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RESEARCH ARTICLE

Factors Impacting Satisfaction and Continuance Intention of MOOCs Learning among Medical Students in Chengdu, China

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Abstract

MOOCs, which stand for Massive Open Online Courses, have become an important tool for promoting educational reform in local medical colleges. This article constructed a conceptual framework using the expectation confirmation model (ECM), technology acceptance model (TAM), and unified theory of acceptance and use of technology (UTAUT), to investigate the factors impacting satisfaction and continuance intention of MOOCs learning among medical students. Structural equation modeling is used to evaluate the model using data from a survey with 500 medical students in Chengdu, China. The results showed that the proposed theoretical model can explain the causal relationship between factors very well. Task-technology fit, perceived usefulness, and facilitating conditions are important determinants of students' satisfaction, furthermore, satisfaction plays a vital role in motiving or influencing medical students' continuance intention of MOOCs learning. It is recommended that the MOOC platform should focus on improving task-technology fit, perceived usefulness, facilitating conditions and satisfaction toward medical students' MOOCs learning, the education institutions ought to strengthen medical students' interaction by establishing various online learning communities in MOOCs. The findings provide a reference model for future research toward impacting factors of MOOCs learning and contribute to improving the teaching management of MOOCs in local medical colleges.

Keywords

MOOCs learning, Satisfaction, Continuance Intention, Medical students, China

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Introduction

MOOCs, which stands for Massive Open Online Courses, are a relatively new form of online education. Online courses known as MOOCs have gained popularity since 2012. They offer interactive learning experiences, to encourage community interactions between students, professors, and teaching assistants (Leontyev & Baranov, 2013). As the internet has become a common tool for students to access information anytime and anywhere (Ifeanyi & Chukwuere, 2018), MOOCs have gained popularity due to their free and open access to anyone who wants to learn, regardless of their location or education level (Bederson et al., 2015).

Since 2013, China has been operating MOOCs, with over 52,000 available as of February 2022 and nearly 370 million registered participants. China ranks first in the world for the number of MOOCs constructed and used, which is a natural result of the deep integration of information technology and education over the past decade. The active promotion of MOOC by Chinese universities is an important engine for promoting the transformation of higher education (Zhu, 2023). In the future, China MOOC will still have great potential in innovating traditional education models and promoting classroom changes.

Medical education has traditionally focused on the technical aspects of medical science, often neglecting the humanistic nature of medicine. As a result, medical students may lack a sense of humanistic spirit (Chen, 2023). To address this, there is a growing consensus that medical education should include a stronger emphasis on humanistic qualities. MOOCs offer a wealth of resources for humanities courses that can help fill this gap. This makes MOOCs an important tool for promoting educational reform in medical colleges.

However, in reality, MOOCs learning can also encounter various problems, which may affect the further development of MOOCs. What are the influencing factors of these issues? What is the connection between the influencing factors? These issues deserve special attention from researchers in MOOCs teaching, developers of MOOCs platforms, and higher education institutions using MOOCs.

Research Objectives

There are few surveys and studies on the use of MOOCs by medical students in existing literature, and no one has systematically analyzed the behavioral intention of medical students to continue using MOOCs for learning and proposed corresponding strategies. Therefore, it is necessary to study the influencing factors of medical students' intention to continue using MOOCs for learning behavior, in order to further promote the construction and development of relevant MOOCs platforms and the teaching management reform of MOOCs in medical colleges.

Based on previous research results and theories, this study comprehensively explores the impacting factors of medical students' intention to continue learning using MOOCs as much as possible. This study focuses on constructing relevant theoretical models and provides a reference model for future researchers dedicated to the influencing factors of MOOCs learning. This study has created reference value for enriching the learning theory of MOOCs and may also contribute to improving the teaching management of MOOCs in local medical colleges.

Literature Review

Theories Used in the Study

This research constructed a conceptual framework using the expectation confirmation model (ECM), technology acceptance model (TAM) and unified theory of acceptance and use of technology (UTAUT).

Bhattacherjee (2001) proposed ECM to describe how user satisfaction, perceived usefulness, and expectation-confirmation all have an impact on continuous use an information system. The ECM has been widely utilized over the years to forecast user satisfaction and continuance behavior in a variety of scenarios (Ramadhan et al., 2022).

The TAM model was proposed by Davis (1989) and used to predict individuals' acceptance behavior. The Technology Acceptance Model (TAM) offers a strong theoretical foundation to explain why users adopt certain technologies (Kim, 2006).

Venkatesh et al. (2003) proposed the Unified Theory of Acceptance and Use of Technology (UTAUT) as a model to explain how users intend to use information systems and their subsequent usage behavior. The UTAUT model is a recognized approach for analyzing user usage behavior and intention to utilize an information system (Attuquayefio & Addo 2014).

