pISSN: 1906 - 3296 © 2020 AU-GSB e-Journal.
eISSN: 2773 - 868x © 2021 AU-GSB e-Journal.
https://assumptionjournal.au.edu/index.php/AU-GSB

Drivers of Satisfaction and Commitment in MOOC Learning: Insights from College Undergraduates in Sichuan, China

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Received: September 01, 2025. Revised: May 18, 2025. Accepted: May 24, 2025

Abstract

Purpose: This quantitative study looked at the behavioral intention and satisfaction of college undergraduate students at Xihua University in the Sichuan province of China with Massive Open Online Course learning and the key determinants that significantly impacted it. The study assesses perceived usefulness, confirmation, learning engagement, performance expectancy, and facilitating conditions. **Research design, data, and methodology:** The researcher employed statistical exploration techniques to assess 486 valid data points by distributing quantitative surveys to target university undergraduate students. The current study selected undergraduate students as the sample's participants using the quota and judgmental sampling approaches. Structural Equation Modeling (SEM) and Confirmatory Factor Analysis (CFA) were used to assess the causal relationship between the factors that were being examined. **Results:** All the hypotheses were supported, according to the statistical analysis, with perceived usefulness having the biggest impact on satisfaction, and satisfaction is indeed the most critical factor affecting behavioral intention. **Conclusions:** The findings contribute to a deeper examination of the class's characteristics, facilitate its integration with traditional classroom instruction, and establish a strong theoretical framework for the creation of a MOOC education system in the future and for the advancement of blended learning. Furthermore, it will offer front-line teachers a theoretical framework for enhancing their MOOC teaching strategies.

Keywords: Massive Open Online Course, Satisfaction, Behavioral Intention, Confirmation, Learning Engagement

JEL Classification Code: E44, F31, F37, G15

1. Introduction

Information has become a symbol of The Times since the turn of the century. Internet technology development has increased in the information era (Xun, 2023). With the pooling of resources made possible by modern technology, the most recent research findings from other nations may be known more rapidly. This is the setting in which the collaboration and exchanges in the field of education have seen seismic shifts. The emergence of the new Massive Open Online Course or "MOOCs" teaching approach is the most notable feature of the 2012 surge in networked information in the sphere of education (Manzoor et al., 2019).

MOOC originated in Canada in 2008 and gained widespread traction in the US school system in 2011 (Zou, 2017). The open educational resource movement gave birth to it, and it later flourished under the behaviorist learning philosophy and connectionism learning theory. It makes innovative use of the Internet to maximize and integrate top-notch international education resources, and it quickly fosters the development of new educational models, including online education, MOOCs, blended learning, and the creation of new open online courses (Wiley, 2017). It provides students with a free, convenient, rich, interactive, and cost-saving learning environment.

MOOCs were first made available in China in 2013, and by 2022, over 370 million users had registered for 61,900 MOOCs. MOOCs' impact on China's higher education system cannot be understated, which is why the Ministry of Education has given them much attention and received

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positive feedback from instructors and local universities (Wu & Zhang, 2021). Published in January 2022, the "14th Five-Year Plan for Digital Economy Development" by the State Council outlines plans to promote "Internet + education" sustainably and healthily, improve online learning support services, and advance smart education. As online education continues to grow and develop in China, MOOCs are becoming an increasingly significant component.

While MOOCs provide learners with a great deal of ease by circumventing the constraints of time and location and integrating educational materials, there remains a discrepancy between the actual impact of instruction and what is expected of them. The development of MOOCs faces new obstacles due to factors such as a high dropout rate, stylized teaching templates, unitary teaching design, and simplicity of teaching mode (Zhang & Wang, 2019).

Since the behaviorist theory, or "stimulus-response" theory, is the foundation of MOOCs from an educational standpoint, the future development of MOOCs will be mainly determined by the satisfaction and behavioral intention of registrants (Ji et al., 2019). Based on the research results mentioned above, this study will carry out a quantitative investigation on the satisfaction and behavioral intention of six fundamental potential variables of MOOCs for undergraduate students at Xihua University in China.

