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Elements Influencing College Graduate Students' Satisfaction and Behavioral Intention to Employ MOOC in Chengdu, China

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Abstract

Purpose: This article examines the factors that affect learners' behavioral intention and satisfaction with MOOC learning in Chengdu, China. The conceptual framework is based on perceived usefulness, confirmation, learning engagement, performance expectancy, facilitating conditions, satisfaction, and behavioral intention variables. **Research design, data, and methodology:** A quantitative survey evaluation approach was employed throughout the inquiry. The quantitative research method was adopted in this study. 500 graduate students from the target university were selected as the sample size, and the final effective data was 462. Structural Equation Modeling (SEM) and Confirmatory Factor Analysis (CFA) were used to assess the causal relationship between the factors that were being examined. **Results:** According to the survey results, all six hypotheses are valid. The results show that learners' satisfaction with MOOCs is the most important factor affecting their behavioral intention, and satisfaction, perceived usefulness, and learning engagement have more influence. **Conclusions:** For implication, when learners are satisfied with their learning experience with MOOCs, they will choose the MOOC platform when they need to acquire knowledge. In addition, more efforts are made in platform construction and course maintenance, enriching the interactive function design of online courses, focusing on forum maintenance, and enriching course materials.

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 MOOCs are also referred to as "massive open online courses." While they differ from traditional online education, they are undoubtedly directly linked to the growth of the Internet. MOOCs were introduced in China in 2013, which significantly impacted the country's higher education system, drawing the Ministry of Education's close attention and encouraging reactions from local educators and colleges (Chen, 2017). MOOCs make it possible for highly high-quality, globally networked educational resources to be reconnected and combined in novel ways within the context of the Internet (Souza et al., 2023). They also swiftly aid in creating new MOOC platforms, mixed online and offline learning, and other innovative educational models.

Over the past ten years, MOOCs have grown rapidly in China. Numerous colleges have built and promoted MOOCs extensively, with impressive outcomes. During this period, many universities have joined hands to build and share the resources, achievements, and experiences of MOOCs and teaching reform (Zhang & Wang, 2019). Various national, regional, and professional online open course alliances have emerged, forming a MOOCS education and teaching ecosystem with Chinese characteristics. It is noteworthy that with the development of the network society, MOOCs also show three obvious trends: the combination of big data analysis, social learning, and mobile learning (Li et al., 2020).

These three trends in the development of MOOCs also indicate several factors worthy of attention in the future development of MOOCs. For example, in the Internet era, how to use big data to master and analyze factors affecting the satisfaction of MOOCs, and what role does the

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excellence of mobile learning play in improving the satisfaction and behavioral intention, student's learning engagement to what extent determines their satisfaction. Factors such as perceived usefulness, confirmation, and learning engagement are considered in the study. Analyzing factors affecting MOOCs' satisfaction will play an important role in improving MOOC management services.

With MOOCs' wide popularity and development in China, the research achievements in MOOCs have also been quite fruitful. However, it should be noted that China's research in the field of MOOCs mostly focuses on the reform of traditional teaching modes, such as how MOOCs play a role in flipped classrooms and how blended teaching can maximize its advantages (Yang et al., 2009). Moreover, the main research methods are mainly qualitative research, and relatively few quantitative studies accurately analyze the causal relationship between research objects through statistical and mathematical analysis and strict logical reasoning. So, taking quantitative research as the main method, through logical reasoning to analyze the factors that impact students' satisfaction and behavioral intention to act, and based on accurately grasping the causal relationship between them, will help to put forward solutions to the difficulties faced in the development of MOOCs.

To sum up, this study selected graduate students from the School of Management of Xihua University in Sichuan, China, as samples to conduct quantitative research on the potential variables that affect the satisfaction and behavioral intention of MOOCs. The study aims to provide certain references for the better development of MOOCs in the future.