Introduction of Variables

Performance expectation

According to Compeau and Higgins (1995), performance expectation as users' perception of the advantage performing a certain behavior or using a certain technology. Compeau et al. (1999) argued that performance expectation meant user's expectation to achieve value. Moreover, Venkatesh et al. (2012) opined that performance expectation is the advantage that users seek in terms of increased performance. Performance expectation was defined in the user's mind as the level to which user believes that the system can assist them in enhancing their performance in the course (Lwoga & Komba, 2015). Baabdullah et al. (2019) conceptualized performance expectation as the user's view on a certain information system.

It has been established that customers' perceptions have an impact on their continued intention to use those services and products (Alalwan, 2020). The research by Dečman (2015) found that performance expectations have a favorable impact on students' continued intention to employ online courses. The relationship between performance expectation and continuous intention has previously been found was significant. (Yang et al., 2017; Ye et al., 2019). Performance expectation has a favorable effect on continued usage and satisfaction (Lwoga and Komba, 2015). When using the learning systems effectively and efficiently, participants should feel satisfied. This may be described as a perceptual belief of satisfaction (Du, 2023). Hence, the following hypothesis was proposed by the researchers:

H1: Performance expectation has a significant impact on continuance intention.

H2: Performance expectation has a significant impact on satisfaction.

Self-efficacy

Bandura (1986) defined self-efficacy as an individual's beliefs regarding their ability to effectively accomplish tasks and generate desired outcomes. Self-efficacy is the term used to describe an individual's belief in their own ability to successfully complete tasks and achieve desired results (Bandura, 1991). Based on the reference of Liaw (2008), self-efficacy was defined as the conviction that a task can be completed. According to Alfany et al. (2019), self-efficacy refers to a person's evaluation of their capability to carry out a specific behavior in a given circumstance. In addition, Shankar and Datta (2018) defined self-efficacy as the extent to which a person has confidence in their ability to carry out any given task.

Self-efficacy is the capacity to plan and carry out the actions required to achieve particular sorts of achievements (Bandura, 1991). Zhao et al. (2008) stated that self-efficacy has a positive influence on both user satisfaction and ease of use. Self-efficacy has been identified as a crucial personal trait that has a significant impact on the adoption of technology and information systems, as the research conducted by Prior et al. (2016). Additionally, another study found a strong positive correlation between satisfaction and self-efficacy, as noted by Hong et al. (2016). Hence, the following hypothesis was proposed by the researchers:

H3: Self-efficacy has a significant impact on satisfaction.

Perceived usefulness

According to Davis (1989), perceived usefulness refers to the extent to which a person believes that using a particular technology would improve the individual's performance. Perceived usefulness has been scientifically confirmed as an important antecedent of users' views regarding their intention of usage (Davis, 1989). Perceived usefulness was defined as the degree to that an individual feel that utilizing a certain application would improve his or her work performance (Lo´pez-Nicola., 2008). Agudo-Peregrina et al. (2014) defined perceived usefulness as the belief of students that an e-learning system can support their learning and enhance their learning capacity. When a user perceives that a certain technology will offer unique benefits, they are more likely to use it. This is referred to as perceived usefulness, as explained by Aslam et al. (2017).

Revels et al. (2010) suggest that the utilitarian benefit of mobile technology is one of the main factors that leads to innovative utilization. Lee and Jun (2007) contend that perceived usefulness, the TAM's key concept, can also predict the satisfaction of customers in a mobile business scenario. Additionally, the perceived usefulness is greatly influenced by user satisfaction, according to Park et al. (2013). Hence, the following hypothesis was proposed by the researchers:

H4: Perceived usefulness has a significant impact on satisfaction.

Perceived ease of use

Davis (1989) defined perceived ease of use as the extent to that a person thinks utilizing a specific system would feel effortless. According to Chuleeporn (2014) research, perceived ease of use is defined as how easy a person thinks it would be to use a specific system. For Venkatesh et al. (2003), perceived ease of use refers to how easy and straightforward people think new technology is to use. Perceived ease of use is conceptualized as a measure of the extent which individuals think that using a certain system makes it easy for them to experience pleasure (Oh et al., 2009). In addition, Su et al. (2018) pointed out perceived ease of use also means the extent to which potential users anticipate using the new system without encountering any issues.

Rezaei and Amin (2013) discovered that perceived ease of use had a favorable effect on user satisfaction. Moreover, Amin et al. (2014), confirmed this conclusion, showing that perceived ease of use had a beneficial effect on user satisfaction. Wilson et al. (2021) investigated the impact of perceived ease of use on user loyalty in the Chinese computer sector. User satisfaction was found to favorably moderate the impact of perceived ease of use on user loyalty in this study. Hence, the following hypothesis was proposed by the researchers:

H5: Perceived ease of use has a significant impact on satisfaction.