2. Literature Review

2.1 Perceived Usefulness

Perceived usefulness is the degree to which a user feels that implementing OLRs would enhance his or her performance at work (Park et al., 2009). People are more willing to use technology when it significantly enhances their quality of work. Perceived usefulness measures how much students think MOOCs are a helpful tool for improving academic accomplishment (Wu & Chen, 2017; Yang & Su, 2017). According to Baki et al. (2019), "perceived usefulness" refers to how much students believe they will benefit from online learning environments. The user's assessment of the anticipated benefits of utilizing the QR code m-payment is known as perceived usefulness. In the context of MOOCs, perceived usefulness, according to Zhou Junjie, explicitly relates to a student's perception of how much learning through MOOCs would enhance their performance at work or in the classroom (Zhou, 2017).

H1: Perceived usefulness has a significant impact on satisfaction.

2.2 Confirmation

According to Venkatesh et al. (2011), confirmation is the degree of agreement between users' views of an information system and their actual performance and prior expectations. Oliver defines confirmation as a client's objective evaluation of how their experience deviates from their expectations (Oliver, 1980). Confirmation refers to users' assessments of an information system's performance compared to their expectations (Zhang et al., 2020). Confirmation of expectation is the term used to describe the subjective evaluation of an individual's performance regarding their expectations (Ankton & McKnight, 2012). Confirmation is the extent to which a user perceives that their initial expectations are fulfilled throughout actual use (Rahi & Ghani, 2018).

H2: Confirmation has a significant impact on satisfaction.

2.3 Learning Engagement

This study's term "engagement" refers to various behaviors, such as active participation in rigorous academic pursuits, significant interactions with instructors and fellow students, involvement in enriching learning opportunities, and integration into the broader collaborative learning process. Van defines consumer engagement as conduct that, as a result of motivational drives, leads to both the usage of services and care for the brand or company (Van Doorn et al., 2010). The amount of time and effort students put into their academic endeavors is what Heflin defines as learning engagement (Heflin et al., 2017). In MOOC contexts, learning engagement refers to students' inclination to actively participate in social interactions and commit their mental resources and efforts to the ongoing learning process to achieve the desired performance (Jung & Lee, 2018).

H3: Learning engagement has a significant impact on satisfaction.

2.4 Performance Expectancy

Ibrahim defines "Performance Expectancy" as the degree to which students believe that using the FLCL technique and WBI will help them finish their work outside of class. According to Li, performance expectancy accurately captures students' opinions of how MOOCs enhance their learning outcomes and provide them with a competitive edge (Li et al., 2020). Venkatesh claims that performance expectancy is the advantage consumers seek when utilizing innovation to increase productivity and performance (Venkatesh et al., 2012). Performance expectancy is people's opinions about how well a certain piece of technology can carry out particular tasks (Zheng et al., 2015). According to

Compeau and Higgins (1995), performance expectancy is the anticipated outcome of engaging in a particular behavior.
H4: Performance expectancy has a significant impact on satisfaction.

2.5 Facilitating Conditions

The facilitation conditions are the presumption that a system may be used with adequate technical and non-technical support from a particular institution (Venkatesh et al., 2003). In Wan's opinion, facilitating conditions mainly pertain to various hardware or software configurations that let users access or utilize MOOCs (Wan et al., 2020). A facilitating condition is the belief that facilities, infrastructure, knowledge, and support are ready to implement innovation (Jinal & Monica, 2022). A facilitating condition is the person's perception that the organization and the technology infrastructure it provides will facilitate the usage of the system (Bruce et al., 2003). The term "facilitating conditions" refers to how users perceive that important technological and organizational infrastructures support technology use (Bataineh, 2015).
H5: Facilitating conditions has a significant impact on satisfaction.

2.6 Satisfaction

Seddon defines satisfaction as a user's positive attitude about using open-learning resources (OLRs) (Seddon, 1997). According to Delone and Mclean, user satisfaction gauges how much a person thinks employing a specific tactic would increase their productivity at work (Delone & Mclean, 2003). Delone and Mclean define satisfaction as the extent to which consumers are content with reports, websites, and support services (Delone & Mclean, 2016). Sweeney and Ingram (2001) define satisfaction as the state in which an individual is content and achieves academic success. What is referred to as satisfaction is the accumulation of unmet expectations and old sensations in the local environment (Oliver, 1980).
H6: Satisfaction has a significant impact on behavioral intention.