2. Literature Review

2.1 Perceived Usefulness

According to Venkatesh (Venkatesh et al., 2003), one advantage of information technology is that people find it helpful in their work. Therefore, the belief in implementing a specific system is perceived as useful. Perceived usefulness (PU) can be described as a user's perception of how much their online purchase would improve the success of their transaction, according to Chen and Chiu (2009). Perceived usefulness is the extent to which technology makes it possible for someone to do a task completely and accurately; thus, users can finish jobs quickly and react to user inputs quickly (Babic et al., 2014). According to Bhattacherjee (2001), perceived usefulness is a crucial ECM construct that encapsulates the instrumentality of IS use. Perceived usefulness is the conviction that a certain system is worthwhile.

H1: Perceived usefulness has a significant impact on satisfaction.

2.2 Confirmation

According to Bhattacherjee (2001), confirmation is the manifestation of a user's expectations of the performance of an information system. In this study, "confirmation" refers to the degree to which users' initial expectations of the M-payment system have come true. Franque defines "confirmation" as a user's assessment of technology, service, or product (Franque et al., 2021). Oghuma defines confirmation as the extent to which one's initial hypothesis is validated by the actual use experience (Oghuma et al., 2015). Several other researchers have found that confirmation is positively connected with satisfaction and perceived quality of IT products/services for intention to use (Hayashi et al., 2020; Hsu et al., 2015; Lee et al., 2010).

H2: Confirmation has a significant impact on satisfaction.

2.3 Learning Engagement

According to Brodie et al. (2019), engagement is characterized as an activity inclination that manifests itself in the resources, energy, etc., that players devote to interacting with one another inside the service system through a dynamic and iterative process. According to Coates (2006), engagement is the term used to describe the consistent effort students make toward their learning process to meet their targeted learning outcomes. According to Fredricks et al. (2004), student engagement is a multifaceted concept with behavioral, emotional, and cognitive components. According to Mollen and Wilson (2010), engagement is the outcome of internal evaluations that are impacted by a learner's interactions with other students or the learning environments. One of the most significant and unique characteristics that affect online learners' cognitive response and subsequent behaviors is the engagement found in the learning environment, such as MOOC platforms (Liu et al., 2011; Li et al., 2020, b; Shao et al., 2017; Yang et al., 2017).

H3: Learning engagement has a significant impact on satisfaction.

2.4 Performance Expectancy

As Venkatesh et al. (2003) stated, performance expectancy is the "amount of belief that an individual has that using a system will help them improve their ability to perform the job." Performance expectancy, as defined by Compeau and Higgins (1995) is the belief that a specific approach would improve an individual's performance at work. Performance expectancy is another element of the

UTAUT paradigm, defined as "the degree to which people believe the system will help to improve job performance" (Zheng et al., 2015). Performance expectancy refers to an individual's expectation of how much using the system will improve their performance at work (Li et al., 2020). According to Davis (1989) and Venkatesh et al. (2003), performance expectancy gauges the extent to which an SME's management feels that digital technology would improve working performance. According to the previous literature, the researcher suggested the following hypothesis:
H4: Performance expectancy has a significant impact on satisfaction.

2.5 Facilitating Conditions

A facilitating condition factor is the extent to which an individual believes an organization has altered to make using the system easier (Venkatesh et al., 2003; Yang et al., 2017). According to Venkatesh et al. (2012), facilitation conditions are the degree to which an individual believes that resources and assistance are available to use a certain technology when needed. According to Liebenberg and Pieterse (2018), "facilitating conditions" relate to the lecturer's perception of how simple it is to install and use an automatic assessor and how well it fits with their current teaching methodology. One facilitating condition is the belief about the infrastructure, facilities, expertise, and support available to apply innovation (Jinal & Monica, 2022). Previous research summarized that the facilitating conditions are strong predictors which can be used for forecasting technology acceptances and usages (Hagan, 2014), so the researcher suggested the following hypothesis:
H5: Facilitating conditions has a significant impact on satisfaction.