Task-technology Fit

Goodhue and Thompson (1995) observed that task-technology fit is a key concept, which pays more attention to the relationship between technology and tasks. According to Ammenwerth et al. (2006), task-technology fit is the extent to which technology functionality matches task requirements and individual abilities. The degree to which a system matches interests, suits activities, and meets wants has been referred to as Task-technology Fit, or TTF (Lin and Wang 2012). For Fuller and Dennis (2009), TTF is defined as the extent to which the technology features fit the requirements of the task. Howard and Rose (2019) conceptualized TTF as the degree to which a technology supports the completion of a task by matching the requirements of the task and the capabilities of the technology.

According to Robles-Flores and Roussinov (2012), TTF has been found to have a positive impact on user satisfaction. There is a positive correlation between TTF and satisfaction with mobile payment services (Zhou et al., 2010). User satisfaction is greatly influenced by TTF, and both TTF and user satisfaction play a mediating role in the relationship between actual usage and performance impact (Isaac et al., 2017). Based on a study by Lin (2012), TTF played a crucial role in determining satisfaction levels in virtual educational learning systems. Hence, the following hypothesis was proposed by the researchers:

H6: Task- technology Fit has a significant impact on satisfaction.

Facilitating conditions

According to Venkatesh et al. (2003), the facilitating conditions refer to the perceived amount of usage of technological and organizational infrastructure to sustain utilize new systems. For Venkatesh et al. (2012), facilitating conditions comprises how users perceive the tools and assistance they need to carry out a behavior. Lwoga and Komba (2015) defined facilitating conditions as the belief among students that technology facilities can create physical conditions for the use of web-based learning systems. Nikou and Economides (2017) pointed out that facilitating conditions is anything that helps the assessment procedure to be implemented. Al Sayegh et al. (2023) argued that facilitating conditions refers to the perceptions of the resources and support available to users.

Previous research in the field of Information Systems has demonstrated that facilitating conditions can influence the level of user satisfaction directly or indirectly (Kaium et al., 2020). According to Venkatesh et al. (2011), the facilitating conditions of the e-government website was found to be a significant factor affecting user satisfaction, in a research of information systems continuance intention. Teo and Wong (2013) discovered that facilitating conditions may indirectly influence satisfaction by affecting perceived ease of use. Hence, the following hypothesis was proposed by the researchers:

H7: Facilitating conditions has a significant impact on satisfaction.

Satisfaction

According to Ives et al. (1983), satisfaction of the user was defined as the extent to which users believe the information system available to them meets their information requirements. For Sweeney and Ingram (2001), satisfaction was defined as the user's perceived interest and sense of accomplishment, in the online learning. According to Adamson and Shine (2003), satisfaction referred to a dimension of attitude since it measures emotional aspects. Based on the research of Sun et al. (2012), satisfaction of user is defined as the overall emotional reaction of the user to the cognitive evaluation of the worth of an IT service. Du (2023) stated that satisfaction was the extent of agreement between expectations and perceptions of the learning experience.

According to Bhattacharjee (2001), post-adoption beliefs include satisfaction and continuance intention. Existing studies have found a favorable association between satisfaction and continuing intention (Huang, 2019; Singh, 2020). There is the assumption that a user's usage continuance intention of the information system is influenced by their previous satisfaction of the whole system (Bhattacherjee, 2001). Previous studies have shown that learner satisfaction has a substantial impact on the intention to continue taking MOOCs (Joo et al., 2018). Hence, the following hypothesis was proposed by the researchers:

H8: Satisfaction has a significant impact on continuance intention.

Continuance Intention

Based on Bhattacherjee (2001), continuance intention refers to a user's decision whether to keep using an application after adopting it. According to Hellier et al. (2003), continuance intention refers to a decision-making process whereby an individual chooses to stick with a particular product or service. According to Park (2014), continuance intention can also refer to a person's intention to engage in a behavior after having already done so. Based on research of Chen et al. (2021), continuance intention refers to the situation when someone decides to continue using a product, service or action that they have already taken.

Research Methods and Materials

Conceptual Framework

Three earlier theoretical frameworks serve as the foundation for the research conceptual framework. The first theoretical framework was developed by Chen and Hsiao (2018), who studied the effect of satisfaction, performance expectation, subjective norms and openness on continuance intention for non-MOOCs and MOOCs platform. The second theoretical framework was proposed by Singh and Sharma (2021), who focused on relationships between social influence, facilitating condition, self-efficacy, perceived ease of use, perceived usefulness, satisfaction. The third theoretical framework was proposed by Wan et al. (2020), who studied the influencing factors such as TTF and satisfaction on a student's continued intention to learn by MOOCs. Figure 1 shows the conceptual framework of the current research:

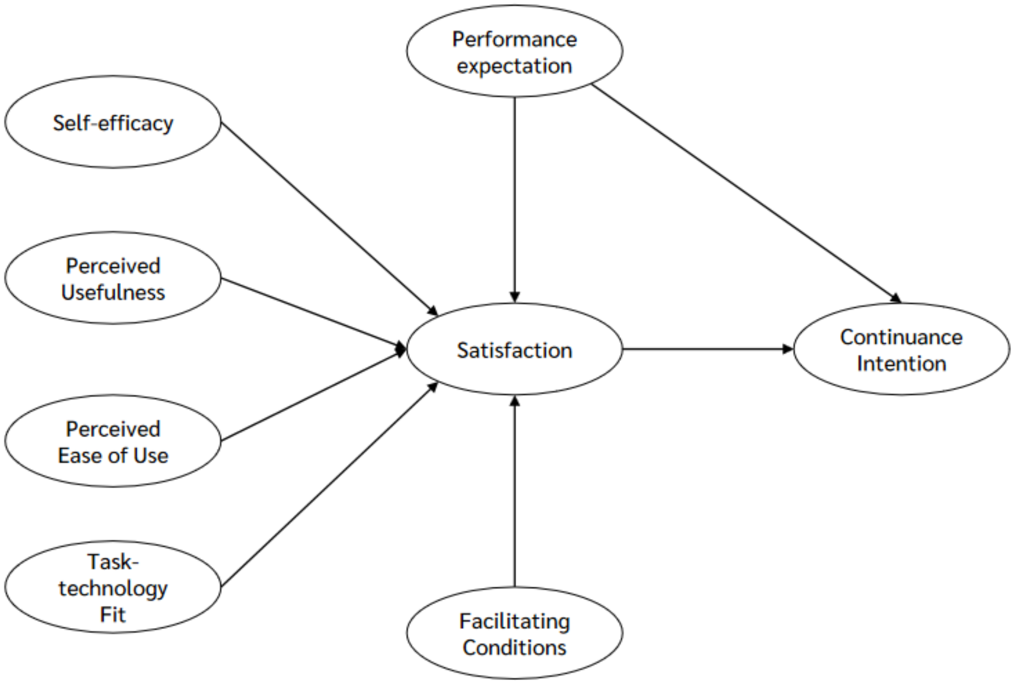

Figure 1. Conceptual Framework of study

Source: Author

This research aimed to explain association between performance expectation, self-efficacy, perceived usefulness, perceived ease of use, TTF, facilitating conditions, satisfaction, and continuance intention to use MOOCs learning among medical students in Chengdu, China.

Methodology

In this research, a quantitative method was used to collect and analyze data from medical students in Chengdu Medical College. The target population consists of undergraduate students from four different faculties, ranging from sophomore to senior level. The sample size was 500. A questionnaire was used to collect data from the target population, and its reliability and validity were tested using Item Objective Congruence (IOC). A 5-point Likert scale was used to measure the scale items, with 1 denoting strongly disagree and 5 denoting strong agreement.

In order to evaluate the content validity of the data collection tool, the researcher first administered online questionnaires using the Index of Item-Objective Congruence (IOC) test. To do this, scale items for each of the eight variables were sent to three experts in the field. A pilot test was conducted with 50 respondents who completed the questionnaire online. The reliability of the questionnaire was measured using Cronbach's alpha. After collecting data from a total of 500 respondents, chosen using multi-stage sampling in proportion to the four different faculties, the measurement model was tested using Confirmation Factor Analysis (CFA), and the structure model was tested using Structural Equation Models (SEM) to illustrate the eight hypotheses among eight variables in the conceptual framework.

Target Population and Sample Size

The target population was defined as individuals or participants who possess specific attributes of interest and relevance (Creswell, 2003). In this study, the target population is sophomore, junior, and senior medical undergraduates who participated in MOOCs learning in Chengdu. In selecting the respondents for the study, the researchers excluded first-year medical students due to their limited experience in studying and using MOOCs in medical college, as well as fifth-year medical students who have little time to study MOOCs during clinical internships in teaching hospitals.

Sample size was defined by Milic (2008) as a representative portion of the target population used in the research. The minimum sample size of 444 was recommended by Soper's (2006) calculator due to the presence of 8 latent variables and 35 observed variables. The researchers distributed roughly 600 valid questionnaires and used 500 of those to conduct the study after discarding incomplete or erroneous questionnaires.

Sampling Procedures

The target population for this study had to fulfill the following criteria: (1) Chinese medical students in Chengdu; (2) Medical students from their second to fourth year in one of the four faculties of Chengdu medical college; and (3) Students with a minimum of six months of experience in MOOCs learning. Hence, the researcher used convenience sampling and purposive or judgmental sampling as techniques to choose and reach the target sample. A purposive sampling approach was employed to carefully choose four specific faculties situated in Chengdu Medical College. Then a stratified random sampling technique was used to create strata. The number of questionnaires was then distributed to each faculty, as shown in Table 1.

