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Exploring Perceived Learning Impact of Students in School of Art Design and Animation Towards Massive Open Online Courses at a University in Sichuan, China

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Abstract

Purpose: To achieve its goal of online education development, the regional differences in the development of e-learning have been accounted. This study aims to investigate factors influencing students' perceived learning impact of massive open online courses at Sichuan university of media and communication, China including self-efficacy, perceived usefulness, knowledge quality, service quality, satisfaction, actual use, and perceived impact on learning. **Research Design, Data, and Methodology:** This study focuses on 500 students in School of Media and Communication, who enrolled in School of Art Design and Animation. Sampling methods utilized in the study comprised judgmental, quota, and convenience sampling techniques. Before data collection, the researcher conducted both the index of item-objective congruence and Cronbach's Alpha test. Data analysis involved the utilization of confirmatory factor analysis and structural equation modeling techniques. **Results:** Self-efficacy, perceived usefulness, knowledge quality, and actual use were all found to significantly influence satisfaction. Interestingly, service quality did not significantly impact satisfaction. Furthermore, satisfaction was found to significantly predict perceived impact on learning. **Conclusions:** This research lies in its tailored approach to studying students at a specific university, and provides valuable insights into factors influencing students' experiences and behaviors within the context of media and communication education.

Keywords : Knowledge Quality, Service Quality, Satisfaction, Actual Use, Perceived Impact on Learning

JEL Classification Code: E44, F31, F37, G15

1. Introduction

Over the past three decades, education in the twenty-first century has undergone notable transformations in teaching methodologies, largely driven by technological advancements. This evolution is particularly evident with the rise of information and communication technologies (ICTs) such as the Internet (Ditimi & Ayanda, 2013; Musaka, 2015; Yunusa et al., 2019). Students are expected to engage in coursework subsequent to viewing video lectures. Moreover, professional forum discussions on Massive Open Online Courses (MOOC) platforms serve as valuable resources for tackling complex problems. The widespread availability of the Internet has democratized access to education, enabling a growing number of individuals to benefit from it, as underscored by Barclay and Logan (2013). Additionally, individuals now have the opportunity to interact with esteemed educational institutions at minimal or no cost (Wu & Chen, 2017), particularly in developing nations.

MOOCs represent the evolution and extension of online education. Although home-based learning has gained traction in China, its reach remains limited, predominantly attracting participants aged 18 to 25. However, factors such as geography and culture hinder broader access to MOOCs within this demographic. Consequently, MOOCs have yet to achieve widespread adoption in China despite its vast population (Durksen et al., 2017). In recent years, there has been a significant upsurge in registrations for massive open

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online courses (MOOCs), with more than 100 million students enrolling in 2018 alone (Shah et al., 2018).

The issue of access to higher education is frequently debated in China, with the number of students in tertiary education projected to soar from 99.4 million in 2000 to 414.2 million. This exponential growth poses challenges for developing countries and regions. While the expansion of higher education has its benefits, it also exacerbates existing issues such as a shortage of high-quality teachers and learning materials, financial constraints, and institutional capacity limitations. Addressing these challenges will require innovative approaches, including distance teaching and collaborative learning methods, to ensure continued access to university education courses. Moreover, universities can be incentivized to develop high-quality Massive Open Online Courses (MOOCs), thereby democratizing access to education and enabling broader participation.

The present study delves into the effective impact of MOOC-based online education at Sichuan University of Media and Communication on student learning, with the aim of enhancing students' practical application of MOOCs and optimizing mobile app MOOCs for interactive learning. Furthermore, the Academic Affairs Office of Sichuan University of Media and Communication has decided to promote effective MOOC online education applications to all faculty members to enhance students' learning across various grades, majors, and courses. Therefore, this research delves into the determinants affecting the effectiveness of student learning on an online education MOOC platform at Sichuan University of Media and Communication.

2. Literature Review

2.1 Self-Efficacy

The concept of self-efficacy underscores the importance of individual attributes, making it an indispensable variable in the context of technology utilization (Mahdavian et al., 2016). Self-efficacy emerges as one of the most crucial determinants of learning success, varying across different stages of study and professional subjects (Bandura, 1991). Particularly in online settings, self-efficacy has proven instrumental in distance learning, empowering students to overcome the challenges of independent learning while fostering self-directed learning among already productive learners (Aldholay et al., 2018). Consequently, self-efficacy stands as a crucial determinant of success in online learning environments. Previous research consistently indicates a positive association between self-efficacy and satisfaction (Hong et al., 2016), as well as system utilization (Yu, 2012). Furthermore, studies suggest that self-efficacy towards courses can predict students' satisfaction with the internet (Shen et al., 2013). Based on these prior inquiries, this study formulates the following hypothesis:

H1: Self-efficacy has a significant impact on satisfaction.