2.6 Satisfaction

According to Bhattacherjee (2001), "a psychological situation derived from a mental and cognitive judgment of the expectation-performance inconsistency" is what satisfaction is. According to Locke (1976), "a happy or positive emotional state that results from a positive assessment of one's learning or learning experience" is the definition of learning satisfaction. According to Chen et al. (2010), satisfaction can be defined as the level of satisfaction or dissatisfaction experienced after evaluating how well a product or service performed in terms of expectations. According to Almarashdeh (2016), instructor satisfaction is the extent to which instructors feel the LMS satisfies their expectations and information demands. Lee et al. (2017) claims that the user's sense of accomplishment and interest in an online learning environment determines user satisfaction. Behavioral intention and use behavior are typically associated with the pre-acceptance stage of technology (Venkatesh et al., 2003), so to the previous literature, the researcher suggested the following hypothesis:
H6: Satisfaction has a significant impact on behavioral intention.

2.7 Behavioral Intention

Consequently, one may evaluate academics' behavioral intention toward online teaching by looking at how resolutely they accept and use online technology resources to achieve their learning goals (Jalil et al., 2019). Behavioral intention refers to the extent to which an individual would use an application (Yueh et al., 2003). Behavioral intention is the propensity for an individual to act in a certain way. Accordingly, behavioral intention was determined by evaluating students' subjective likelihood of using mobile learning as a learning aid (Alkhowaiter, 2020). Behavioral intention is the degree to which an individual in the present environment consciously plans for a specific action that might take place in the future (Shaya et al., 2023). Behavioral intention is defined as "the extent to which an individual has made deliberate plans for whether to engage in a specific future activity" by Venkatesh and a few other experts on this subject (Venkatesh et al., 2003).

3. Research Methods and Materials

3.1 Research Framework

According to Miles and Huberman (1994), the conceptual framework of research is a theoretical framework created by combining concepts, hypotheses, beliefs, expectations, and other factors with various theories. First, Professor Cheng confirmed the association between perceived usefulness, confirmation, learning engagement, and satisfaction (2022). 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. This quantitative research aims to investigate the factors that affect the satisfaction and behavioral intention of graduate students in the School of Management of Xihua University when they use MOOCs. The study employed a latent variable approach, utilizing seven variables from the conceptual framework: five independent variables (perceived usefulness, confirmation, learning engagement, performance expectancy, and facilitating conditions), one mediator variable (satisfaction), and one dependent variable (behavioral intention). In Figure 1, the investigation's conceptual framework is displayed.

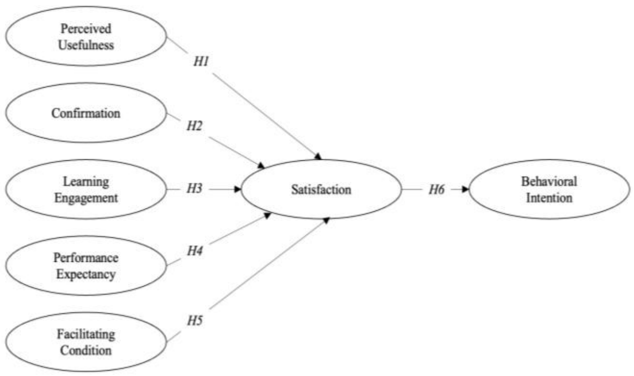

Figure 1: Conceptual Framework

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

This study mainly adopts the method of questionnaire to study the factors affecting the satisfaction and behavioral intention of the graduate students in the School of Management of Xihua University when they use MOOCs. Questionnaires are the most popular way of gathering data for the assessment or evaluation of inputs in applied research, they can provide much valuable information and are a very important research tool in conducting socio-demographic, economic, and KAP (Attitude, Knowledge, and Practice) research.

In this study, the sampling produced includes judgment sampling and quota sampling, and questionnaires are used to analyze the factors affecting the satisfaction and behavioral intention of graduate students in the School of Management of Xihua University. Additionally, the estimation of the data was combined and analyzed to identify the critical components that significantly impacted the respondents' satisfaction and behavioral intention for MOOC. Additionally, 28 observed variables from previous literature were employed to assess the constructs, including four variables for perceived usefulness, four variables for confirmation, four variables for learning engagement, four variables for performance expectancy, four variables for facilitating conditions, three variables for satisfaction, and seven variables for behavioral intention. A five-level Likert scale was used in the study to assess each scale item.