Table 1. Number of Questionnaires Distributed to Each Faculty

Faculties	Population Size	Proportional Sample Size (N=500)
Faculty of Clinical Medicine (FCM)	3,354	230
Faculty of Nursing (FN)	1,536	106
Faculty of Pharmacy (FP)	1,287	88
Faculty of Laboratory Medicine (FLM)	1,104	76
Total	7,281	500

The overarching aim of this sampling approach is to gather data from individuals who are readily accessible to the researcher (Etikan, 2015). The researcher distributed questionnaires through a convenience sampling method to engage willing respondents for questionnaire participation.

Results and Discussion

Demographic Information

As shown in Table 2, among the 500 respondents, 42.8% were males and 57.2% were females. The second year of college had the highest proportion of respondents, accounting for 41.8%. Most respondents use MOOCs for learning more than 3 times per week, 34.4% more than 5 times per week. The most commonly used device for MOOCs learning is smartphone, accounting for 65.8%. Over half the sample (55.0%) hope to study medical courses through MOOCs.

Table 2. Demographic Information

Demographic and General Data (N=500)		N	%
Gender	Male	214	42.8
	Female	286	57.2
Grade	Sophomore	209	41.8
	Junior	188	37.6
	Senior	103	20.6
Times of MOOCs learning sessions per week	No more than 1 time	43	8.6
	2-3 times	119	23.8
	3-5 times	166	33.2
	more than 5 times	172	34.4
A Device prefer for MOOCs learning	Smartphone	329	65.8
	Tablet computer	107	21.4
	Personal computer	53	10.6
	Other	11	2.2
Required content of MOOCs learning	Medical Professional Courses	275	55.0
	Courses related to medicine	169	33.8
	Non-medical course learning	56	11.2

Confirmatory Factor Analysis (CFA)

Brown (2015) characterized CFA as a specific type of SEM dedicated to the measurement model, aimed at investigating the relationship between observed variables and latent variables. Through CFA, discriminant validity and convergent validity (factor loading, composite reliability, average variance retrieved) could be verified. According to the general guidelines that state that the Cronbach's Alpha value should be 0.60 or above, the constructs in Table 3 have a coefficient of internal consistency (Hair, et al., 2007). Each variable's factor loading was also above 0.5 at p-value<0.5 and t-value >1.98 (Hair et al., 2010). For every variable, the average variance extracted (AVE) was more than 0.5, and the composite reliability (CR) was above 0.7 (Fornell & Larcker, 1981). To sum up, the statistical estimations showed significance.

The square root of the variables' AVEs is displayed in Table 4. Fornell and Larcker (1981) state that the square root of each AVE is calculated and compared to the component correlations in order to assess discriminant validity. Because the discriminant validity values in this investigation were all greater than the inter-construct correlations, the discriminant validity was deemed acceptable.

Table 3. Confirmatory Factor Analysis (CFA), Composite Reliability (CR), and Average Variance Extracted (AVE) Results

Variables	Source of Questionnaire (Measurement Indicator)	No of Items	Cronbach's Alpha	Factor Loading	CR	AVE
Performance expectation (PE)	Chen et al., 2018	4	0.909	0.826-0.864	0.909	0.714
Self-efficacy (SE)	Singh & Sharma, 2021	4	0.805	0.679-0.916	0.854	0.597
Perceived usefulness (PU)	Singh & Sharma, 2021	4	0.812	0.633-0.882	0.814	0.527
Perceived ease of use (PEOU)	Singh & Sharma, 2021	4	0.898	0.818-0.853	0.898	0.687
Task-technology Fit (TTF)	Wan et al., 2020	4	0.822	0.664-0.792	0.824	0.541
Facilitating conditions (FC)	Wan et al., 2020	5	0.834	0.650-0.745	0.834	0.503
Satisfaction (SAT)	Wan et al., 2020	5	0.896	0.742-0.897	0.893	0.627
Continuance Intention (CI)	Wan et al., 2020	5	0.878	0.735-0.874	0.878	0.592

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

Table 4. Discriminant Validity

Variables	Factor Correlations							
	PE	SE	PU	PEOU	TTF	FC	SAT	CI
PE	0.845							

SE	0.242	**0.773**						
PU	0.385	0.147	**0.726**					
PEOU	0.512	0.181	0.340	**0.829**				
TTF	0.341	0.127	0.355	0.318	**0.736**			
FC	0.379	0.153	0.359	0.389	0.390	**0.709**		
SAT	0.501	0.267	0.494	0.457	0.504	0.519	**0.792**	
CI	0.296	0.081	0.328	0.303	0.324	0.360	0.454	**0.770**

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

Structural Equation Model (SEM)

Ainur et al. (2017) describe SEM as a statistical technique that amalgamates elements from traditional multivariate models, such as factor analysis and regression analysis. SEM serves the crucial purpose of assessing the model's consistency with data through an examination of model fit (Hair et al., 2010). Table 5 presents an illustration of the model's fitness, comparing the statistical indices values from the SEM with the acceptable criterion. The values of the indices and their corresponding RMSEA values are as follows: CMIN/DF = 1.516, GFI = 0.915, AGFI = 0.899, NFI=0.920, CFI = 0.971, TLI = 0.968, and RMSEA = 0.032. The model's fitness has been confirmed as all index values fall inside the permitted range.

