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Key Influencers of College Students' Learning Outcomes in Online Education in Chengdu

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Abstract

Purpose: This study aims to identify and explore the factors influencing college students' satisfaction and learning outcomes in online education in Chengdu, China. **Research design, data and methodology:** A quantitative research method was employed, with data collected through questionnaires distributed to the target population. A total of 500 valid responses were obtained for analysis. To ensure the validity and reliability of the instrument, item-objective congruence (IOC) and Cronbach's Alpha tests were conducted before survey distribution. The collected data were analyzed using confirmatory factor analysis (CFA) and structural equation modeling (SEM) to test the research hypotheses, assess the model's goodness of fit, and explore causal relationships between variables. **Results:** The analysis results indicate that the proposed conceptual model effectively predicts and explains learning outcomes (LO) in online education. Student satisfaction (SS) emerged as a key predictor of learning outcomes, directly influencing student engagement and performance. Additionally, factors such as teachers' technology readiness, structured teaching approaches, students' technology readiness, and self-efficacy were found to have a direct impact on student satisfaction. **Conclusions:** Based on these findings, the study recommends that higher education institutions enhance both students' and faculty members' technological readiness and foster students' self-efficacy to improve satisfaction and learning outcomes in online education.

Keywords: Technology Readiness, Self-efficacy, Perceived Benefits, Student Satisfaction, Learning Outcome

JEL Classification Code: A20, I23, L86, O30

1. Introduction

With the advancement of technology, modern online teaching and learning has become a global trend. Online education technology relies on electronic media and devices to enhance the teaching experience through interactive learning platforms, course management systems, and communication tools. Learning Management Systems (LMS) serve as the core platform to support online learning, providing essential teaching and assessment functions. As more educational institutions shift from traditional classrooms to LMS-driven instruction, understanding the factors influencing its effectiveness becomes critical.

E-learning incorporates digital media and adaptive technologies to enable learners to study flexibly, anytime and anywhere (Basak et al., 2018). Technologies such as artificial intelligence (AI), chatbots, virtual reality (VR), and augmented reality (AR) are reshaping traditional education through personalized and immersive learning experiences (Fryer et al., 2020). Mobile learning (M-learning) also promotes flexibility by enabling students to access learning materials via smart devices (Demiraj, 2020). While the integration of these technologies opens new possibilities, it also raises essential questions about how such tools influence actual learning outcomes and student satisfaction, especially in higher education.

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Online learning provides various modes such as e-learning platforms and virtual communities, offering cost-effective and time-flexible alternatives to traditional education. However, it faces challenges related to teacher-student interaction, technological barriers, and student self-regulation. These challenges have made it increasingly important to explore how different teaching approaches, technological readiness, and learner attributes affect student engagement and performance (Cunningham, 2020; Kumar et al., 2021). Designing equitable and effective online courses requires attention to accessibility, teacher training, and pedagogical strategies that promote active learning.

In the Chinese context, especially following the rapid digital shift during and after COVID-19, online education has seen remarkable growth, particularly in higher education. With strong policy and technological support, online education in China now plays a central role in expanding access to quality learning resources. Although its growth has stabilized, critical issues remain concerning teaching quality, interaction, and disparities in digital access, highlighting the need for ongoing evaluation of online learning effectiveness.

As a major educational hub in Southwest China, Chengdu has made substantial investments in online education infrastructure, platform development, and curriculum reform. Despite this progress, local universities continue to face challenges in delivering high-quality online education due to varying levels of teacher readiness, course design quality, and technological limitations. With the widespread adoption of online education platforms, there is a growing need to assess the factors that contribute to student satisfaction and learning outcomes to ensure long-term sustainability (Szopinski & Bachnik, 2022).

This study addresses these concerns by surveying students from different types of universities in Chengdu who have over one year of online education experience. The research aims to fill the gap in empirical studies focused specifically on the Chengdu higher education context, identifying key determinants of online learning effectiveness and analyzing their interrelationships. By doing so, it contributes to the broader discourse on optimizing online education delivery and enhancing student outcomes in regional contexts.