Three professors or associate professors with doctorates were invited to participate in an item objective congruence (IOC) test that the researchers conducted to assess the content validity of the research instrument. After completing the content validity conformance test, 50 graduate students were selected for a pilot test to confirm the research instrument's validity. The internal consistency reliability of the scale items was evaluated using Cronbach's Alpha grading.

The questionnaires were distributed to 500 postgraduate students from Xihua University's School of Management after the methodology of reliability and validity evaluations for the research instrument was effectively completed. The investigator examined the data using statistical analysis tools. Confirmatory factor analysis (CFA) was also conducted to evaluate construct validity. Furthermore, the assumptions and the overall, indirect, and direct consequences of the interconnection among the linked variables were assessed using the structural equation model (SEM).

3.3 Population and Sample Size

The study's target population is postgraduates from the School of Management of Xihua University, Sichuan, China. With seven latent and twenty-eight observable variables in this thesis, the calculator suggested a sample size of 425. However, the researcher chose to sample an additional 75 postgraduates to ensure that no potentially inaccurate data would be generated. After filtering, screening, and non-probability selection, 500 graduate students were chosen as the final sample data from 978 graduate students in this quantitative study conducted by Xihua University.

3.4 Sampling Technique

500 graduate students in business administration, accounting, logistics management, and economics from Xihua University's School of Management had their MOOCs learning experience as the sample data obtained from the researchers' judgmental sampling and quota sampling. Table 2 displayed the data about the sampling units and the corresponding proportional sub-sample sizes:

Table 1: Sample Units and Sample Size

Target Group	For Main Subjects	Population	Sample Units and Sub-Sample Size
Undergraduate Student	Business administration	543	278
	Accounting	182	93
	Logistics management	191	97
	Economic	62	32
Total		**978**	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

After screening invalid data, 500 people finally participated in the experiment with 462 valid data. The detailed information is presented in Table 3. The major of Business administration constituted 57.14% of the entirety, Accounting comprised 18.18%, Logistics management accounted for 18.61%, and economics accounted for 6.07%.

Table 2: Demographic Profile

Demographic Profile (n=462)	Frequency	Percentage
Business administration	264	57.14%
Accounting	84	18.18%
Logistics management	86	18.61%
Economic	28	6.07%

4.2 Confirmatory Factor Analysis (CFA)

According to Malhotra et al. (2007) confirmatory factor analysis (CFA) is a technique used to assess the effectiveness of measurement models in which the number of factors and their direct links are stated. According to Yong and Pearce (2013), factor loading is a metric that quantifies the extent to which a variable contributes to a factor. Large factor loading ratings suggest that the variables can better explain the dimensions of the factors.

Fornell and Larcker (1981) state that each construct's AVE value should be at least 0.50. According to Table 5, every of the seven reflective variables surpassed the CR and AVE threshold values; the CR values were higher than 0.70, and the AVEs were higher than the 0.50 threshold value (Hair et al., 2017). These results demonstrate that the reflective variables of the research model met the reliability and convergent validity requirements.

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	0.906	0.734-0.799	0.849	0.585
Confirmation (CONF)	Oliver (1980)	4	0.890	0.778-0.813	0.837	0.632
Learning Engagement (LEA)	Van Doorn et al. (2010)	5	0.878	0.759-0.788	0.851	0.587
Performance Expectancy (PE)	Li et al. (2020)	4	0.946	0.760-0.795	0.823	0.608
Facilitating Conditions (FC)	Venkatesh et al. (2003)	6	0.892	0.659-0.825	0.844	0.576
Satisfaction (SAT)	Seddon (1997)	3	0.905	0.762-0.797	0.822	0.606
Behavioral Intention (BI)	Davis (1989)	4	0.961	0.757-0.809	0.914	0.603