Table 5. Goodness of Fit for Structural Equation Model (SEM)

Index	Criterion	Statistical Value
CMIN/DF	< 5.00 (Awang, 2012; Al-Mamary and Shamsuddin, 2015)	1.516
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.915
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.899
NFI	≥ 0.80 (Wu & Wang, 2006)	0.920
CFI	≥ 0.80 (Bentler, 1990)	0.971
TLI	≥ 0.80 (Sharma et al., 2005)	0.968
RMSEA	< 0.08 (Pedroso et. al., 2016)	0.032
Model summary		Acceptable Model Fit

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

Research Hypothesis (H) Testing Result

The structural model's regression weights and R2 variances are used to measure how significant a link is between variables. With the exception of H1, the findings showed that all of the stated hypotheses are supported. TTF was the strongest predictor of satisfaction, following by perceived usefulness. Furthermore, Satisfaction had a significant impact on continuance intention. Table 5 displays the causal connections between the variables.

The following describes the structural path results from Table 5 and Figure 2:

H1: The standardized path coefficient between performance expectation toward MOOCs learning and continuance intention to MOOCs learning was 0.037, and t-value at 0.794. Therefore, the result indicates that performance expectation toward MOOCs learning did not have an impact on continuance intention to MOOCs learning. Although the finding contradicts with the findings of Yang et al. (2017) and Ye et al. (2019) (i.e., that performance expectations have a favorable impact on students' continued intention in fields such as online courses), it aligns with findings of Bhattacherjee (2001) where a user's usage continuance intention of the information system is determined by their previous satisfaction of the whole system instead of their expectations.

H2: Performance expectation had a positive impact on satisfaction with standardized path coefficient of 0.194, and t-value at 4.529*. The hypothesis was supported with UTAUT (Koh et al., 2010). That finding is consistent with previous empirical studies (Venkatesh et al., 2011; Wan et al., 2020; Cheng et al., 2020; Shah and Khanna 2023) which found that students who have greater performance expectations are likely to be more satisfied with the MOOC platform.

H3: The standardized path coefficient between self-efficacy and satisfaction was 0.189, and t-value at 4.326*. Therefore, self-efficacy had a positive effect on satisfaction. Consequently, this finding implies that students with high self-efficacy tend to have a better understanding and appreciation of the features and functions of MOOCs. This finding is consistent with prior studies by Aldholay et al. (2018), Shen et al. (2013), Federici and Skaalvik (2012), Fianu et al (2018).

H4: The hypothesis is supported, in that perceived usefulness had a positive effect on satisfaction from standardized path coefficient of 0.330, and t-value at 6.623*. From the results, it can be seen that perceived usefulness has a significant impact on the satisfaction of MOOCs learning, second only to TTF. The researcher combined the expectation-confirmation model with MOOC features and found that perceived usefulness directly correlates with satisfaction, thus emphasizing the usefulness of courses to ensure student satisfaction. This corresponds to research conducted by Liao et al. (2007), Singh and Sharma (2021), and Rekha et al. (2023).

H5: The standardized path coefficient between perceived ease of use and satisfaction toward MOOCs learning was 0.196, and t-value at 4.500*. Therefore, H5 was supported, in that perceived ease of use had a significant impact on satisfaction toward MOOCs learning. This finding is aligned with studies of Tu et al. (2012), Wu and Zhang (2014) and Yang and Su (2017). Students would likely have favorable satisfaction toward MOOCs learning if the

MOOCs can help them achieved the task while exerting lesser effort and time. Perceived ease of use is a crucial factor in determining a learner's satisfaction that using MOOCs will be effortless.

H6: TTF had a positive effect on satisfaction toward MOOCs learning, with a supporting standardized path coefficient of 0.344, and t-value at 6.890*. Consequently, H6 was supported by this study. TTF was the highest contributor to satisfaction, compared with perceived usefulness, facilitating conditions, perceived ease of use, performance expectation, and self-efficacy. This indicates that, when studying the factors that affect student satisfaction with MOOC learning, the perception of technology and the degree of matching between tasks and technology are crucial factors. This result is consistent with studies by Huang et al. (2017), Xiong et al (2020), and Wan et al. (2020).

H7: The standardized path coefficient between facilitating conditions and satisfaction to MOOCs learning was 0.323, and t-value at 6.657.* This finding supports H7, in that facilitating conditions had a significant impact on satisfaction to MOOCs learning. Chan et al, (2010), Teo and Wong (2013), Shah and Khanna (2023) found that the relevance of facilitating conditions in the mandatory context is proved by its significant direct effect on user satisfaction, and that is supported by this study.