2. Literature Review

2.1 Teachers' Technology Readiness

Teacher technology readiness plays a crucial role in the effective use of instructional technology and is often assessed through the lens of technology acceptance. High technology readiness enhances student success and learning efficiency. The perceived usefulness and ease of use directly influence technology adoption (Venkatesh & Bala, 2008). Teachers' readiness affects their interaction with students, varying based on factors like autonomy and preference. It is closely associated with achieving teaching goals, supporting student learning, and integrating technology in the classroom, while also impacting teachers' emotional well-being. Meadows and Leask (2002) found a strong link between technological maturity and willingness to adapt classroom practices, and Singh and Chan (2014) highlighted that attitudes toward technology depend on teaching experience and technical expertise. For less experienced teachers, institutional training becomes especially important.

Technology suitability in instructional activities directly affects user satisfaction (Goodhue & Thompson, 1995). Studies have consistently found that task-technology fit (TTF) enhances performance and satisfaction. Furthermore, IT support and institutional preparedness are essential, as they foster confidence in practical technology use and create a more effective online learning environment (Norzaidi et al., 2009). Although previous studies emphasize technology readiness among teachers, its specific influence on students' satisfaction in online learning settings, particularly in local educational contexts, remains underexplored. Based on existing research, the following hypothesis is proposed.

H1: Teachers' technology readiness significantly influences students' online learning satisfaction.

2.2 Teachers' Structured Approach

A structured teaching approach involves organizing content and instructional methods systematically to promote effective learning outcomes. Research shows that such pedagogy enhances student outcomes when supported by teacher training, real-time feedback, and motivation (Chakera et al., 2020). Collaborative planning, peer observation, and evidence-based instructional design are key in optimizing online course delivery. Biggs (1989) emphasized that structured teaching methods align well with students' learning styles, promoting motivation and cognitive engagement. Brown (2022) reinforced the importance of this approach in strengthening teacher-student interaction. Furthermore, teaching effectiveness has been associated with resource utilization and students' analytical development.

In online education, a well-structured course and frequent teacher interaction can offset feelings of isolation among students. Hung et al. (2014) demonstrated that teacher preparation and attitude toward digital tools directly impact student satisfaction. Moreover, engagement, motivation, and learning outcomes are all tied to the degree of structure in digital learning environments. Despite evidence of the benefits of structured teaching, there is limited research addressing how this translates into student satisfaction within the online learning environments of Chinese higher education. Based on existing research, the following hypothesis is proposed:

H2: Teachers' structured approach significantly influences students' online learning satisfaction.

2.3 Students' Technology Readiness

Student technology readiness refers to learners' ability and willingness to effectively engage with technology in academic, work, and everyday contexts. It includes dimensions such as optimism, innovation, discomfort, and insecurity (Parasuraman, 2001). Johnson (2006) further noted the importance of previous experience, technical competence, and training. Students lacking in readiness may find it difficult to operate learning systems effectively, impacting their educational progress.

Studies show that ICT readiness supports adoption and usage, influencing learners' willingness to interact with online platforms (Gombachika & Khangamwa, 2013). The Technology Readiness Index (TRI) has proven useful across different cultural contexts to evaluate behavioral outcomes. Fogerson (2005) and Yilmaz (2017) both found a strong connection between technological readiness and satisfaction with learning environments, reinforcing the role of preparedness in shaping the digital learning experience. While much of the literature emphasizes readiness as a driver for system adoption and satisfaction, fewer studies investigate how student readiness directly influences satisfaction in long-term, real-world educational settings. This presents an opportunity to explore its relevance in localized contexts. Based on existing research, the following hypothesis is proposed:

H3: Students' technology readiness significantly influences students' online learning satisfaction.

2.4 Students' Self-efficacy

Self-efficacy refers to an individual's belief in their capacity to execute tasks and reach objectives in specific contexts (Schunk, 1989; Solomon & Fernald, 1991). This psychological trait has long been linked to academic performance. As technology becomes more integral to education, confidence in navigating digital tools has enhanced students' self-efficacy (Darmanto & Yuliari, 2018). Engagement in programming and problem-solving activities further strengthens this belief.

