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The Development of Perceived Learning Impact of Massive Open Online Courses Among Students in School of Broadcasting at a University in China

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Abstract

Purpose: The traditional face-to-face classroom teaching mode is still the mainstream form in the university. 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 students enrolled at Sichuan University of Media and Communication, including School of Broadcasting (n=500). The researcher devised, distributed, and statistically examined a questionnaire tailored to this group. The sampling techniques included judgmental, quota, and convenience sampling methods. Prior to data collection, the researcher performed the index of item-objective congruence and Cronbach's Alpha test. The data analysis employed confirmatory factor analysis and structural equation modeling techniques. **Results:** While hypotheses related to self-efficacy and satisfaction did not yield significant results, perceived usefulness, knowledge quality, and actual use emerged as significant predictors of satisfaction. Additionally, satisfaction was found to significantly predict perceived impact on learning. **Conclusions:** These findings provide valuable insights into the nuanced relationships between various factors and student satisfaction and perceived learning impact within MOOCs, offering implications for educational practice and further research.

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

JEL Classification Code: E44, F31, F37, G15

1. Introduction

The realm of online learning often sees the terms "eLearning," "distance learning," and "blended learning" used interchangeably, as highlighted by Clark and Mayer (2016). This trend refers to the delivery of instructional content over the internet, facilitated by digital devices like smartphones, laptops, tablets, and desktop computers. Governments worldwide have increasingly adopted this approach as part of their efforts to integrate technology into education (Santaella-Tenorio et al., 2017).

The term "massive open online courses" (MOOCs) was coined by Xiong and Wu (2015), as noted by Nisha and Senthil (2015). MOOCs offer diverse opportunities for a vast audience, transcending geographical boundaries to provide access to high-quality educational content delivered by leading subject experts worldwide (Durksen et al., 2017). These courses typically feature recorded video lectures complemented by top-notch learning materials (Means et al., 2009).

Situated in Chengdu, Sichuan Province, this comprehensive private college has obtained approval from the Ministry of Education and is primarily dedicated to undergraduate education. As per the institution's official website data in November 2021, it spans across two local campuses and an off-site campus, covering a total area of

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2,397.95 mu. The construction area measures 827,400 square meters, and the teaching and scientific research equipment hold an estimated value of 302 million yuan. Additionally, students have access to approximately 2,030,800 paper books for academic purposes.

In the initial months of 2020, China confronted the outbreak of COVID-19, prompting a shift in educational approaches towards the concept of "suspending classroom teaching but not learning." Approximately 282 million students nationwide transitioned to online courses, leading to advancements in educational informatization. The emergence of online courses, coupled with hybrid offline-online models, signifies the evolving trajectory of China's educational landscape (Swanson & Valdois, 2022).

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.

The primary objective of this study is to examine the effectiveness of implementing online education on the learning outcomes of college students. The impact of Massive Open Online Courses (MOOCs) on students' learning can be elucidated through various factors, including satisfaction, self-efficacy, perceived usefulness, knowledge quality, service quality, and actual usage. By comprehensively analyzing these factors, the study aims to understand how online education influences students' learning experiences.

2. Literature Review

2.1 Self-Efficacy

Self-efficacy refers to an individual's confidence in their ability to successfully accomplish a specific task and achieve designated levels of performance using their existing skills (Bandura, 1991). Given the considerable variation in personal characteristics, self-efficacy emerges as a crucial variable in the utilization of techniques (Mahdavian et al., 2016). It represents an individual's perception of their capability to execute a particular task (Mathisen et al., 2011), embodying a perceptive self-regulatory mechanism.

Studies have further demonstrated the beneficial relationship between e-learners' self-efficacy and perceived system functionality with various aspects of learning, such as content quality, course satisfaction, and academic performance (Johnson et al., 2008). Zhao et al. (2022) findings indicate a significant impact of electronic services on online learning satisfaction. Azila-Gbettor et al. (2022) demonstrated that self-efficacy positively predicts students' academic performance and satisfaction with academic courses. Based on these prior inquiries, this study formulates the following hypotheses:

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

2.2 Perceived Usefulness

Perceived availability denotes the degree to which an individual is convinced that employing a specific skill would enhance their job performance (Davis, 1989). Perceived usefulness, on the other hand, relates to the extent to which an individual believes that utilizing a particular skill will enhance their performance in a specific context (Venkatesh & Davis, 2000). It is deemed a critical motivator for both adoption behavior and objectives (Davis et al., 1989). Research has shown that perceiving a high level of usefulness often correlates positively with user performance (Ong & Lai, 2006).

