



## Factors Impacting Undergraduate Students' Satisfaction and Continuous Intention to Use MOOCs in Chengdu China

Yi Wu<sup>1</sup> and Changhan Li<sup>2</sup>

<sup>1</sup>Ph.D. Candidate, Graduate School of Business and Advanced Technology Management, Assumption University, Thailand

<sup>2</sup> Corresponding Author, Program Director of M.Ed. Teaching and Technology, Graduate School of Business and Advanced Technology Management, Assumption University, Thailand

Email: wuyi9081@163.com, ORCID ID: <https://orcid.org/0009-0006-6278-0542>

Email: lichanghan@au.edu, ORCID ID: <https://orcid.org/0009-0004-5768-6733>

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### Abstract

**Background and Aims:** The objective of this article was to investigate the influence of MOOC implementation factors on the continuous intention and satisfaction of undergraduates in Chengdu, China, performance expectancy (PE), social influence (SI), perceived usefulness (PU), confirmation (CON), flow experience (FE), satisfaction (SAT), and continued intention (CI) were all interconnected in the conceptual framework. The objective of the research is to determine the extent to which each variable influences the use of MOOCs, to provide insights that can help improve the learning experience and ensure learners' long-term investment.

**Materials and Methods:** The researcher utilized the quantitative investigation strategy with 500 samples and distributed the questionnaire to the selected undergraduate students at Xihua University. In this survey, a multistage sampling strategy was used to collect data from the investigation, using judgmental and quota sampling. Confirmatory factor analysis (CFA) and structural equation model (SEM) have been implemented to analyze data. In addition, goodness of model fits, correlation validity, and reliability testing for each component were utilized.

**Results:** The result demonstrated that MOOC implementation factors, including performance expectancy, social influence, perceived usefulness, confirmation, and flow experience significantly affect students' continuance intention and satisfaction, with flow experience (FE) providing the greatest consequence on satisfaction. The entire hypotheses have been evidenced to achieve the research purposes.

**Conclusion:** The study provides empirical evidence on how MOOC implementation factors affect engineering students' satisfaction and continuance intention. It suggests that the findings could be useful for university management and lecturers to increase teaching and learning quality in the course and develop new strategies and approaches that suit modern-day learners. The study also aims to enhance the efficiency and effectiveness of class delivery and improve student engagement in the learning process.

**Keywords:** Massive open online courses; MOOC; UTAUT; Satisfaction; Continuance intention

### Introduction

Massive open online courses (MOOCs) have received much attention from educational administrators, instructors, and learners worldwide, and have further taken the world of higher education by storm (Sun et al., 2020; Hossain et al., 2022). This trend will revolutionize higher education by increasing the availability of knowledge to students. MOOCs are free, easily accessible online courses that allow large numbers of students to enroll while acquiring quality knowledge and giving them the opportunity to collaborate and teachers from anywhere, anytime, even without standard classroom settings (Aparicio et al., 2019; Zhao et al., 2020). Therefore, distance learning via MOOCs has proven to be the most flexible and preferred way to acquire an education. Compared to traditional online courses, the advantages of MOOCs are extensive interactive participation, collaboration, freedom of character, non-discrimination, openness, and self-organization, which allows the MOOC model to be used as an excellent complement to traditional e-learning. (Wu and Chen, 2017; Shao, 2018; Sun et al., 2020). MOOCs are based on the principle that independent learning can take place anywhere, anytime (de Barba et al., 2020). By sharing learning resource platforms, universities can learn from each other's educational outcomes based on MOOCs to encourage global sharing of learning resources (Verhulst and Lambrechts, 2015).

The MOOC model, in contrast to the conventional teacher-centered teaching approach, is a student-





centered learning approach in which students actively choose online courses, construct the didactic structure of these courses, plan their learning paths, and modify the learning goals to suit their learning requirements. Thus, learning (Lin and Wang, 2012; Zhang et al., 2018; Lambert, 2020) enables students to attend free and open courses from renowned universities, which attract many more students and offer flexible courses. MOOCs can also assist teachers in developing more effective teaching practices comparing the learning process to traditional online courses (Wu and Chen et al., 2017).

