisfied and anticipate achieving the required performance when they perceive e-learning services as easy to use and requiring minimal effort.

H2: Information quality also plays a crucial role showing a standardized path coefficient of 0.187 and a t-value of 3.898. The accessibility, timeliness, accuracy, and relevance of information influence students' perceptions of LMS usefulness. This finding is consistent with the research of Hayfaa (2021), Pérez-Pérez et al. (2020), and Koceska and Koceski (2020).

H3: Performance expectancy directly affects student satisfaction, as indicated with a standardized path coefficient of 0.279 and a t-value of 5.849. This result is consistent with the findings of Violaine and Hwang (2019), Koceska and Koceski (2020), and Hayfaa (2021), demonstrating that higher performance expectancy leads to greater student satisfaction.

H4: Course structure did not show a significant impact on student satisfaction, as indicated by the path coefficient of 0.064 and a t-value of 1.434. While structured content and organized course design are traditionally considered important (Grandzol & Grandzol, 2006; Moore, 1991), this study's findings suggest that in Chengdu's online learning environment, students prioritize usability, peer interaction, and accessible content over rigid course layouts. This may be due to the flexible and asynchronous nature of online learning, where students value adaptability and self-directed learning paths more than predefined structures. These results align with Nashaat et al. (2021), who found that course structure alone may not drive satisfaction without interactive and supportive learning experiences.

H5: Student-student interaction primarily influences student engagement. The standardized path coefficient is 0.377, with a t-value of 6.932. This result aligns with studies by Jaggars and Xu (2016) and Kim and Kim (2021), which suggest that the quality of interpersonal interaction in an online learning environment significantly impacts students' academic performance.

H6: Student engagement is another significant factor influencing student satisfaction. The standardized path coefficient is 0.380, with a t-value of 7.425. This suggests that interaction and active communication enhance student satisfaction, aligning with findings from Dziuban et al. (2019), Gray and DiLoreto (2016), and Kim (2021).

5. Conclusions and Recommendation

5.1 Conclusions

This study examines the factors influencing student satisfaction with online learning in higher education institutions in Chengdu, Sichuan. As online learning becomes increasingly integral to education, understanding student satisfaction is essential for enhancing educational quality and teaching models. The research tests six hypotheses, adapted from theoretical models such as UTAUT and DeLone and McLean's Information System Success Model, to assess the impact of Effort Expectancy, Information Quality, Performance Expectancy, Course Structure, Student-Student Interaction, and Student Engagement on Student Satisfaction.

Participants included students from four Chengdu universities with at least one year of online learning experience. A non-probability sampling method was employed, incorporating judgment sampling, quota random sampling, and convenience sampling. Data were collected through a questionnaire using a five-point Likert scale, with reliability ensured via expert review and a pre-test. A total of 515 questionnaires were distributed, and data were analyzed using Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) to evaluate the validity and reliability of the research model and examine factors influencing the use of learning management systems. Five out of six hypotheses were supported, confirming the study's objectives.

This study highlights two key findings. First, Effort Expectancy is the strongest predictor of Student Satisfaction, surpassing Student Engagement. It refers to the effort required to use a technology, indicating ease of use when adopting a new system. Enhancing Effort Expectancy is critical to improving student satisfaction.

Second, Student-Student Interaction (SI) significantly influences Student Engagement. In online learning, informal peer interactions create open communication spaces, fostering a more engaging and collaborative environment compared to formal instructor-led interactions. Both peer engagement and instructor feedback enhance student participation, emphasizing the need for universities to prioritize peer communication to improve online learning experiences and satisfaction.

In contrast, Course Structure (CS) did not show a significant impact on Student Satisfaction. This finding is different from what many studies suggest, where well-organized courses are thought to improve learning experiences (Grandzol & Grandzol, 2006; Moore, 1991). One possible reason could be that in Chengdu's online learning environment, students might value flexibility more than rigid course designs. Online platforms often allow students to access materials at their own pace, making strict course organization less important. Additionally, Chinese online learning platforms tend to emphasize technology and adaptability, which may reduce the impact of traditional course structuring. This suggests that to truly enhance student satisfaction, universities should focus not just on course design but also on making learning experiences more interactive and flexible. Future research could explore how adaptive learning and modular course designs affect student satisfaction in online settings.