2.7 Behavioral Intention

Behavioral intention is the willingness of an individual to perform a particular task (Venkatesh et al., 2003). Behavioral intention is the direct result of behavioral action and can be used to gauge an individual's preparedness to participate in a certain activity (Alkhowaiter, 2020). Behavioral intention can be defined as an individual's probability of participating in a specific behavior (Venkatesh et al., 2003). According to Shaya et al. (2023), behavioral intention is the arbitrary likelihood that students will incorporate mobile learning into their coursework. Davis (1989) defines behavioral intention (BI) as the extent to which an individual has made deliberate preparations to either participate in or abstain from a specific course of behavior in the future.

3. Research Methods and Materials

3.1 Research Framework

This study's conceptual framework integrates the ideas from the three previously examined theoretical frameworks and is based on combining the ECM and UTAUT theoretical models. First, Cheng (2022) confirmed the association between perceived usefulness, confirmation, learning engagement, and satisfaction. Subsequently, Professor Final Shah presented the connection between performance expectancy, facilitation conditions, and satisfaction. Munadi et al. (2022) have finally demonstrated the relationship between behavioral intention and satisfaction. The conceptual framework for this investigation is displayed in Figure 1.

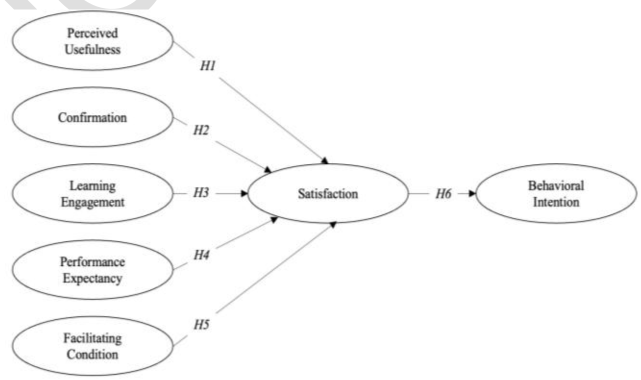

Figure 1: Conceptual Framework

H1: Perceived usefulness has a significant impact on satisfaction.
H2: Confirmation has a significant impact on satisfaction.
H3: Learning engagement has a significant impact on satisfaction.
H4: Performance expectancy has a significant impact on satisfaction.
H5: Facilitating conditions has a significant impact on satisfaction.
H6: Satisfaction has a significant impact on behavioral intention.

3.2 Research Methodology

The current study selected individuals from Xihua University undergraduate students for the sample using quota and judgmental sampling approaches. The research mainly uses questionnaires to screen questions and study the potential variables that affect MOOCs' satisfaction and behavioral intention. The information was interpreted and merged with other data to ascertain the crucial elements that significantly influenced participants' behavioral intention for MOOC learning. The five-level Likert scale is used to investigate each observable trait.

To assess the validity and reliability of research instruments, the rigor and appropriateness of procedures, and the validity of data, three experts and scholars with doctorates and notable research accomplishments in the field of MOOCs were invited to evaluate item-objective congruence (IOC). Following the assessment of validity and content reliability, 40 undergraduate students were asked to participate in a pilot study. The internal consistency reliability of the scale items was then assessed using Cronbach's Alpha.

Upon completion of the validity and reliability testing for the research instrument, 500 undergraduate students from the target academy received the questionnaires. A researcher used statistical tools to assess the data. Additionally, the created validity was examined using the confirmatory factor analysis (CFA), and the hypotheses were assessed using the structural equation model (SEM), along with the direct, indirect, and total influence of the interactions among the associated variables.

3.3 Population and Sample Size

This investigation focused on 1152 undergraduate students at Xihua University in China. Based on the total number of latent and observable variables, 425 samples were suggested as the minimal sample size for the advanced research framework in the structural equation model. In the quantitative study at Xihua University, 500 specimens were selected as the final sample from 845 respondents after screening, filtration, and non-probability selection.