2.2 Perceived Usefulness

Perceived usefulness (PU) is defined as the extent to which an individual can enhance their job performance by utilizing a specific system (Davis, 1989, p. 320). The concept of perceived usefulness also encompasses the level of confidence consumers have in how using health-related internet resources can enhance their productivity (Davis, 1989). Essentially, this notion suggests that individuals believe that integrating technology into their work will lead to improved performance (Ahadzadeh et al., 2015, 2018). Furthermore, perceived usefulness has been identified as a major predictor of satisfaction with educational curriculum content (Arbaugh, 2002). Perceived usefulness is aimed at the stage where the user believes that using a skill can help them perform better in work or study (Venkatesh et al., 2003). Previous research on technology adoption in educational settings consistently shows a positive association between perceived usefulness and satisfaction with such technologies (e.g., Sørebø et al., 2009; Stone & Baker-Eveleth, 2013). Based on these previous studies, this research posits these assumptions:

H2: Perceived usefulness has a significant impact on satisfaction.

2.3 Knowledge Quality

The caliber of knowledge mirrors the internal business capabilities that bolster the efficiency and potential of an R&D company. Regarding knowledge utilization, it is not solely acquired but also amalgamated from diverse sources by various teams (Kleis et al., 2012). However, due to the absence of universally accepted criteria defining 'quality,' researchers have proposed varied interpretations based on contextual considerations throughout their studies (Mancilla-Amaya et al., 2010). Consequently, researchers investigating knowledge quality have adopted a similar approach to defining it as the broader definitions for overall quality (Eppler, 2006). Waheed et al. (2021) supported the hypothesis that researchers' satisfaction with ASM websites significantly correlates with the quality of relational knowledge. Similarly, research by Ifinedo (2017) on performance management, knowledge management, and organizational management indicates a positive association between knowledge quality and satisfaction. Yuce et al. (2019) revealed a direct impact of knowledge, systems, and services quality on overall satisfaction levels. Consequently, based on prior research findings, the researchers propose the

following hypothesis:
H3: Knowledge quality has a significant impact on satisfaction.

2.4 Service Quality

High-quality service provision plays a crucial role in gaining a competitive advantage by offering unique products or additional value to existing goods, thereby enhancing customer satisfaction (Santos, 2003). The SERVQUAL metric serves as a widely used tool for assessing service quality from the buyers' perspective, aiding in evaluating service expectations and comparing them with perceived performance (Parasuraman et al., 1985). Comprising five dimensions, SERVQUAL allows for the evaluation of service quality over the long term, while satisfaction provides a more immediate and specific assessment of individual transactions (Cronin & Taylor, 1994). Chaudhary and Dey (2021) uncovered a strong correlation between students' perception of the quality of educational services and their views on sustainable practices within universities, ultimately affecting their satisfaction levels. Moreover, the implementation of sustainable development initiatives played a significant role in predicting student satisfaction. Yuce et al. (2019) conducted data analysis revealing a direct impact of knowledge, systems, and services quality. Consequently, the researchers propose the following hypothesis based on their prior investigation:
H4: Service quality has a significant impact on satisfaction.

2.5 Actual Use

Actual use pertains to the extent, frequency, and manner in which an information system is utilized, encompassing factors such as its acceptance rate, characteristics, scope, quantity, and duration of skill application (DeLone & McLean, 2016). When examining the perspective of Yemeni students on online learning, actual use also includes considerations of frequency and duration of usage (Kim et al., 2015). Moreover, DeLone and McLean (2016) posit that actual usage can be determined by tallying instances of skill utilization and quantifying the time devoted to its application (Kim et al., 2015)

Singh and Suri (2024) provide valuable recommendations for educational institutions, advocating for the provision of mobile learning during crises such as the COVID-19 pandemic, along with suggestions for its effective implementation. Their research confirms that practical utilization has a positive impact on overall satisfaction. Isaac et al. (2017) emphasized the significance of exploring the relationship between actual usage and performance, echoing the directions proposed by Venkatesh et al. (2003). However, few studies have delved into the connection between actual usage and individual or organizational performance (Norzaidi, 2008). Therefore, drawing from prior research, the researcher proposes the following hypotheses:
H5: Actual use has a significant impact on satisfaction.
H7: Actual use has a significant impact on perceived impact on learning.