A limitation of this study is its focus on four universities in Chengdu, which may limit generalizability. Future research could explore a broader range of institutions and incorporate qualitative methods for deeper insights.

5.2 Recommendations

This study identifies key factors influencing student satisfaction with online learning at four universities in Chengdu, Sichuan, including Effort Expectancy (EE), Information Quality (IQ), Performance Expectancy (PE), Course Structure (CS), Student-Student Interaction (SI), Student Engagement (SE), and Student Satisfaction (SS). Among these, Effort Expectancy and Student Engagement are the strongest predictors of satisfaction, while Information Quality has a comparatively weaker impact.

Theoretical Contributions

This study contributes to the existing body of knowledge by highlighting the crucial role of Effort Expectancy and Student Engagement in determining online learning satisfaction. The findings support previous theoretical models, such as the UTAUT and DeLone and McLean's Information System Success Model, confirming that perceived ease of use and active peer interactions significantly impact satisfaction. Additionally, the study reveals that Course Structure (CS) does not significantly influence satisfaction in Chengdu's online learning context, challenging traditional assumptions that structured course design directly enhances student experiences. This insight contributes to understanding how the flexibility and adaptability of online learning environments may reduce the importance of rigid course layouts.

Furthermore, the study adds value by demonstrating that Information Quality (IQ), while important, has a less significant effect on satisfaction compared to engagement factors. This indicates that online learning environments should focus more on interactive elements and ease of use rather than solely on content quality.

Practical Recommendations

To enhance student satisfaction with online learning, educators and institutions should prioritize ease of use and accessibility in Learning Management Systems (LMS). Since Effort Expectancy emerged as the most influential factor, universities should ensure that platforms are user-friendly, offer seamless navigation, and provide adequate technical support. This can reduce barriers to adoption and improve the overall learning experience.

Given the significant impact of Student Engagement, universities should design more interactive and participatory learning environments. This includes incorporating peer collaboration tools, discussion forums, and real-time communication features to create a dynamic online experience. Instructors play a key role by facilitating active learning strategies and fostering consistent student-instructor interactions.

Since Information Quality influences perceptions of LMS usefulness, it is crucial for institutions to maintain accurate, relevant, and easily accessible course materials. This involves real-time content updates, clear instructional guidance, and reliable assessment methods. Additionally, integrating adaptive learning technologies that tailor content delivery based on student progress can further enhance satisfaction.

Although Course Structure did not directly impact satisfaction, institutions should continue to develop well-organized courses that balance structured learning pathways with flexibility. Clear objectives, logical assignment sequences, and engaging instructional methods can make courses more adaptable, allowing students to customize their learning experiences according to personal needs.

By implementing these practical improvements, universities can foster more effective, engaging, and student-centered online learning environments, ultimately leading to improved learning outcomes and higher satisfaction levels.

5.3 Limitation and Further Study

This study has several limitations and offers recommendations for future research. Its focus on higher education and data collection from four universities in Chengdu, Sichuan, limits the scope and generalizability of the findings. Future studies should consider expanding the research to other educational levels, such as primary and secondary schools, as well as professional learning environments like freelancers and small and medium-sized enterprises (SMEs). This broader scope could enhance the understanding of online learning satisfaction across diverse educational and professional contexts.

Additionally, future research could benefit from adopting a mixed-method approach. Combining quantitative surveys with qualitative interviews or focus groups would provide richer insights into student experiences, capturing both measurable outcomes and personal perceptions. This approach would allow for deeper exploration of how technological ease of use, information quality, and engagement strategies affect satisfaction in different learning settings.

To further strengthen findings, longitudinal studies are recommended to track changes in student satisfaction and engagement over time. Such studies would offer insights into how student perceptions evolve with prolonged exposure to online learning platforms, highlighting long-term effects and potential areas for improvement. This would be particularly valuable for understanding the sustainability of online learning satisfaction in rapidly changing digital environments.

Future research could also investigate Student Engagement and Behavioral Intention to offer a more comprehensive perspective on online education experiences. Employing experimental methods could help control variables and analyze causal relationships, such as how specific quality factors influence satisfaction. Integrating longitudinal and mixed-method designs would further enrich understanding by capturing both short-term impacts and long-term trends, as well as the lived experiences of students in online learning settings.

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