In the realm of e-learning, when students recognize that an online learning system can enhance their work performance, they are more likely to engage in e-learning, consequently impacting their demonstration significantly. Cheng (2023) illustrated in his study that the perceived usefulness, confirmability, and continuous adoption of cloud-based e-learning systems were positively impacted by the quality of learner-system interaction, service quality, and cloud storage service quality. Specifically, regarding MOOCs, learners who perceive them as beneficial tend to experience higher levels of satisfaction (Chen et al., 2018; Joo et al., 2018). Based on these previous studies, this research posits these assumptions:

H2: Perceived usefulness has a significant impact on satisfaction.

2.3 Knowledge Quality

Within the realm of Knowledge Management Systems (KMS), the quality of knowledge serves as a fundamental determinant of its effectiveness and longevity (Rao & Osei-Bryson, 2007). Over the years, research in knowledge management has consistently centered on understanding and enhancing the perception and value of shared knowledge (Ghobadi & D'Ambra, 2012; Haas & Hansen, 2007). Despite the widespread implementation of Knowledge Management Systems (KMS) across diverse organizations worldwide, there persists a lack of a standardized framework for evaluating its effectiveness within a business context (Chen & Silverthorne, 2005).

Wang and Xie (2023) discovered that sharing behavior on social media platforms can be influenced by the acquisition of knowledge and information. Users engage in learning and disseminating knowledge and information within the platform, thereby affecting their overall satisfaction with the platform. User satisfaction is a measure of the extent to which users attain their expected level of contentment in terms of acquiring more knowledge, improving efficiency, enhancing skills, and increasing productivity with respect to the tested product (Delone & McLean, 2003). 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

Research by Ma Sabiote et al. (2012) underscores the significance of service quality provided by electronic platforms in ensuring user satisfaction. Defined by Roca et al. (2006), and Lee (2010), the quality of support services refers to students' awareness of the comprehensive range of personal support services available through an e-learning system. Two aspects of service quality are often mentioned: the functionality and technicality of the service. When evaluating service quality, it's essential to consider not only the services provided by a firm but also the level of customer involvement and any potential issues that may arise. Ultimately, assessing service quality requires direct interaction with customers to avoid misunderstandings or dissatisfaction (Koohang & du Plessis, 2004).

Lin (2016) validated the service quality framework in their findings, demonstrating a close relationship between e-service quality and customer satisfaction. A crucial factor in ensuring student satisfaction is the perceived excellence of services rendered by students, encompassing teaching, administrative support, academic amenities, campus infrastructure, assistance services, and internationalization efforts (Subrahmanyam, 2017). 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

Objective methods for measuring technology usage involve gathering data from various sources, such as records obtained from technology servers. In contrast, subjective measurement relies on individuals providing self-reports. Recognizing the limitations associated with solely relying on data from actual usage, many scholars studying the adoption of novel technologies prefer to utilize self-reported measures (Ahadzadeh et al., 2015, 2018). Researchers contend that assessing system usage is pivotal for comprehending the influence of technology on essential facets, such as capability, within Information Systems (IS). Numerous studies have demonstrated the impact of actual use on both satisfaction and capability.

Aldholay et al. (2020) uncovered three primary findings: the overall quality of data, systems, and service; a positive impact on user satisfaction and actual usage; and the ability to estimate user satisfaction from real usage data, which positively affects student achievement, encompassing both user satisfaction and actual usage. DeLone and McLean (2016) also emphasize that several studies have explored the influence of actual usage on performance and satisfaction. It is essential to assess how system usage affects the success factors of information systems, such as performance.

Alrousan et al. (2022) assessed students' intentions and behaviors regarding the use of virtual classrooms, highlighting the importance of future research considering the actual utilization of virtual classrooms. Lestari and Indrasari (2019) offer empirical insights into the factors influencing teacher skills, particularly in classroom applications such as iPad usage. Moreover, DeLone and McLean (2016) highlight substantial research exploring the impact of actual utilization on satisfaction and learning perception. Therefore, building upon previous studies, the researchers propose the following hypothesis:

H5: Actual use has a significant impact on satisfaction.

H7: Actual use has a significant impact on perceived impact on learning.