2.6 Satisfaction

Xinli (2015) defines satisfaction as the assessment and emotional response of individuals toward their overall experience with a service or product (Oliver, 1980). Continuously evaluating user satisfaction is a crucial metric used to gauge the success of IS/e-learning systems (Arbaugh, 2002; Levy, 2007; Sun et al., 2008; Wang, 2003). Furthermore, Daud et al. (2011) have underscored a significant association between user satisfaction and perceived revenue. It's noteworthy that while the correlation between user satisfaction and outcomes may be minimal, a consecutive hypothesis can be formulated: User satisfaction may serve as a favorable indicator or alternative for IS accomplishment (Wang, 2003). The research findings by Wang et al. (2014) indicate a correlation between system success and six variables. The overall quality of online learning is influenced by factors such as perceived impact on learning, user satisfaction, system usage, content quality, link quality, and context. Previous studies have established a relationship between researcher satisfaction and perceptual learning in various network environments (Hsieh et al., 2011). These studies concluded that the effectiveness of learning outcomes is directly affected by the level of satisfaction experienced while using online learning platforms. Therefore, building upon previous studies, the researchers propose the following hypothesis:
H6: Satisfaction has a significant impact on perceived impact on learning.

2.7 Perceived Impact on Learning

Perceived impact on learning (PIL) serves as an indicator for evaluating the influence of e-learning on students' academic achievements, providing insights into their perceived performance impact (McGill & Klobas, 2009). Performance impact refers to the extent to which a system enhances work quality by facilitating prompt task completion, enabling effective control over work processes, improving overall performance, minimizing errors, and increasing work efficiency (Aldholay et al., 2018; Norzaidi, 2008). Within the context of this study, expression impact is delineated as the degree to which online learning influences student performance in terms of resource conservation, productivity levels, acquired capabilities, and knowledge outcomes (Isaac et al., 2017). Performance impact involves an individual fulfilling a combination of responsibilities, while increased expression signifies an amalgamation of improved productivity, enhanced efficiency, and/or elevated quality levels (Goodhue & Thompson, 1995).

3. Research Methods and Materials

3.1 Research Framework

A theoretical framework was investigated to construct a concpetual framework in this study. Aldholay et al. (2018) investigated the interrelationships among overall quality, with a particular focus on self-efficacy as a critical determinant of household satisfaction and actual usage. The study of Ifinedo (2017) aims to contribute to existing literature by examining factors that positively influence satisfaction and learning techniques. Yuce et al. (2019) aims to investigate how various parameters of ITS (such as knowledge, system functionality, service quality, and task technology matching) motivate, satisfy, and assist students in improving their abilities with regards to academic performance. Building upon the theoretical frameworks of previous studies, this research develops the conceptual framework as of Figure 1.

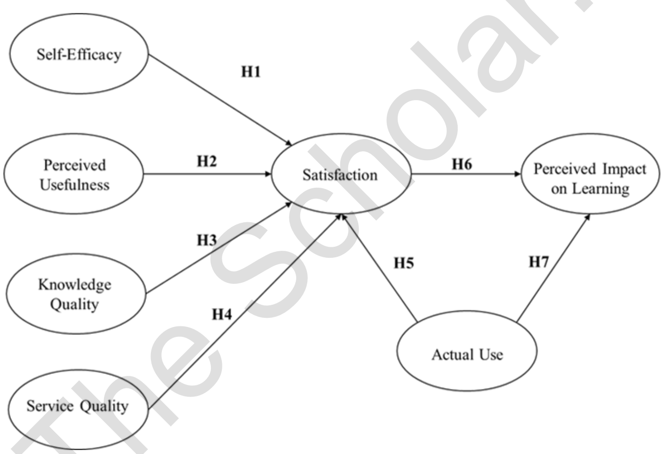

Figure 1: Conceptual Framework

H1: Self-efficacy has a significant impact on satisfaction.
H2: Perceived usefulness has a significant impact on satisfaction.
H3: Knowledge quality has a significant impact on satisfaction.
H4: Service quality has a significant impact on satisfaction.
H5: Actual use has a significant impact on satisfaction.
H6: Satisfaction has a significant impact on perceived impact on learning.
H7: Actual use has a significant impact on perceived impact on learning.