In online education, self-efficacy predicts course satisfaction and is positively correlated with variables such as social support and perceived usefulness (Artino, 2008; Smallheer & Dietrich, 2019). Kumar et al. (2020) found that self-efficacy influences not only academic achievement but also the quality of the learning experience. Although the literature establishes a clear link between self-efficacy and satisfaction, its role in influencing satisfaction within online environments specific to regional university settings is not sufficiently addressed. Based on existing research, the following hypothesis is proposed:

H4: Students' self-efficacy significantly influences students' online learning satisfaction.

2.5 Students' Perceived Benefits

Perceived benefits encompass the degree to which users recognize advantages such as time savings, convenience, and ease of use when adopting new technologies (Featherman & Pavlou, 2003; Peter & Tarpey, 1975). In education, this concept helps explain how students weigh the trade-offs between traditional learning methods and digital alternatives.

Rogers (1995) noted that individuals evaluate new technologies based on perceived value versus cost. Kim et al. (2020) found that perceived benefits influence satisfaction, emotions, and intentions to continue using a system. Dubey and Sahu (2021) also confirmed its role in promoting user satisfaction and loyalty. Yet, while these studies confirm the importance of perceived benefit in tech adoption, less attention has been paid to how students' perceived benefits relate to satisfaction in blended or fully online higher education systems. This research aims to address that gap. Based on existing research, the following hypothesis is proposed:

H5: Students' perceived benefits significantly influence students' online learning satisfaction.

2.6 Students' Satisfaction

Satisfaction is the emotional response to a service or product meeting expectations. In educational contexts, student satisfaction encompasses perceptions of course design, teacher interaction, technology tools, and academic support (Ali et al., 2016; Muhsin et al., 2020). Teacher satisfaction has a reciprocal effect on student satisfaction—engaged educators often promote better student experiences (Bolliger et al., 2014). Satisfaction also serves as a predictor of loyalty and long-term engagement (Permana et al., 2020). Although motivation and participation enhance learning outcomes, their impact on satisfaction varies. According to Eom et al. (2006), satisfaction remains a core predictor of learning outcomes in online settings, shaped by both system and information quality. While substantial evidence supports the role of satisfaction in education, few studies fully examine how it mediates the link between upstream variables (like technology readiness and teaching methods) and student learning outcomes, particularly in non-Western contexts. Based on existing research, the following hypothesis is proposed:

H6: Students' online learning satisfaction significantly influences learning outcomes.

2.7 Learning Outcome

Learning outcomes are the measurable changes in knowledge, skills, and attitudes that result from educational activities. In e-learning and MOOC environments, they represent students' behavioral and cognitive responses to digital tools and course structures (Cheng et al., 2019; Zhao et al., 2020). Zulfiqar et al. (2021) demonstrated that self-efficacy is a strong predictor of performance, while Aparicio et al. (2019) emphasized that a weak connection between technology use and outcome can limit educational gains. Liu et al. (2020) suggested that teaching strategies must align with learner needs and contexts to maximize effectiveness.

Despite increasing attention to online learning globally, existing studies often lack detailed examinations of how learning outcomes are shaped by interconnected factors like satisfaction, technology readiness, and teaching strategies—especially in regional educational settings. This study aims to close this research gap.

3. Research Methods and Materials

3.1 Research Framework

The conceptual framework has been developed from the previous research frameworks of the study, which draws on three theoretical models. The first theoretical framework, proposed by Maini et al. (2021), examines predictors of student satisfaction, focusing on different aspects of teacher preparation and student preparation in online classrooms. It examines the relationship between teachers' technical preparation and teachers' structured approach, as well as students' technical preparation, self-efficacy, and satisfaction. The second theoretical framework is proposed by Dubey and Sahu (2021). The influence of students' perceived benefits on students' satisfaction is studied. The third theoretical framework is Darawong and Widayati (2022). The research confirmed that student satisfaction has a significant impact on learning outcomes. The conceptual framework of this study is shown in Figure 1.