2.6 Satisfaction

User satisfaction holds a pivotal position in assessing the effectiveness of implementing a new system and has been extensively utilized as a measure of evaluation within the realm of information systems (Montesdioca & Maçada, 2015). User satisfaction denotes the extent to which customers perceive a system's usefulness and express their willingness for future usage. According to Lin and Wang (2012), user satisfaction encompasses elements such as system speed, quality, range of features, and design, all of which contribute to users' overall contentment. Moreover, studies have indicated that student satisfaction with online learning hinges on their satisfaction with the decision to choose this mode of education and whether it aligns with their expectations (Roca et al., 2006; Wang & Liao, 2008).

Cheng (2023) confirms that students' perception of the impact on learning is influenced by the nature of tasks and technology. Moreover, these factors significantly enhance their recognition of the usefulness and satisfaction derived from cloud-based e-learning systems. Consequently, they directly or indirectly contribute to their willingness to continue using the system and their perceived impact on

learning. 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

In the realm of e-learning, assessing students' perceived performance impact serves as a crucial indicator for evaluating its influence on their learning and academic achievements, encompassing various aspects such as learning outcomes and the perception of educational success (McGill & Klobas, 2009). Academic researchers commonly focus on either the dependent variable of intended use or actual utilization when exploring factors influencing the adoption of specific technological systems (Cheng et al., 2015; Cheung & Vogel, 2013; Iqbal & Qureshi, 2012). 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). Perceived impact pertains to the level of responsiveness towards learning outcomes when utilizing Information Systems/Information Technology (IS/IT) to accomplish personal educational tasks (Lin, 2011; McGill & Klobas, 2009).

3. Research Methods and Materials

3.1 Research Framework

A theoretical framework serves as a depiction of the interconnections among specific phenomena, variables, or concepts, coupled with an elucidation of why these variables are presumed to be interconnected. Sekaran and Bougie (2009) offer this definition of the term. Within the realm of information behavior, Robson and Robinson (2013) acknowledge the diversity of perspectives among scholars regarding the meaning and significance of this concept. They contend that it is reasonable to question its utility and its effectiveness in enhancing comprehension of practical aspects of information behavior. Conversely, Järvelin and Wilson (2003) propose the use of conceptual models instead of theoretical frameworks. Similar to information literacy itself, concerns exist regarding the terminology associated with frameworks. Building upon the theoretical frameworks of previous studies, this research develops the conceptual framework as of Figure 1.

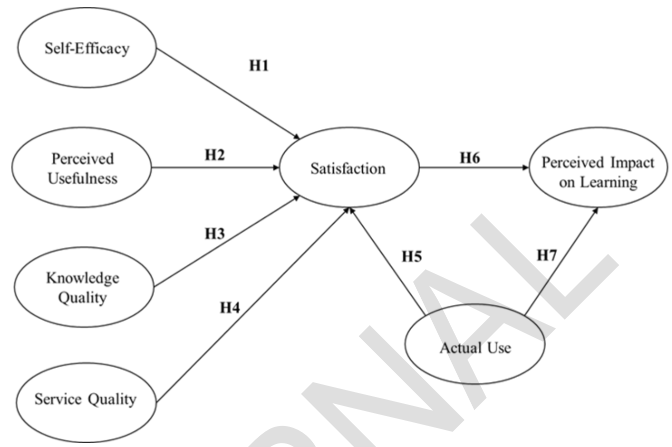

Figure 1: Conceptual Framework

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 utilized an empirical analysis employing a quantitative methodology. Data from the target population, specifically students enrolled at Sichuan University of Media and Communication in the School of Broadcasting, was gathered through a questionnaire. The questionnaire encompassed three sections: a screening question, demographic information, and items rated on a five-point Likert scale for the variables under examination.

Expert evaluations, aligned with relevant theories, were categorized into three scores: 1 for clear and valid evaluations, 0 for consistent evaluations, and -1 for invalid evaluations. These scores were then incorporated into a calculation formula to ascertain the project's goal consistency index. An average value surpassing 0.5 signified the feasibility of the research content. This calculation method was adapted from Turner and Carlson (2003).