3.2 Research Methodology

This study employed an empirical analysis utilizing a quantitative methodology. Data were collected from the target population, specifically students enrolled at Sichuan University of Media and Communication in the School of Art Design and Animation, through a questionnaire. The questionnaire consisted of three sections: a screening question, demographic information, and items rated on a five-point Likert scale for the variables under investigation.

Expert evaluations, grounded in relevant theories, were assigned three scores: 1 for clear and valid evaluations, 0 for consistent evaluations, and -1 for invalid evaluations. These scores were then integrated into a calculation formula to determine the project's goal consistency index. An average value exceeding 0.5 indicated the feasibility of the research content. This calculation method was adapted from Turner and Carlson (2003).

To refine the scale's appropriateness, a preliminary test involving 50 participants was conducted. Generally, Cronbach's alpha results exceeding 0.7 indicate minimal error in the measured scores, ensuring high reliability for sample analysis and interpretation (Hair et al., 2019).

Following the preliminary test, 500 in-person questionnaires were distributed to participants from the target university. Data analysis was conducted using statistical software. Confirmatory Factor Analysis (CFA) was employed to evaluate factor loading, t-value, composite reliability (CR), average variance extracted (AVE), and discriminant validity. Subsequently, Structural Equation Modeling (SEM) was utilized to validate the hypothesis results and investigate the direct, indirect, and total effects of relationships between latent variables (Hair et al., 2010).

3.3 Population and Sample Size

The focus of this study was on students enrolled at Sichuan University of Media and Communication within the School of Art Design and Animation. To determine the appropriate sample size, the researcher utilized Soper's (2006) quantitative calculator. Input parameters included an anticipated effect size of 0.2, a desired statistical power level of 0.8, 7 latent variables, 30 observable variables, and a significance level of 0.05. Based on the computed results, it was determined that a minimum sample size of 425 individuals was necessary for this empirical research. Consequently, the study targeted students enrolled at Sichuan University of Media and Communication in the School of Art Design and Animation, with a sample size of 500 participants.

3.4 Sampling Technique

The sampling methods utilized in this study encompassed judgmental, quota, and convenience sampling techniques. Judgmental sampling was employed to select students enrolled at Sichuan University of Media and Communication within the School of Art Design and Animation. For quota sampling, a proportional representation was drawn from distinct groups, including students specializing in art design and animation, as well as those majoring in Art Design and Animation, as outlined in Table 1. Additionally, convenience sampling was utilized, wherein the researchers approached readily accessible groups and distributed questionnaires among the target population.

Table 1: Sample Units and Sample Size

Faculty	Undergraduate	Population Size Total = 2272	Proportional Sample Size Total = 500
School of Art Design and Animation	1 Year	418	92
	2 Year	485	107
	3 Year	681	150
	4 Year	688	151

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

In Table 2, demographic data provides valuable insights into the composition and characteristics of student populations within different academic disciplines. In this essay, the researcher analyses demographic and general data collected from the School of Art Design and Animation, consisting of 500 students. By examining variables such as gender, year of study, frequency of Massive Open Online Courses (MOOCs) use, and time spent on MOOCs per session. The data shows that the percentage of male students, accounting for 53.0%, with females comprising 47.0%. Seniors constitute the highest proportion of students at 32.8%, followed by juniors at 24.6%, sophomores at 20.2%, and freshmen at 22.4%. In addition, a larger proportion of students use MOOCs always (30.8%) compared to those who use them often (45.4%). A higher percentage of students spend 3-4 hours per session (38.4%), followed by 1-2 hours (27.2%), over 4 hours (20.6%), and below 1 hour (13.8%).