3.4 Sampling Technique

The current study selected participants from Xihua University's undergraduate student body for the sample using quota and judgmental sampling approaches. The remaining 1032 students will be designated as the new target group and split into four groups based on their degree level and subject characteristics. The data from the sampling units and the matching proportional sub-sample size were displayed in Tables 1:

Table 1: Sample Units and Sample Size

Target Group	Main Subjects	Population	Sample Units and Sub-Sample Size
Undergraduate Student	Business administration	578	280
	Accounting	204	99
	Logistics management	190	92
	Economic	60	29
Total		**1032**	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

After filtering and screening invalid data from the sample of 500 people, the effective population information data left behind is 486. Table 4 summarizes the information on the 486 respondents' overall demographic data. According to the majors of undergraduate students, business administration accounted for 23.46%, accounting accounted for 25.93%, logistics management accounted for 21.19%, and economics accounted for 29.42%.

Table 2: Demographic Profile

Demographic Profile (n=486)	Frequency	Percentage
Business administration	114	23.46%
Accounting	126	25.93%
Logistics management	103	21.19%
Economic	143	29.42%

4.2 Confirmatory Factor Analysis (CFA)

Malhotra et al. (2007) state that CFA is used to determine whether the load satisfies theoretical expectations or whether the measurements of a structure are compatible with the researcher's theory regarding the nature of the structure (or factor).

Table 3 showed that all of the factor loading scores (Hair et al., 2010), all of the average extracted variance (AVE) coefficients (Hair et al., 2010), and all of the composite reliability (CR) values were greater than 0.70 (Hair et al., 1998). Fornell and Larcker (1981) state that the discriminant validity is shown by the fact that all construct correlations are smaller than the square root of the AVE for each construct.

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
Perceived Usefulness (PU)	Park et al. (2009)	4	0.824	0.725-0.869	0.861	0.608
Confirmation (CONF)	Oliver (1980)	4	0.812	0.765-0.806	0.825	0.611
Learning Engagement (LEA)	Van Doorn et al. (2010)	5	0.863	0.786-0.803	0.871	0.629
Performance Expectancy (PE)	Li et al. (2020)	4	0.916	0.766-0.779	0.815	0.595
Facilitating Conditions (FC)	Venkatesh et al. (2003)	6	0.773	0.714-0.810	0.839	0.567
Satisfaction (SAT)	Seddon (1997)	3	0.851	0.762-0.768	0.808	0.584
Behavioral Intention (BI)	Davis (1989)	4	0.944	0.740-0.790	0.912	0.597

As shown in Table 4, this study's relevant criteria for the incremental fit evaluations (CFI, NFI, and TLI) and the absolute fit indicators (CMIN/DF, GFI, AGFI, and RMSEA) matched the requirements. As a result, every goodness of fit indicator used in the CFA assessment was suitable.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 3.00 (Hair et al., 2006)	1.915
GFI	≥ 0.90 (Hair et al., 2006)	0.919
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.900
NFI	≥ 0.90 (Hair et al., 2006)	0.043
CFI	≥ 0.90 (Hair et al., 2006)	0.955
TLI	≥ 0.90 (Hair et al., 2006)	0.911
RMSEA	< 0.08 (Pedroso et al., 2016)	0.948
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 = normalized fit index, CFI = comparative fit index, TLI = Tucker Lewis index, and RMSEA = root mean square error of approximation

Table 5 includes the results of the analysis and illustrations of discriminant validity. The square root of the AVE is the diagonally recognized quantity, and none of the correlations that intersected any two latent variables were greater than 0.80 (Fornell & Larcker, 1981). As a result, this study's discriminant validity is legitimate.

Table 5: Discriminant Validity

	PU	CONF	LEA	PE	FC	SAT	BI
PU	**0.780**						
CONF	0.188	**0.782**					
LEA	0.094	0.178	**0.793**				
PE	0.149	0.178	0.195	**0.771**			
FC	0.129	0.169	0.137	0.191	**0.753**		
SAT	0.314	0.337	0.244	0.289	0.257	**0.764**	
BI	0.236	0.229	0.218	0.239	0.122	0.466	**0.773**

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 results of the CFA evaluation were verified by the researchers using the Structural Equations Model (SEM). According to Mueller and Hancock (2018), structural equation modeling (SEM) is a theory-driven data analysis method that evaluates the theory of causes and causes between latent variables and preset observable variables. SEM works better than standard regression models because it may evaluate related hypotheses about correlations between latent and observable variables by combining numerous independent and dependent variables (de-Carvalho et al., 2014). When AMOS was used to analyze the data, the CMIN/DF, GFI, AGFI, CFI, NFI, TLI, and RMSEA verification results exceeded the limit value. Table 6's data was used to determine the goodness of fit of the SEM.