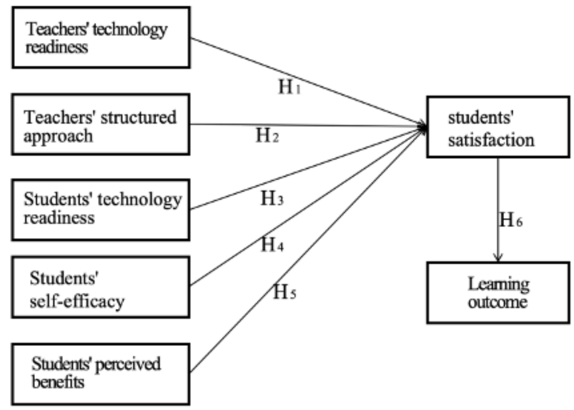

Figure 1: Conceptual Framework

This study aims to explore the factors influencing student satisfaction and learning outcomes in online education among university students in Chengdu. These factors include teachers' technology readiness, teachers' structured approach, students' technology readiness, students' self-efficacy, and students' perceived benefits. Additionally, this study examines the causal relationships among these variables.

3.2 Research Methodology

Quantitative research is scientific and uses standardized techniques for information transmission, clustering, and processing while ensuring the intrinsic quality of validity (Kumar, 2010). This study adopted a quantitative approach and designed a structured questionnaire using an online survey platform (e.g., Questionstar) to collect data conveniently and efficiently. Before distribution, experts were invited to evaluate the content validity of each item through the item-objective congruence (IOC) technique, and a pilot test was conducted to assess internal consistency and reliability using Cronbach's Alpha.

Ultimately, the study collected 500 valid responses from undergraduates at four universities in Chengdu via online questionnaires. While online distribution ensured accessibility and efficiency, this method may introduce response bias, as participants self-select into the survey and may differ in motivation or digital literacy from the general population. After data collection, SPSS and AMOS software were used for analysis. Confirmatory factor analysis (CFA) and structural equation modeling (SEM) were applied to empirically test the conceptual framework and research hypotheses.

3.3 Population and Sample Size

The target population consisted of sophomore to fourth-year undergraduates from four universities in Chengdu, China, all of whom had more than one year of online learning experience. First-year students were excluded due to their limited exposure to online education, which could hinder their ability to provide meaningful feedback.

Based on standard requirements for structural equation modeling (SEM), a minimum sample size of 425 is considered adequate. After data screening and cleaning, a total of 500 valid responses were retained for analysis. However, focusing solely on universities in Chengdu may limit the generalizability of the findings. Educational infrastructure, technological resources, and student characteristics can vary significantly across different regions in China and abroad. Therefore, the applicability of these results to other Chinese cities or international contexts should be interpreted with caution.

3.4 Sampling Technique

Based on established research methods, this study employs a multi-stage sampling approach, combining probabilistic and non-probabilistic techniques. First, five representative universities in Chengdu were selected through non-probability sampling, focusing on undergraduate students with at least one year of online education experience. Next, stratified random sampling was used, treating each university as an independent stratum. To enhance representativeness, proportional stratified sampling was applied, categorizing the target population into four groups based on their online education background. A total of 500 samples were allocated proportionally, as shown in Table 1.

Table 1: Number of Questionnaires Distributed to Each University

University Name	Population Size	Proportional Sample Size
Sichuan University	28,096	148
Southwest Jiaotong University	24,755	130
Southwest Minzu University	24,039	126
Sichuan University of Media and Communications	18,365	96
Total	**95,255**	**500**

Source: Constructed by author

Over a seven-month period, sample data was collected primarily through online surveys. The use of preset response options minimized human input errors and allowed automatic electronic storage, enhancing data accuracy. Following data collection, screening was conducted to ensure the inclusion of the target group and maintain the quality of valid samples.

4. Results and Discussion

4.1 Demographic Profile

The study surveyed a total of 500 undergraduate students from four universities in Chengdu. Of the respondents, 58.2% were female and 41.8% were male, indicating a slightly higher female representation in the sample. All participants were over the age of 18, aligning with the criteria for higher education enrollment in China.