Table 2: Demographic Profile

Demographic and General Data		School of Art Design and Animation (n=500)	
		Frequency	Percentage
Gender	Male	265	53.0%
	Female	235	47.0%
Year of Study	Freshmen	112	22.4%
	Sophomore	101	20.2%
	Junior	123	24.6%
	Senior	164	32.8%
Frequency of MOOCs Use	Always	154	30.8%
	Often	227	45.4%
	Sometime	95	19.0%
	Seldom	24	4.8%
Time Spent on MOOCs per time	Below 1 hour	69	13.8%
	1-2 hours	136	27.2%
	3-4 hours	192	38.4%
	Over 4 hours	103	20.6%

4.2 Confirmatory Factor Analysis (CFA)

Stevens (1992) established criteria for satisfactory items in Confirmatory Factor Analysis (CFA), suggesting that factor loadings exceeding 0.40 with a significance level below 0.05 indicate acceptable performance. Furthermore, to evaluate the measurement model's quality, recommendations from Fornell and Larcker (1981) were taken into account. They proposed that for adequate convergent validity, the Average Variance Extracted (AVE) should ideally exceed 0.5. However, if the AVE falls below this threshold, the Composite Reliability (CR) can compensate if it exceeds 0.6. Additionally, the assessment of convergent validity was aligned with the criteria proposed by Fornell and Larcker (1981), indicating that even if the AVE fell below 0.5, the construct's reliability remained adequate due to a high Composite Reliability (CR).

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
Self-efficacy (SF)	Lwoga and Komba (2015)	6	0.895	0.792-0.821	0.895	0.589
Perceived Usefulness (PU)	Davis (1989)	4	0.841	0.691-0.815	0.842	0.572
Knowledge Quality (KQ)	Yuce et al. (2019)	4	0.772	0.618-0.730	0.775	0.464
Service Quality (SYQ)	Wang and Chiu (2011)	4	0.835	0.720-0.777	0.836	0.561
Satisfaction (STS)	Yuce et al. (2019)	5	0.829	0.683-0.724	0.830	0.494
Actual Use (AU)	Davis (1989)	4	0.778	0.666-0.696	0.778	0.467
Perceived Impact on Learning (PIL)	Goodhue and Thompson (1995)	3	0.884	0.825-0.847	0.884	0.718
Self-efficacy (SF)	Lwoga and Komba (2015)	6	0.895	0.792-0.821	0.895	0.589

The assessment of the measurement model entails analyzing the connections between observed variables (indicators) and latent constructs (factors) within the model. This evaluation is commonly conducted through structural equation modeling (SEM) techniques, such as confirmatory factor analysis (CFA), enabling researchers to assess the compatibility of the proposed measurement model with the collected data. Model fit indices are utilized for this evaluation. Overall, the measurement models demonstrate excellent fit to the empirical data, as demonstrated in Table 4.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 3.00 (Hair et al., 2006)	528.671/384 = 1.377
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.935
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.921
NFI	≥ 0.80 (Wu & Wang, 2006)	0.925
CFI	≥ 0.80 (Bentler, 1990)	0.978
TLI	≥ 0.80 (Sharma et al., 2005)	0.975
RMSEA	< 0.08 (Pedroso et al., 2016)	0.027
Model Summary		**Acceptable Model Fit**

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = Goodness-of-fit index, AGFI = Adjusted goodness-of-fit index, NFI = Normed fit index, CFI = Comparative fit index, TLI = Tucker-Lewis index and RMSEA = Root mean square error of approximation

Table 5 presents the outcomes of discriminant validity assessment, following the criteria advocated by Fornell and Larcker (1981). Alongside the confirmation of convergent validity, these results offer substantial evidence to endorse the construct validity of the measurement model. Such findings significantly bolster the overall assurance in the precision and dependability of the measurement instrument within the study's context.

Table 5: Discriminant Validity

	STS	SF	PU	KQ	SYQ	AU	PIL
STS	**0.703**						
SF	0.232	**0.768**					
PU	0.493	0.192	**0.756**				
KQ	0.531	0.182	0.569	**0.681**			
SYQ	0.155	0.119	0.360	0.324	**0.749**		
AU	0.518	0.252	0.551	0.613	0.411	**0.683**	
PIL	0.563	0.282	0.443	0.508	0.362	0.643	**0.847**

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

4.3 Structural Equation Model (SEM)

Based on the goodness of fit results for the structural model of students in the School of Art Design and Animation, the model demonstrates a good fit to the empirical data, as shown in Table 6.