Table 6: Goodness of Fit for Structural Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 3.00 (Hair et al., 2006)	1.849
GFI	≥ 0.90 (Hair et al., 2006)	0.916
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.901
NFI	≥ 0.90 (Hair et al., 2006)	0.042
CFI	≥ 0.90 (Hair et al., 2006)	0.957
TLI	≥ 0.90 (Hair et al., 2006)	0.910
RMSEA	< 0.08 (Pedroso et al., 2016)	0.952
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 = 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 hypothesis test results are presented in Table 7, which indicates that behavioral intention is directly and significantly impacted by satisfaction, with a t-value of 9.433*** and a standardized path coefficient of 0.536. Perceived usefulness is the factor that has the biggest impact on satisfaction in the hypothesis testing of the factors influencing satisfaction, with the β at 0.302 and the t-value at 5.801***. The second factor that significantly affects satisfaction with the β at 0.294 and t-value at 5.653*** is confirmation. With the β at 0.227 and the t-value at 4.347***, the graphic suggests that performance expectancy is the third factor that significantly affects satisfaction. Satisfaction is similarly impacted by learning engagement, albeit not to the same extent as the other three; the β value is 0.192, and the t-value is 3.852***. Ultimately, although facilitating conditions are the least powerful component, they have some effect on satisfaction, as evidenced by the t-value of 3.312*** and the value of β at 0.168.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: PU→SAT	0.302	5.801***	Supported
H2: CONF→SAT	0.294	5.653***	Supported
H3: LEA→SAT	0.192	3.852***	Supported
H4: PE→SAT	0.227	4.347***	Supported
H5: FC→SAT	0.168	3.312***	Supported
H6: SAT→BI	0.536	9.433***	Supported

Note: *** p<0.001
Source: Created by the author

Furthermore, as demonstrated by Table 7, the structural approach acknowledges that H1's standardized path coefficient was 0.302. you are implying that a key factor influencing satisfaction is perceived usefulness. Like the expectancy-confirmation paradigm, perceived usefulness influences satisfaction favorably by serving as a benchmark for comparison with confirmation assessments. Helson (1964) adaptation level theory provides theoretical justification for this link.

After verification, H2 with β at 0.294 indicates that confirmation also significantly impacts satisfaction. Numerous research has shown a direct and positive correlation between consumer satisfaction and confirmation (Alraimi et al., 2015; Bhattacherjee, 2001; Oliver, 1980; Venkatesh et al., 2011).

The verification results of H3 show that learning engagement directly affects satisfaction, as evidenced by the standardized path coefficient of 0.192. As demonstrated by previous studies, the degree of student engagement while learning in virtual worlds is directly correlated with their level of enjoyment (Goel et al., 2013).

With a standardized path coefficient of 0.227, it was shown in the term of H4 that performance expectancy significantly impacted satisfaction. Student satisfaction and the expected level of techno-complexity performance were related. Pappas et al. (2014) corroborated the beneficial impact of performance expectancy on the satisfaction of highly experienced online buyers.

With an effective path coefficient of 0.168, H5 demonstrates again how essential facilitating conditions are in determining satisfaction. Technology and the facilitating conditions offered by their institutions are crucial for students' success and satisfaction in virtual learning, according to Passmore (2000).

The fact that the standardized path coefficient of H6 is 0.536 indicates that behavioral intention is significantly influenced by satisfaction. According to Ruby Roy Dholakia, most research has established a favorable correlation between behavioral intentions and satisfaction (Baker & Sivadas, 2000; Oliver, 1999).

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

This study examines the variables that influence Xihua University undergraduates' behavioral intention and level of satisfaction when using MOOCs. Six hypothetical relationships are established by setting up a conceptual framework that includes perceived usefulness, confirmation, learning engagement, performance expectancy, facilitating conditions, satisfaction, and behavioral intention. 500 undergraduate students were taken as sample data, and after eliminating invalid data, the final valid data was 486. CFA evaluation was successfully finished in order to look into the potential for a relationship between the variables that are being observed and the latent construct that underlies them. Additionally, the SEM was used to evaluate the key variables that influence behavioral intention and satisfaction-related variables, and the main results supported all of the hypotheses that had been proposed.