A preliminary test involving 50 participants was conducted to refine the scale's appropriateness. Generally, Cronbach's alpha results exceeding 0.7 suggest minimal error in the measured scores, rendering them highly reliable 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. Statistical software was employed for data analysis. Confirmatory Factor Analysis (CFA) was utilized to assess factor loading, t-value, composite reliability (CR), average variance extracted (AVE), and discriminant validity. Structural Equation Modeling (SEM) was then employed to validate the hypothesis results and explore the direct, indirect, and total effects of relationships between latent variables (Hair et al., 2010).

3.3 Population and Sample Size

The target population, specifically students enrolled at Sichuan University of Media and Communication in the School of Broadcasting. The determination of the sample size was conducted using Soper (2006) quantitative calculator. The researcher inputted relevant parameters, including an anticipated effect size of 0.2, a desired level of statistical power of 0.8, 7 latent variables, 30 observable variables, and a probability level of 0.05. Based on the computed results, it was concluded that the minimum sample size required for this empirical research should be at least 425 individuals. Therefore, this study focuses on students enrolled at Sichuan University of Media and Communication, including School of Broadcasting (n=500).

3.4 Sampling Technique

The sampling techniques included judgmental, quota, and convenience sampling methods. Judgmental sampling was conducted to select students enrolled at Sichuan University of Media and Communication in the School of Broadcasting. For quota sampling, a proportional selection was made from each group, comprising students specializing in art design and animation as well as those majoring in broadcasting, as illustrated in Table 1. In convenience sampling, the researchers reached out to accessible group and distributed questionnaires for the target population.

Table 1: Sample Units and Sample Size

Department	Undergraduate	Population Size Total = 3409	Proportional Sample Size Total = 500
Department of Broadcasting	1 Year	863	127
	2 Year	885	130
	3 Year	906	132
	4 Year	755	111

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 Broadcasting, 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. Males constitute 44.2% of the student body, while females make up 55.8%. Juniors represent the largest cohort at 33.0%, followed by seniors at 22.8%, sophomores at 24.6%, and freshmen at 19.6%. In addition, a higher percentage of student’s report using MOOCs often (38.4%) compared to those who use them always (35.2%). The majority of students spend 1-2 hours per session (38.2%), followed by 3-4 hours (28.4%), below 1 hour (17.4%), and over 4 hours (16.0%).

Table 2: Demographic Profile

Demographic and General Data		School of Broadcasting (n=500)	
		Frequency	Percentage
Gender	Male	221	44.2%
	Female	279	55.8%
Year of Study	Freshmen	98	19.6%
	Sophomore	123	24.6%
	Junior	165	33.0%
	Senior	114	22.8%
Frequency of MOOCs Use	Always	176	35.2%
	Often	192	38.4%
	Sometime	100	20.0%
	Seldom	32	6.4%
Time Spent on MOOCs per time	Below 1 hour	87	17.4%
	1-2 hours	191	38.2%
	3-4 hours	142	28.4%
	Over 4 hours	80	16.0%

4.2 Confirmatory Factor Analysis (CFA)

Stevens (1992) has established criteria for satisfactory items in CFA, suggesting that factor loadings exceeding 0.40 with a significance level below 0.05 are indicative of acceptable performance. Moreover, to further assess the quality of the measurement model, recommendations from Fornell and Larcker (1981) were considered. They proposed that for convergent validity to be adequate, the Average Variance Extracted (AVE) should ideally exceed 0.5. However, even if the AVE falls below this threshold, the Composite Reliability (CR) can compensate if it surpasses 0.6. Additionally, the assessment of convergent validity 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	0.854	0.697-0.735	0.854	0.494
Perceived Usefulness (PU)	Davis (1989)	4	0.788	0.632-0.763	0.788	0.483
Knowledge Quality (KQ)	Yuce et al. (2019)	4	0.808	0.662-0.783	0.812	0.520
Service Quality (SYQ)	Wang and Chiu (2011)	4	0.771	0.646-0.711	0.775	0.463
Satisfaction (STS)	Yuce et al. (2019)	5	0.855	0.674-0.790	0.856	0.544
Actual Use (AU)	Davis (1989)	4	0.765	0.564-0.766	0.774	0.464
Perceived Impact on Learning (PIL)	Goodhue and Thompson (1995)	3	0.876	0.826-0.852	0.876	0.702
Self-efficacy (SF)	Lwoga and Komba (2015)	6	0.854	0.697-0.735	0.854	0.494