Table 6: Goodness of Fit for Structural Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 3.00 (Hair et al., 2006)	956.553/398 = 2.403
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.878
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.858
NFI	≥ 0.80 (Wu & Wang, 2006)	0.865
CFI	≥ 0.80 (Bentler, 1990)	0.916
TLI	≥ 0.80 (Sharma et al., 2005)	0.908
RMSEA	< 0.08 (Pedroso et al., 2016)	0.053
Model Summary		**Acceptable Model Fit**

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = Goodness-of-fit index, AGFI = Adjusted goodness-of-fit index, NFI = 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

After conducting the Structural Equation Model (SEM) analysis on the dataset, the results pertaining to hypothesis verification are outlined in Table 7. The values depicted in the table indicate that all hypotheses have garnered support, substantiated by the standardized path coefficients and corresponding T-values, which exhibit significance levels of $p<0.05$.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: SF→STS	0.126	2.621*	Supported
H2: PU→STS	0.290	5.571*	Supported
H3: KQ→STS	0.324	5.817*	Supported
H4: SYQ→STS	-0.086	-1.740	Not Supported
H5: AU→STS	0.266	4.888*	Supported
H6: STS→PIL	0.360	7.077*	Supported
H7: AU→PIL	0.466	8.467*	Supported

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

Hypothesis H1 posits that self-efficacy significantly influences satisfaction among students in the School of Art Design and Animation. The statistical analysis strongly supports this hypothesis, revealing a significant positive relationship between self-efficacy and satisfaction ($\beta = 0.126$, $t = 2.621$). This suggests that students who feel confident in their abilities are more likely to report higher levels of satisfaction with their educational experience.

H2 suggests that perceived usefulness significantly predicts satisfaction. The analysis provides strong support for this hypothesis, showing a significant positive relationship between perceived usefulness and satisfaction ($\beta = 0.290$, $t = 5.571$). This indicates that students who perceive the educational resources and materials as useful are more likely to experience higher levels of satisfaction with their educational experience in the School of Art Design and Animation.

H3 proposes that knowledge quality significantly predicts satisfaction. The statistical analysis strongly supports this hypothesis, revealing a significant positive relationship between knowledge quality and satisfaction (β = 0.324, t = 5.817). This suggests that students who perceive the quality of knowledge imparted to them as high are more likely to experience higher levels of satisfaction with their educational experience.

H4 suggests that service quality significantly impacts satisfaction. However, the analysis does not support this hypothesis, revealing a non-significant relationship between service quality and satisfaction (β = -0.086, t = -1.740). This indicates that factors other than service quality may be more influential in shaping students' satisfaction levels in the School of Art Design and Animation.

H5 proposes that actual use significantly predicts satisfaction. The statistical analysis strongly supports this hypothesis, showing a significant positive relationship between actual use and satisfaction (β = 0.266, t = 4.888). This suggests that students who actively engage with educational resources and materials are more likely to experience higher levels of satisfaction with their educational experience.

H6 posits that satisfaction significantly predicts perceived impact on learning. The analysis strongly supports this hypothesis, revealing a significant positive relationship between satisfaction and perceived impact on learning (β = 0.360, t = 7.077). This suggests that students who are satisfied with their educational experience perceive a greater impact on their learning outcomes in the School of Art Design and Animation.

H7 suggests that actual use significantly predicts perceived impact on learning. The statistical analysis strongly supports this hypothesis, showing a significant positive relationship between actual use and perceived impact on learning (β = 0.466, t = 8.467). This indicates that students who actively engage with educational resources and materials perceive a greater impact on their learning outcomes in the School of Art Design and Animation.

These detailed analyses provide comprehensive insights into the relationships between various factors and student satisfaction and perceived impact on learning in both academic contexts.

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

The findings revealed significant associations between several factors and students' satisfaction with MOOCs. Specifically, self-efficacy, perceived usefulness, knowledge quality, and actual use emerged as significant predictors of satisfaction. However, contrary to expectations, service quality did not significantly influence satisfaction. Furthermore, satisfaction was found to be a significant predictor of perceived impact on learning, indicating its crucial role in shaping students' overall learning experiences.

This research contributes to the field by offering tailored insights into the factors influencing students' experiences and behaviors within the context of media and communication education at Sichuan University. By focusing on a specific university and student demographic, we were able to provide nuanced understanding and actionable recommendations for educators and policymakers to enhance the effectiveness of MOOCs in this particular setting.