This study revealed that satisfaction is a key factor significantly influencing undergraduate students' behavioral intention toward using MOOCs. The research also reveals the factors that impact satisfaction, which are perceived usefulness, confirmation, performance expectancy, learning engagement, and facilitating conditions. In addition, among the factors that directly affect satisfaction, perceived usefulness has the greatest impact, followed by confirmation and performance expectancy.

5.2 Recommendation

Based on the findings of the H1 test, undergraduates at the target college believe that perceived usefulness is the most significant factor influencing how satisfied they are with using MOOCs. Students will only use MOOCs when they believe that the MOOC learning platform is an effective way to assist learning and can make them gain something in learning. Thus, it will be more likely to improve the MOOC design output by considering the learners' points of view, requirements, and expectations to satisfy many learners and provide them with a picture of their learning directions.

Confirmation is another significant aspect that directly affects satisfaction, second only to perceived usefulness, according to H2's verification data. When the user experience is better than expected, or the level of service provided by MOOCs is beyond expectation, target undergraduates will be more satisfied, thus improving their behavioral intention to use MOOCs. Therefore, from the level of platform construction, the MOOC platform should continue to enrich the course content, cooperate with colleges and universities to add focused courses, and take "information-based teaching - personalized learning" as the course construction positioning so as to meet the needs of more learners. At the same time, expand the source of resources, realize the effective integration of high-quality educational resources, maintain the updating frequency of courses, and optimize course design so that learners can get the latest scientific research results. In addition, the platform should continue to do a good job in supervision, constantly improve management services, and enhance users' satisfaction.

According to the test result of H3, learning engagement also has a certain impact on learners' satisfaction with MOOCs. When learners can actively interact with tutors and other learners using MOOCs and get effective help when encountering difficulties, they will be more willing to participate in MOOC learning. Therefore, MOOCs should focus more on discussing interaction and learning social needs in development. In the course design of MOOCs, more consideration should be given to how to take learners as the center, mobilize the enthusiasm of learners to participate in the course, encourage students to take the initiative to learn, change the traditional communication mode of "the teacher asks students to answer," guide students to actively post questions, and teachers or other learners to respond actively.

The test results for H4 indicate that performance expectancy is one of the variables that significantly affects MOOC satisfaction. Learners will be more satisfied When they improve their learning efficiency and meet their professional needs by using MOOCs. Therefore, MOOCs should integrate the demands of learners of different majors in the course design and platform construction level and maintain the frequency of updates.

The verification results of H5 show that facilitating conditions are still one of the important factors affecting satisfaction, but they are relatively weaker than other factors. However, since the development of MOOCs, the convenience of learning "anytime and anywhere" as long as there is a network is a key factor for the vigorous development of MOOCs. Therefore, in the future MOOC platform construction, more consideration should be given to simplicity and facilitating conditions. The page design or learning classification of course learning should be optimized from a more intuitive perspective so that everyone can use it.

The test of H6 proves that the most crucial factor that influenced learners' behavioral intention toward MOOCs was satisfaction; in other words, only when learners are satisfied with the use experience of MOOCs will they be willing to continue to use MOOCs or to share MOOCs with their relatives and friends, so that more people will choose MOOCs as the main way to acquire knowledge. This study analyzes the key factors that affect the satisfaction and behavioral intention of MOOCs, which will also provide references for the future development of MOOCs and the improvement of platform construction.

5.3 Limitation and Further Study

The concepts of comprehensiveness and correctness are carefully considered when building the MOOC satisfaction and behavioral intention model, and seven variables are chosen as the main research subjects. More factors might be chosen in the following study; however, some significant variables might still be left out of the model.

Certain limitations exist in the selection of the target population because the research was primarily based on Xihua University in Chengdu, Sichuan Province, China. Due to the limitations of the objective conditions, the research did not choose primary and secondary schools as the research object or more universities in other parts of China.

Since the author's conceptual framework is based on ECM and UTAUT theories, in the following research, the author will consider more research theories, such as ISSM, TAM, TRA, etc., to investigate potential variables and integrate them into the conceptual framework. In addition, in the following research, the author will further expand the scope of research objects, such as including high school students in the research scope. To enhance the feasibility and representativeness of research.

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