According to Hair et al. (2006), absolute fit measures indicate how well the whole model fits the observed correlation matrix or covariance. As indicated in Table 4, all the incremental fit evaluations (CFI, NFI, and TLI) requirements and absolute fit indicators (CMIN/DF, GFI, AGFI, and RMSEA) were met. Consequently, every goodness of fit metric used in the CFA evaluation was sufficient.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 3.00 (Hair et al., 2006)	1.710
GFI	≥ 0.90 (Hair et al., 2006)	0.926
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.908
NFI	≥ 0.90 (Hair et al., 2006)	0.039
CFI	≥ 0.90 (Hair et al., 2006)	0.964
TLI	≥ 0.90 (Hair et al., 2006)	0.918
RMSEA	< 0.08 (Pedroso et al., 2016)	0.959
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 also included the analysis results and discriminant validity illustrations. 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, the discriminant validity of this study has been demonstrated.

Table 5: Discriminant Validity

	PU	CONF	LEA	PE	FC	SAT	BI
PU	**0.765**						
CONF	0.110	**0.795**					
LEA	0.206	0.177	**0.766**				
PE	0.274	0.164	0.219	**0.780**			
FC	0.117	0.196	0.161	0.208	**0.759**		
SAT	0.389	0.268	0.350	0.319	0.285	**0.778**	
BI	0.283	0.218	0.234	0.252	0.193	0.424	**0.777**

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

4.3 Structural Equation Model (SEM)

Following the CFA assessment, the researchers quantified and looked into the relationships between observable and latent variables using a structural equations model. SEM is a group of techniques used to assess complex hypotheses against multivariate data, especially those incorporating networks of path interactions (de-Carvalho et al., 2014). The objective of structural equation modeling

(SEM), according to Mueller and Hancock (2018), is to identify the most parsimonious account of the interrelationships across variables that accurately capture the correlations shown in the data. Following AMOS correction, the cumulative values of CMIN/DF, GFI, AGFI, CFI, NFI, TLI, and RMSEA were all over permissible bounds. Table 6 presents information that has been used to establish 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)	1.726
GFI	≥ 0.90 (Hair et al., 2006)	0.916
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.900
NFI	≥ 0.90 (Hair et al., 2006)	0.040
CFI	≥ 0.90 (Hair et al., 2006)	0.962
TLI	≥ 0.90 (Hair et al., 2006)	0.914
RMSEA	< 0.08 (Pedroso et al., 2016)	0.958
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

With a standardized path coefficient of 0.485 and a t-value of 8.359***, Table 7's hypotheses on accomplishments demonstrated that satisfaction had a direct and significant impact on behavioral intention. This produced the strongest effective strength of the quantitative research. Regarding the second most important impact, which came from perceived usefulness to satisfaction, the t-value for this quantitative investigation was 6.590***, and the β was 0.352. The learning engagement produced a third place, considerably, and substantially higher level of pleasure, with a β of 0.295 and a t-value of 5.674***. Similarly, in the fourth position, the association from performance expectancy to satisfaction with the β was 0.223, the t-value was 4.361***, and for facilitating conditions to satisfaction with the standardized path coefficient was 0.216, and the t-value was 4.255***. Confirmation, the lowest affecting factor overall, had a clear effect on satisfaction, with a t-value of 3.906*** and a value of β at 0.198.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: PU→SAT	0.352	6.590***	Supported
H2: CONF→SAT	0.198	3.906***	Supported
H3: LEA→SAT	0.295	5.674***	Supported
H4: PE→SAT	0.223	4.361***	Supported
H5: FC→SAT	0.216	4.255***	Supported
H6: SAT→BI	0.485	8.359***	Supported

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

As shown in Table 7, the structural method acknowledges that the standardized path coefficient of H1 was 0.352, indicating that perceived usefulness significantly impacts satisfaction. Numerous researches discovered that users should be highly satisfied with MOOC systems if they believe them to be useful; a substantial body of research has confirmed that perceived usefulness significantly impacts user attitudes, which has a relative impact on user satisfaction (Davis, 1989; Detlor et al., 2013; Martins et al., 2014; Morosan, 2012).