Moreover, the study underscores the importance of considering diverse factors such as self-efficacy, perceived usefulness, and actual use when designing and implementing MOOCs in higher education institutions. Our findings highlight the complex interplay between these factors and students' satisfaction and perceived learning outcomes, emphasizing the need for a holistic approach to course design and delivery.

In conclusion, this research contributes valuable insights that can inform educational practices and policies aimed at improving students' learning experiences and outcomes in the rapidly evolving landscape of media and communication education. Further research in this area can build upon our findings to explore additional factors and potential interventions to enhance the effectiveness of MOOCs in higher education settings.

5.2 Recommendation

In today's digital age, Massive Open Online Courses (MOOCs) have emerged as a popular and accessible form of education, offering students the opportunity to access high-quality learning resources and engage with course materials from anywhere in the world. At Sichuan University of Media and Communication, MOOCs play a significant role in providing students with diverse learning opportunities in the field of media and communication. However, to maximize the effectiveness and impact of MOOCs, it is essential to identify and address factors that influence students' experiences and outcomes. In this essay, we will discuss key recommendations for enhancing students' learning experiences in MOOCs at Sichuan University of Media and Communication.

One of the critical factors influencing students' satisfaction and engagement in MOOCs is the quality of course content. Therefore, Sichuan University should prioritize efforts to improve the quality and relevance of course materials. This can be achieved through collaborations between faculty members, instructional designers, and industry experts to develop high-quality content that meets the educational needs and interests of students.

User satisfaction is paramount in ensuring the success of MOOCs. Sichuan University should place a greater emphasis on understanding and addressing students' needs and preferences to enhance their satisfaction with MOOCs. This may involve implementing feedback mechanisms to gather student input, providing personalized support and assistance, and fostering a sense of community and belonging among participants.

Self-efficacy beliefs and perceptions of the usefulness of MOOCs significantly influence students' engagement and motivation. Therefore, Sichuan University should design interventions aimed at enhancing students' self-efficacy and perceived usefulness of MOOCs. This can be achieved through targeted initiatives such as providing opportunities for skill-building and mastery experiences, highlighting the practical applications of course content, and showcasing success stories of past participants.

Quality support services are essential for students' success in MOOCs. Sichuan University should address any shortcomings in the quality of support services provided to students, including technical assistance, academic advising, and administrative support. Ensuring that students have access to timely and responsive support will help address any issues or concerns they may encounter while participating in MOOCs.

Active participation is key to effective learning in MOOCs. Sichuan University should implement strategies to promote active engagement and participation among students, such as interactive learning activities, group projects, and discussions. Encouraging students to apply their learning in real-world contexts and providing opportunities for collaborative problem-solving and knowledge-sharing will enhance their learning experiences.

Ongoing monitoring and evaluation of MOOCs are essential to assess their effectiveness and identify areas for improvement. Sichuan University should establish mechanisms for collecting feedback from students, analyzing course metrics and performance data, and making data-driven decisions to optimize course design and delivery.

Faculty members and instructional staff involved in designing and delivering MOOCs play a crucial role in the success of these courses. Therefore, Sichuan University should offer professional development opportunities for faculty members to enhance their skills in online course design, technology integration, and effective pedagogical practices. Providing training and support will ensure the quality and effectiveness of MOOC offerings.

In conclusion, enhancing students' learning experiences in MOOCs at Sichuan University of Media and Communication requires a multifaceted approach that addresses various factors influencing student satisfaction, engagement, and success. By implementing the recommendations outlined in this essay, Sichuan University can create an environment conducive to effective online learning and empower students to achieve their educational goals in the field of media and communication

5.3 Limitation and Further Study

While this study has provided valuable insights, it is crucial to acknowledge its limitations. Firstly, the findings may be context-specific to Sichuan University of Media and Communication and may not be readily applicable to other institutions or student populations. Secondly, the reliance on self-reported data collected through questionnaires introduces the potential for bias, as respondents may provide socially desirable responses or inaccurately recall their experiences with MOOCs. Additionally, the utilization of judgmental, quota, and convenience sampling methods may introduce sampling bias, limiting the representativeness of the sample. Furthermore, the cross-sectional design of the study restricts the ability to establish causality between variables and examine long-term effects or changes over time. Addressing these limitations in future research endeavors will be crucial for advancing our understanding of the factors influencing student satisfaction and perceived learning impact in MOOCs.

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