In terms of academic level, the sample included a balanced distribution of students across different stages of their undergraduate studies. Sophomores accounted for 27.6% of the respondents, juniors comprised the largest group at 38%, and seniors made up 34.4%. This spread ensures that the study reflects a range of experiences and levels of exposure to online learning, providing a well-rounded perspective on how students at various academic stages perceive and engage with online education.

4.2 Confirmatory Factor Analysis (CFA)

A confirmatory factor analysis (CFA) was conducted in this study. The results indicated that all items within each variable were significant and adequately represented the factor load used to assess discriminant validity. The factor loadings for each item were significant and met the acceptable criteria, demonstrating a good model fit (Hair et al., 2006). Specifically, all factor loading values exceeded 0.50, and the p-value was below 0.05. The construct reliability exceeded 0.7, and the average variance extracted (AVE) was greater than 0.5, meeting the criteria established by Fornell and Larcker (1981). All estimates were statistically significant.

Table 2: 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
Teachers' Technology Readiness (TTR)	Maini et al. (2021)	3	0.798	0.744-0.766	0.799	0.569
Teachers' Structured Approach (TSA)	Maini et al. (2021)	4	0.818	0.626-0.796	0.823	0.541
Students' Technology Readiness (STR)	Maini et al. (2021)	4	0.851	0.709-0.837	0.855	0.597
Students' Self-efficacy (SSE)	Maini et al. (2021)	4	0.826	0.672-0.792	0.828	0.547
Students' Perceived Benefits (SPB)	Dubey and Sahu (2021)	4	0.857	0.713-0.819	0.858	0.602
Students' Satisfaction (SS)	Darawong and Widayati (2022)	4	0.838	0.719-0.806	0.840	0.568

Variable	Source of Questionnaire (Measurement Indicator)	No. of Item	Cronbach's Alpha	Factor Loading	CR	AVE
Learning Outcome (LO)	Darawong and Widayati (2022)	4	0.860	0.737-0.803	0.861	0.608

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

Additionally, in the CFA test, model fit was evaluated using GFI, AGFI, NFI, CFI, TLI, and RMSEA. The results confirmed that both convergent and discriminant validity exceeded acceptable criteria, as shown in Table 3. Therefore, the validity of the measurement model is fully supported, reinforcing the reliability of the subsequent structural model estimation.

Table 3: Goodness of Fit for Measurement Model

Index	Criterion	Statistical Value
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	3.146
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.870
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.838
NFI	≥ 0.80 (Wu & Wang, 2006)	0.873
CFI	≥ 0.80 (Bentler, 1990)	0.909
TLI	≥ 0.80 (Sharma et al., 2005)	0.895
RMSEA	< 0.08 (Pedroso et al., 2016)	0.066

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

To verify the correlation between variables, the square root of the AVE was compared with the correlation coefficients. The results showed that all variable correlations were higher than their respective correlation values, as presented in Table 4.

Table 4: Discriminant Validity

Variable	Factor Correlations						
	TTR	TSA	STR	SSE	SPB	SS	LO
TTR	**0.754**						
TSA	0.348	**0.736**					
STR	0.363	0.580	**0.773**				
SSE	0.399	0.537	0.444	**0.740**			
SPB	0.261	0.261	0.476	0.215	**0.776**		
SS	0.468	0.561	0.569	0.619	0.347	**0.754**	
LO	0.318	0.411	0.371	0.615	0.179	0.580	**0.780**

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

4.3 Structural Equation Model (SEM)

The structural equation model (SEM) was introduced by Sewall Wright, who provided a theoretical framework for regression equations based on direct and indirect effects on observed variables within a specific domain. In this study, the SEM fit indices are presented in Table 5 Acceptable criteria were applied, appropriate fit indices were selected, and calculations were performed using SEM. The model was adjusted using SPSS AMOS 26, and the results indicated a good model fit.

Table 5: Goodness of Fit for Structural Model

Index	Criterion	Statistical Value
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	3.658
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.850
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.802
NFI	≥ 0.80 (Wu & Wang, 2006)	0.860
CFI	≥ 0.80 (Bentler, 1990)	0.893
TLI	≥ 0.80 (Sharma et al., 2005)	0.870
RMSEA	< 0.08 (Pedroso et al., 2016)	0.073

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 research model evaluates the significance of each variable using regression weights and R^2 variance. The results in Table 6 indicate that all hypotheses are supported at a significance level of $p = 0.05$. Among the factors, students' online learning satisfaction has the strongest impact on learning outcomes ($\beta = 0.651$).