The H2 assessment found that, with a β value of 0.198, there is a positive link between satisfaction and confirmation. Academic accomplishments and the ECM theory indicate that confirmation is a major satisfaction predicate (Bhattacherjee, 2001; Fu et al., 2018; Lee et al., 2010; Hong et al., 2006).

H3 proves that learning engagement is another key factor that can affect the satisfaction of the target population with MOOCs, with a β score of 0.295. According to Roca et al., the higher degree of students' satisfaction with MOOCs may be positively correlated with the level of immersion learning engagement by the e-learning system. Many studies have shown that Learning engagement significantly impacts satisfaction (Goel et al., 2013; Gray & Diloreto, 2016; Reychav & Wu, 2015;).

The standardized path coefficient of H4 is 0.223, which proves that performance expectancy is another factor affecting the satisfaction of target students using MOOCs. According to Bhattacherjee (2001), when a user believes a system is useful, he feels satisfied and wants to continue using it. Many previous studies have examined the relationship between performance expectancy and satisfaction (Alalwan, 2020; Kalinic et al., 2019; Martirosyan et al., 2015).

The standardized path coefficient of H5 is 0.216, which proves that facilitating conditions are a factor that can influence the satisfaction of learners when they use MOOCs. Looking at much research on online learning and MOOCs, the promotion environment of MOOCs has a positive effect on the degree of satisfaction and continued participation of MOOCs. Recent research works have found that facilitating conditions positively affect learners' satisfaction (Agustina et al., 2019; Alalwan, 2020; Kalinic et al., 2019).

Finally, with a standardized path coefficient of 0.485, H6 proves that satisfaction is the most critical factor affecting behavioral intention, consistent with many previous studies. Many studies have proved that satisfaction has an important effect on behavioral intention (Baker & Sivadas, 2000; Oliver, 1999; Shaya et al., 2023)

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

This study aims to investigate the factors affecting the satisfaction and behavioral intention of graduate students in the School of Management of Xihua University in Sichuan, China. The conceptual framework, which confirmed each relationship between each exogenous and endogenous variable, served as the foundation for establishing all the hypotheses. The scale items were provided to 500 target students, and 462 were valid for data analysis. Confirmatory Factor Analysis (CFA) evaluations were completed to offer a framework for resolving some of the issues related to conventional methods of evaluating the validity and reliability of a measure. Additionally, the SEM was used to examine several continuous or discrete links between behavioral intention and satisfaction and to combine aspects directly or indirectly associated with evaluating hypotheses. All of the hypotheses were supported overall.

The results of hypothesis verification in this study show that satisfaction is an important factor that can directly impact behavioral intention, and the influence is the most powerful. Perceive usefulness, learning engagement, performance expectancy, facilitating conditions, and confirmation directly impact satisfaction but only indirectly impact behavioral intention; among them, perceived usefulness is the factor that has the greatest direct influence on satisfaction.

5.2 Recommendation

According to the statistical analysis of this quantitative research, based on the evaluation findings of H1, As Bhattacherjee (2001) points out, perceived usefulness significantly impacts satisfaction and IS continuance intention. The verification results of the hypothesis in this study once again prove that perceived usefulness is the key factor that affects learners' satisfaction with MOOCs. With the extensive development of MOOCs, more and more learners have recognized them as an effective way to assist learning. The majority of learners will take the initiative to choose MOOCs only when they think that the MOOC platform is helpful for expanding learning. Whether a MOOC platform is useful depends on how well it can meet the needs of learners. We should start with platform improvement, curriculum construction, and a platform for teaching and learning services to constantly improve the management services of MOOCs.