H8: The hypothesis was supported on significant impact of satisfaction on continuance intention to MOOCs learning with standardized path coefficient of 0.461, and t-value at 8.033*. The result demonstrates a favorable association between satisfaction and continuing intention. Satisfaction mediated all of the model's interactions, and had a favorable impact on students' intention to continue MOOCs learning. This finding is supported by the findings of Joo et al. (2018), Alalwan et al. (2020) and Gupta et al. (2021).

Table 5. Hypothesis Testing Result of the Structural Model

Hypothesis		Standardized path coefficients (β)	t-value	Test Result
H1	PE → CI	0.037	0.794	Not Supported
H2	PE → SAT	0.194	4.529*	Supported
H3	SE → SAT	0.189	4.326*	Supported
H4	PU → SAT	0.330	6.623*	Supported
H5	PEOU → SAT	0.196	4.500*	Supported
H6	TTF → SAT	0.344	6.890*	Supported
H7	FC → SAT	0.323	6.657*	Supported
H8	SAT → CI	0.461	8.033*	Supported

Note: *Significant at p-value, $p<0.05$.

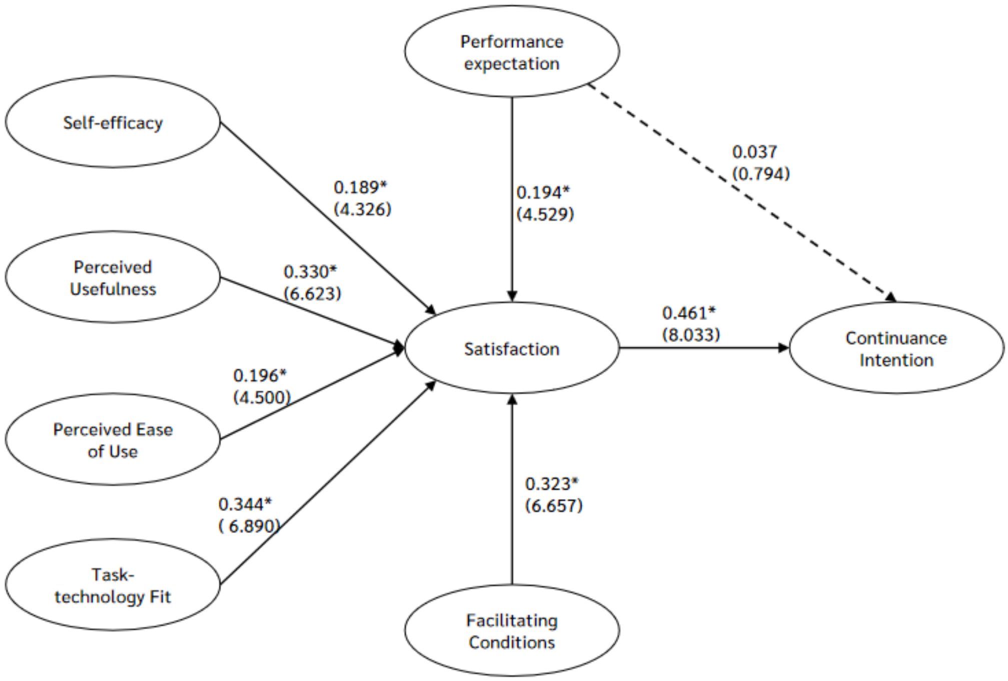

Figure 2. The Results of Structural Model

Note: Solid line denotes the Standardized Coefficient with * as p<0.05, and t-value in Parentheses; Dash line denotes 'Not Significant'

Conclusions and Implications

Conclusions

This study explored the statistical association between performance expectation, self-efficacy, perceived usefulness, perceived ease of use, TTF, facilitating conditions, satisfaction, and continuance intention to use MOOCs learning among medical students. This study also assessed the factors which impact on medical students' intention to continue learning using MOOCs. In this research, a quantitative method was used to collect and analyze data from medical students in Chengdu Medical College. The target population consists of undergraduate students from four different faculties, ranging from sophomore to senior level. The sample size was 500. A structured questionnaire was used to collect data from the target population, and its reliability and validity were tested using IOC. The reliability of the questionnaire was measured using Cronbach's alpha. After collecting data from a total of 500 respondents, chosen using multi-stage sampling in proportion to the four different faculties, the measurement model was tested using CFA, and the structure model was tested using SEM to test the eight hypotheses among eight variables in the conceptual framework.

The findings from the statistical analysis are summarized as follows:

First, TTF, perceived usefulness, and facilitating conditions have a significant impact on the satisfaction of medical students toward MOOCs learning, and the magnitude of their influence is similar. TTF had the most significant impact on students' satisfaction toward using MOOCs learning. According to the study of Huang et al. (2017), TTF had the most significant impact on satisfaction. In a study conducted by Xiong et al (2020), it was found that enhancing TTF can lead to increased customer satisfaction. The perceived usefulness on the satisfaction of MOOC learning is second only to TTF. Previous studies have found that user's perceived usefulness of an information system was affected by the users' satisfaction (Liao et al., 2007; Amin et al., 2014). Facilitating conditions exerted the third most positive impact on satisfaction to use MOOCs learning. In previous studies concerning information systems continuance intention, Venkatesh et al. (2011) found that the facilitating conditions were a significant factor affecting user satisfaction.