Table 6: Hypothesis Testing Result

Hypothesis	Standardized path coefficients (β)	t-value	Test Result
H1: TTR → SS	0.259	5.530*	Supported
H2: TSA → SS	0.243	5.094*	Supported
H3: STR → SS	0.288	6.296*	Supported
H4: SSE → SS	0.594	10.666*	Supported
H5: SPB → SS	0.100	2.429*	Supported
H6: SS → LO	0.651	9.876*	Supported

Note: *=p-value<0.05

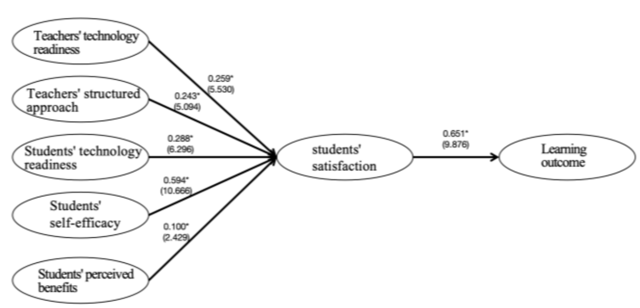

Figure 2: The Results of Structural Model
Note: Solid line reports the Standardized Coefficient with * as p<0.05, and t-value in Parentheses

For hypothesis H1, the analysis reveals a standardized path coefficient of 0.259 for the impact of teachers' structured approaches on student satisfaction and learning outcomes. This confirms that teacher performance is a crucial factor influencing student satisfaction and academic performance, particularly in terms of engagement and motivation.

Similarly, the standardized path coefficient for the impact of teachers' structured teaching on students' online learning satisfaction in hypothesis H2 is 0.243, while hypothesis H3 shows a standardized path coefficient of 0.288 for the effect of students' technology readiness on online learning satisfaction. These findings highlight the importance of teachers' technical readiness in shaping student satisfaction. Yilmaz (2017) also noted that online learners' level of technical readiness positively influences satisfaction. Moreover, teachers' readiness in instructional technology affects students' use of digital tools and their impact on learning outcomes.

Additionally, the analysis supports hypothesis H4, identifying students' self-efficacy as the most influential factor in online learning satisfaction, with a standardized path coefficient of 0.594. This result is consistent with prior research showing that self-efficacy plays a key role in student satisfaction (Liaw, 2008).

The analysis for hypothesis H5 indicates that students' perceived benefits have a weaker but still statistically significant impact ($\beta = 0.100$, $t = 2.429$). This comparatively lower influence may suggest that while students recognize certain advantages—such as flexibility, convenience, or time savings—they may not view these benefits as deeply transformative or personally engaging within the context of their actual learning experience. It is also possible that perceived benefits are more indirect or long-term in nature, whereas variables like self-efficacy and structured teaching have a more immediate and observable impact on satisfaction. This interpretation is consistent with Kim et al. (2020), who found that perceived benefits shape emotional and behavioral responses but may not always directly affect satisfaction when other stronger motivational or instructional factors are present.

Finally, the analysis results confirm that in hypothesis H6, students' online learning satisfaction has a significant impact on learning outcomes, with a standardized path coefficient of 0.651 and a t-value of 9.876. This finding aligns with previous studies demonstrating a positive correlation between user satisfaction, the effectiveness of e-learning systems, and learning outcomes (Eom et al., 2006).

5. Conclusions and Recommendation

5.1 Conclusions

This study aimed to identify the key factors that influence college students' learning outcomes in online education, with a specific focus on higher education institutions in Chengdu, China. The research examined how variables such as teachers' technology readiness, structured teaching approaches, students' technology readiness, self-efficacy, and perceived benefits contribute to student satisfaction, and how this satisfaction, in turn, affects learning outcomes.