Depending on the test result of H2, Numerous studies have documented the positive role of confirmation in influencing satisfaction. This study once again proves that confirmation has a direct impact on satisfaction. When learners' usage experience exceeds their usage expectations, their satisfaction will be greatly improved, thus enhancing their behavioral intention to use MOOCs in the future. Graduate students have a more profound academic background and insight; for graduate students to make MOOCs exceed the use expectations, we need to constantly enrich and improve the course content and scientific research results and further integrate the world's most advanced scientific research results into MOOCs education and teaching.

According to the verification result of H3, learning engagement is another important factor that can affect the satisfaction of target graduate students in using MOOCs. This verification result is slightly different from that of undergraduates. Graduate students have a stronger learning purpose, a more solid professional foundation, a stronger ability to research, analyze, and solve problems, and a stronger independent thinking ability. As a result, graduate students will have more communication and resonance with course instructors when using MOOCs, making learning engagement an important factor affecting satisfaction. When learners' interactive needs are fully met, they will be more willing to use MOOCs to learn and share knowledge. Therefore, in the future development of MOOCs, platform developers should give more consideration to the needs of graduate students in their professional fields and learning participation, support teachers and students to carry out professional research on MOOCs platform, and provide more support for the learning process, improve the setting of course centers and academic forums, and simulate the interaction of traditional classrooms to a certain extent in online form. To realize knowledge sharing and exchange.

According to the hypothesis verification results of H4, performance expectancy is positively associated with satisfaction with MOOC learning. The survey found that postgraduate students have clearer goals when using MOOCs. When the MOOC platform can improve learners' learning efficiency and meet their professional demands, learners will be more satisfied or inclined to use MOOCs. Therefore, we suggest that MOOCs pay more attention to improving their performance in the future development process at the level of platform management and course construction and give more consideration to the learner's experience.

It can be seen from the hypothesis verification results of H5 that facilitating conditions are another factor affecting the satisfaction of MOOCs; facilitating conditions represent user evaluations of the usage environment, and dissonance theory (Festinger, 1957) suggests that in situations where the facilitating conditions act as an inhibitor, individuals may adjust their attitudes negatively to be consistent with the situation. With rapid interaction as the starting point, the implementation of curriculum design enhances the facilitating conditions of learning to serve learners as the purpose, opens teaching resources, and improves the accessibility of courses. In the level of technology development of MOOC platform, it is necessary to make full use of the current advanced information technology, develop additional functions such as text editing, document uploading, instant messaging, and so on in the course teaching, add more experience links to online teaching, such as practical drills, limited time challenges, etc., and integrate the latest VR and AR technologies to MOOC teaching, realize the "small" between teaching resources from courses towards a "great connection" of data between education and all areas of society.

According to the hypothesis verification results of H6, satisfaction is the key core factor that impacts behavioral intention. In using MOOCs, graduate students have a wider range of subjects, stronger professionalism, and clearer selection goals. Therefore, MOOCs should aim to improve learners' satisfaction in the future development process and design reasonable interactive actions based on demand in course design. In addition, more efforts are made in platform construction and course maintenance, enriching the interactive function design of online courses, focusing on forum maintenance, and enriching course materials.

5.3 Limitation and Further Study

A few issues with this study could be resolved in later research. First, because the results were based on graduate students, they could be compared to those of the same model that targeted students at a greater range of educational levels (e.g., senior and vocational high school students). Secondly, this was a quick turnaround study that was cross-sectional. As new information and experiences are gained, students' evaluations of the MOOC's perceived usefulness, confirmation, satisfaction, and behavioral intention may shift over time. Consequently, future research could use a longitudinal approach to get more precise results from a particular group. Finally, the theoretical framework established by the current research is mainly based on the ECM and UTAUT theories and considers the assumptions established by seven variables, including perceived usefulness, confirmation, and learning engagement, without involving more theories such as TAM, ISSM, TRA, etc. It is also possible that some factors affecting satisfaction and behavioral intention should be considered. Therefore, in future studies, researchers will study more theoretical models and find other factors that may affect MOOCs' satisfaction and behavioral intention.

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