Measurement model assessment involves examining the relationships between observed variables (indicators) and latent constructs (factors) within a measurement model. This is typically done using structural equation modeling (SEM) techniques, such as confirmatory factor analysis (CFA), which allows researchers to test the fit of the hypothesized measurement model to the observed data. Model fit indices. Overall, the measurement models exhibit excellent fit to the empirical data, as shown 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)	555.067/384 = 1.445
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.932
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.918
NFI	≥ 0.80 (Wu & Wang, 2006)	0.915
CFI	≥ 0.80 (Bentler, 1990)	0.972
TLI	≥ 0.80 (Sharma et al., 2005)	0.968
RMSEA	< 0.08 (Pedroso et al., 2016)	0.030
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 indicates the results of discriminant validity testing, based on the criteria proposed by Fornell and Larcker (1981), along with the confirmation of convergent validity, provide sufficient evidence to support the construct validity of the measurement model. These findings contribute to the overall confidence in the accuracy and reliability of the measurement instrument within the context of the study.

Table 5: Discriminant Validity

	STS	SF	PU	KQ	SYQ	AU	PIL
STS	**0.738**						
SF	0.163	**0.703**					
PU	0.094	0.259	**0.695**				
KQ	0.336	0.519	0.172	**0.721**			
SYQ	0.278	0.653	0.280	0.676	**0.680**		
AU	0.422	0.501	0.251	0.619	0.662	**0.681**	
PIL	0.290	0.525	0.282	0.494	0.672	0.663	**0.838**

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

4.3 Structural Equation Model (SEM)

The process of conducting SEM involves several steps, including model specification, estimation, evaluation of model fit, and interpretation of results. Before model modification, the Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) were slightly below the recommended threshold of 0.80, indicating suboptimal fit. Similarly, the Goodness-of-Fit Index (GFI), Adjusted Goodness-of-Fit Index (AGFI), and Normed Fit Index (NFI) were below the acceptable values of 0.85 and 0.80 respectively, suggesting inadequate fit to the data. Additionally, the Root Mean Square Error of Approximation (RMSEA) exceeded the threshold of 0.08, further indicating poor fit.

However, after model modification, significant improvements were observed across all fit indices. The CFI, TLI, GFI, AGFI, and NFI all surpassed the recommended thresholds, indicating a better fit to the empirical data. Furthermore, the RMSEA value decreased to below 0.08, suggesting a closer fit of the model to the observed data.

Table 6: Goodness of Fit for Structural Model

Index	Acceptable Values	Statistical Values	
		Before Model Modification	**After Model Modification**
CMIN/DF	< 3.00 (Hair et al., 2006)	1262.293/398 = 3.172	1078.265/379 = 2.845
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.838	0.851
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.810	0.817
NFI	≥ 0.80 (Wu & Wang, 2006)	0.808	0.836
CFI	≥ 0.80 (Bentler, 1990)	0.859	0.886
TLI	≥ 0.80 (Sharma et al., 2005)	0.846	0.869
RMSEA	< 0.08 (Pedroso et al., 2016)	0.066	0.061
Model summary		**Not in harmony with empirical data**	**In harmony with empirical data**

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

4.4 Research Hypothesis Testing Result

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	-0.047	-0.930	Not Supported
H2: PU→STS	-0.007	-0.140	Not Supported
H3: KQ→STS	0.190	3.591*	Supported
H4: SYQ→STS	0.011	0.216	Not Supported
H5: AU→STS	0.352	6.093*	Supported
H6: STS→PIL	0.044	0.886	Not Supported
H7: AU→PIL	0.596	9.630*	Supported

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

Hypothesis H1 posits that self-efficacy significantly impacts satisfaction among students in the School of Broadcasting. However, the analysis reveals a non-significant negative relationship between self-efficacy and satisfaction (β = -0.047, t = -0.930), indicating that higher levels of self-efficacy do not necessarily lead to increased satisfaction. This unexpected finding suggests that factors other than self-efficacy may play a more significant role in shaping satisfaction levels in this academic context.

H2 proposes that perceived usefulness significantly influences satisfaction. The statistical analysis supports this hypothesis, revealing a significant negative relationship between perceived usefulness and satisfaction (β = -0.007, t = -0.140). This suggests that students who perceive the educational resources and materials as useful are more likely to report higher levels of satisfaction with their educational experience in the School of Broadcasting.