The findings reveal that student satisfaction plays a central role in determining learning outcomes in online education. Teachers' technology readiness and structured approaches, along with students' technology readiness and self-efficacy, significantly enhance satisfaction, thereby indirectly contributing to better learning outcomes. Notably, while students' perceived benefits had a statistically significant but relatively weak effect on satisfaction, their influence on learning outcomes was marginal. This suggests that perceived advantages like convenience and efficiency may not be as influential as intrinsic factors like confidence and instructional design in shaping meaningful educational experiences.

This research contributes new insights by integrating multiple individual and instructional factors into a single conceptual model to explain online learning outcomes. While many previous studies have examined these elements in isolation, this study offers a more holistic view of how these dimensions interact in a localized context. In particular, the focus on students from Chengdu, a fast-developing education hub in Southwest China provides empirical evidence from a region that is underrepresented in online education research.

Theoretically, the study advances the understanding of how satisfaction mediates the relationship between instructional design, student readiness, and educational outcomes in online learning. While existing literature acknowledges the importance of satisfaction (e.g., Artino, 2008; Eom et al., 2006), this research strengthens the argument by demonstrating the indirect effects of both teacher- and student-related variables in a unified model. Practically, the findings suggest that universities aiming to improve online education effectiveness should prioritize enhancing teacher training, fostering student self-efficacy, and ensuring that both teachers and students are technologically prepared.

By contextualizing these findings within a regional higher education system, this study fills a research gap in both theoretical generalizability and localized application, offering direction for future interventions in similar educational environments.

5.2 Recommendations

Drawing on the key findings of this study, several evidence-based recommendations are proposed to enhance college students' learning outcomes in online education, particularly in the context of Chinese higher education. Although the constructs explored are well-established, this research offers new knowledge by demonstrating how these factors interact and influence learning outcomes within a specific regional setting. As such, these findings can inform targeted strategies and institutional policies to improve online learning effectiveness.

First, as students' self-efficacy emerged as the most influential factor on satisfaction, colleges and universities should prioritize the development of students' confidence and autonomous learning skills. This can be achieved by integrating structured support systems, mentorship programs, and training workshops focused on digital learning tools and self-regulated learning strategies.

Second, to address the impact of students' technology readiness, institutions should ensure equitable access to digital infrastructure by providing adequate hardware, software, and technical support services. This will help remove barriers to participation and promote a consistent online learning experience across diverse student populations.

The significance of teachers' technology readiness and structured teaching approaches also points to a clear need for continuous professional development. Universities should implement regular training programs that equip educators with both technical and pedagogical skills tailored for online instruction. Emphasizing the design of structured, outcome-oriented online courses—with clearly articulated goals, activities, and assessments—will enhance the overall learning experience.

Furthermore, as student satisfaction was found to be a direct predictor of learning outcomes, institutions must adopt proactive feedback mechanisms. Regular student satisfaction surveys and course evaluations can provide valuable insights for ongoing refinement of online education practices. In addition, efforts should focus on improving interactivity within online courses, offering high-quality digital resources, and ensuring timely, personalized feedback.

These strategic recommendations respond to identified gaps in practice and offer a roadmap for universities seeking to enhance the quality and outcomes of online education. By translating the study's findings into targeted interventions, higher education institutions can foster more effective, engaging, and inclusive digital learning environments.

5.3 Limitation and Further Study

First, the sample is limited to four universities in Chengdu, making it relatively small and not fully representative of students across other regions or institutional types. Future studies should include a broader and more diverse sample across different provinces, institutional tiers, and urban-rural contexts to compare regional variations in online learning outcomes.

Second, as the study uses cross-sectional data, it does not capture the long-term effects of online education. Longitudinal research is recommended to observe how student satisfaction, engagement, and performance evolve over time, particularly in response to shifts in teaching strategies or technology adoption.

Additionally, this study primarily focused on technological readiness, teaching structure, and self-efficacy but did not explore individual differences such as learning motivation and emotional states. Future research should integrate psychological variables and compare their influence across academic disciplines or hybrid learning models, which blend online and face-to-face instruction.

With the rapid integration of emerging technologies like AI and big data in education, future studies should also examine how these innovations interact with traditional pedagogical practices and impact long-term learning outcomes.

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