Second, perceived ease of use, performance expectation and self-efficacy had a significant impact on the satisfaction of medical students toward MOOCs learning. The impact of these three factors is similar, but all are smaller than TTF, perceived usefulness, and facilitating conditions.

Third, satisfaction plays a vital role in motivating or influencing medical college students' continuance intention toward using MOOCs learning (Joo et al., 2018; Alalwan et al., 2020). By contrast, performance expectation played an insignificant role in predicting continuance intention to MOOCs learning. Therefore, in order to promote the improvement of medical students' continuance intention to use MOOCs for learning, it is necessary to improve their satisfaction with the use of MOOCs platforms in terms of functions, services, course content, and course quality.

In sum, the key factor encouraging medical students to continue using MOOCs for learning is their satisfaction with MOOCs learning, and the main factors affecting their satisfaction are TTF, perceived usefulness, and facilitating conditions.

Implications

The proposed theoretical model can explain the factors that affect medical students' satisfaction and continuance intention of using MOOCs very well. TTF, perceived usefulness, and facilitating conditions are important determinants of students' satisfaction toward MOOCs learning. Satisfaction has a significant impact on continuance intention. However, performance expectation did not directly influence continuance intention in the MOOCs, but indirectly affected continued intention, with a mediating role of user satisfaction.

This study demonstrated that TTF exerted the most influence on satisfaction, and indirectly affects medical students' continuance intention to use MOOCs learning. The medical education MOOC platform should accurately obtain and present the learning task needs of medical students from the perspectives of establishing student learning models, collecting learning behavior data, and automatically analyzing data. In addition, the platform should be able to launch learning materials and resources that are suitable for the personal characteristics and learning needs of medical students. As a result, it is essential to create customized technological solutions that satisfy medical students' learning objectives and expectations, while also taking into account the unique features of medical education. It is advised to optimize and coordinate the distribution of course content in order to maximize the fit between the mode of delivery and student demand.

Research has shown that perceived usefulness has a secondary impact on satisfaction. Therefore, the MOOCs platform should focus on the design of course content, making MOOCs more attractive and practical than traditional classroom teaching. For example, in online courses, students can deepen their understanding and explain the key and difficult points of knowledge by inserting vivid animations or video clips. This can help medical students understand medical knowledge more vividly, improve learning effectiveness, increase the perceived usefulness of medical student users, and thus increase their satisfaction with MOOC learning.

As facilitating conditions have a positive influence on satisfaction, the convenience and device compatibility of MOOCs platforms can be improved from multiple aspects, the MOOC platform's technological features should be maximized by the provider in order to uncover and pinpoint the interests and preferences of medical students and offer a convenient and comfortable user experience. Furthermore, it is imperative to ensure that the MOOC platform's webpage links are secure and easily available, that the platform is compatible with various operating systems and terminal devices, and that learners have the autonomy to customize the interface's characteristics and designs. In sum, the MOOCS platform ought to find and pinpoint the interests and preferences of medical students and facilitate a simpler, smarter, more customized user experience.

It is vital to increase the level of platform satisfaction through a variety of strategies since it is the most significant predictor of learners' intentions to continue with MOOCs. Enhancing the MOOC platform's features and services, enhancing the caliber of courses, and adding value to the educational material are all crucial factors in encouraging medical students to stick with MOOCs as their primary learning resource. In order to improve the satisfaction of medical students with course quality, online teachers and course designers should ensure that the courses are applicable to medical topics and have practicality. In addition, it is recommended that course designers stimulate and strengthen student interaction by establishing various online learning communities in MOOCs. These not only help improve the satisfaction of medical students with the MOOC platform, but also enhance their intention to continue using MOOCs for learning.

Limitation and Further Study

There are several limitations of this study that need to be addressed in future research. Firstly, the researchers selected medical students from Chengdu, China as the study population, and these students share many characteristics in their social environment and educational experience. Therefore, the dataset may have some skewness or statistical artifacts. In the future, the scope of the surveyed population can be expanded to further validate the researchers' findings in this select population. Secondly, although the respondents in this study are all medical students, they belong to four different majors and may have had different MOOC courses. These factors may have affected students' perception, thus impacting their satisfaction and continuance intention. Future research should consider these two factors, and further optimize the research model. Thirdly, in this research model, other variables that may have an impact, such as social influence and usage experience, were not considered. In the future, further exploration of the roles of these variables may bring some new findings to research in the field of MOOCs learning.

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