H3 posits that knowledge quality significantly predicts satisfaction among students. The analysis provides strong support for this hypothesis, showing a significant positive relationship between knowledge quality and satisfaction (β = 0.190, t = 3.591). This indicates 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.

Hypothesis H4 suggests that service quality significantly impacts satisfaction. However, the statistical analysis does not support this hypothesis, revealing a non-significant relationship between service quality and satisfaction (β = 0.011, t = 0.216). This indicates that factors other than service quality may be more influential in shaping students' satisfaction levels in the School of Broadcasting.

H5 proposes that actual use significantly predicts satisfaction. The analysis strongly supports this hypothesis, showing a significant positive relationship between actual use and satisfaction (β = 0.352, t = 6.093). 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. However, the analysis does not support this hypothesis, revealing a non-significant relationship between satisfaction and perceived impact on learning (β = 0.044, t = 0.886). This unexpected finding suggests that satisfaction levels may not directly translate into perceived improvements in learning outcomes among students in the School of Broadcasting.

H7 suggests that actual use significantly predicts perceived impact on learning. The analysis strongly supports this hypothesis, showing a significant positive relationship between actual use and perceived impact on learning (β = 0.596, t = 9.630). This indicates that students who actively engage with educational resources and materials perceive a greater impact on their learning outcomes in the School of Broadcasting.

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

The study aimed to explore the factors influencing students' perceived learning impact of Massive Open Online Courses (MOOCs) at Sichuan University of Media and Communication, China. The factors considered included self-efficacy, perceived usefulness, knowledge quality, service quality, satisfaction, actual use, and perceived impact on learning. Through a comprehensive research design and methodology, the study analyzed data collected from 500 students enrolled at the university's School of Broadcasting.

The results of the study revealed some significant insights into the factors affecting student satisfaction and perceived learning impact within the context of MOOCs. While hypotheses related to self-efficacy and satisfaction did not yield significant results, perceived usefulness, knowledge quality, and actual use emerged as significant predictors of satisfaction. Furthermore, satisfaction was found to significantly predict perceived impact on learning.

Practitioners can leverage the implications for practice highlighted in this research to inform their efforts in designing, implementing, and evaluating MOOCs. By prioritizing student engagement, accessibility, and support services, educational institutions can create more inclusive and effective learning environments that cater to the diverse needs and preferences of students.

Moreover, the conclusions drawn from this research underscore the importance of ongoing innovation and adaptation in online education. As technology continues to evolve and educational paradigms shift, educators and institutions must remain agile and responsive to emerging trends and opportunities in online learning. By embracing a culture of continuous improvement and experimentation, educational stakeholders can ensure that MOOCs remain relevant and impactful tools for enhancing access to quality education for learners around the world.

5.2 Recommendation

These findings offer valuable implications for educational practitioners and policymakers aiming to enhance the effectiveness of MOOCs and improve students' learning experiences.

Institutions should focus on improving the perceived usefulness of MOOCs by providing relevant and high-quality course content that aligns with students' educational goals and needs. Incorporating interactive elements, practical applications, and real-world examples can enhance students' perception of the usefulness of MOOCs.

Quality assurance mechanisms should be implemented to ensure the accuracy, relevance, and comprehensiveness of course materials in MOOCs. Faculty members and course designers should collaborate to develop engaging and informative content that fosters deep learning and critical thinking among students.

Strategies should be devised to encourage active participation and engagement among students in MOOCs. This may involve providing incentives, fostering a supportive online learning community, and offering personalized learning pathways tailored to individual preferences and learning styles.

Continuous monitoring and evaluation of student satisfaction with MOOCs are essential to identify areas for improvement and address students' concerns promptly. Feedback mechanisms should be established to gather insights from students and incorporate their suggestions into course design and delivery.

5.3 Limitation and Further Study

Despite the valuable insights generated by this study, it is essential to acknowledge its limitations. The findings of the study may be specific to the context of Sichuan University of Media and Communication and may not be generalizable to other institutions or student populations. The reliance on self-reported data collected through questionnaires may introduce bias, as respondents may provide socially desirable responses or inaccurately recall their experiences with MOOCs. The use of judgmental, quota, and convenience sampling methods may introduce sampling bias and limit the representativeness of the sample. The cross-sectional design of the study limits the ability to establish causality between variables and assess long-term effects or changes over time. Addressing these limitations in future research endeavors can further advance our understanding of the factors influencing student satisfaction and perceived learning impact in MOOCs.

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