Conclude the research problem in one paragraph.

Xihua University is one of the key universities in Sichuan Province, China, and it realizes the importance of integrating MOOC's online platform into its courses, especially in science and engineering majors. As a new generation of college students becomes increasingly proficient in technology, it is important to understand their tendency to use platforms such as MOOCs. This not only helps to optimize teaching methods but also ensures that students are equipped with tools they like.

## Objective

The objective of this study is to use a quantitative survey method to explore the factors that may impact undergraduate students' attitudes and continued intention regarding the use of MOOCs including performance expectancy, social influence, confirmation, perceived usefulness, flow experience, and the between satisfaction and continued intention.

## Review of Literature

### Massive Open Online Courses (MOOCs)

The largest MOOC platform in China, iCourse163, is owned by Higher Education Press Co., Ltd. and is used by China University. More than 10,000 open courses and 1,400 top-notch domestic courses are available through the China University MOOC, which was jointly launched on August 10th, 2022 by Higher Education Press and NetEase Youdao. It has joined forces with 803 universities and grown to be China's biggest MOOC platform. iCourse 163 from China University MOOC was the technology used in the study. The Chinese Ministry of Education and the Ministry of Finance together launched the iCourse platform in 2011, which provides free, high-quality courses from famous Chinese higher education institutions. Over 9 million students have access to over 9,500 courses on the platform in 2020 (Yang, L, 2023).

The most inventive platform independently established in the nation, according to Baggaley, J. (2014), the MOOC platform for Chinese institutions, icourse163, which was introduced by Netease cloud classroom, has system attributes that are quite comparable to Coursera.

### Theory of Acceptance and Use of Technology (UTAUT)

Venkatesh et al.'s (2003) organizational framework, UTAUT, is a condensed framework that compiles disjointed theories on the use of technology. Eight competing models on technology adoption (reasoned action theory, planned behavior theory, technology acceptance model, combined technology acceptance model and planned behavior theory, innovation diffusion theory, social cognitive theory, motivational model, and personal computer usage model) were conceptually and empirically compared (Goh et al., 2013; Nazari et al., 2013). Venkatesh et al. (2003) designed and empirically tested UTAUT based on its similarity to the eight competing models.

### Performance Expectancy

According to Venkatesh et al. (2003), performance expectation is the degree to which one thinks that employing a specific technology would improve the user's performance on a specific task. Decman (2015) looked at the usage of learning management systems (LMS) in higher education and found that performance expectations had a substantial impact on LMS adoption. According to Nair et al. (2015), performance expectations have a considerable impact on how often lecture capture systems are used in higher education.



## Social Influence

According to Venkatesh et al. (2003), social influence is the notion that others in one's social circle and those who are significant to them believe that using a specific technology would be helpful. Alraimi et al. (2015), Yousef et al. (2015), and Chang et al. (2015) have conducted studies that demonstrate how social impact (or subjective norm) affects intention to utilize MOOCs. The introduction of MOOCs was motivated by the perceived need for high-quality instruction from renowned professors and prestigious universities (Alraimi et al., 2015; Yousef et al., 2015), employer and teacher directives on course design and requirements (Chang et al., 2015), and the perceived need to establish one's network (Yousef et al., 2015).

### Perceived usefulness

According to (Venkatesh et al., 2012), perceived usefulness (PU) is "the extent to which a person believes that using a particular system would enhance his/her job performance." Users look to their significant ones for attention and approval. It refers to how much weight a person gives to the opinions of others.

Venkatesh et al. (2003) demonstrated that social influence constructs are relevant in the required situation but not in the voluntary scenario by contrasting eight voluntary and mandatory technology adoption models. Education and career choices, as well as social acceptability and recognition, are influenced by both internal and extrinsic motives. Professionals need their employer's or professional association's official clearance.

### Social Influence

Social influence is the notion that others in one's social circle and those who are significant to them believe that using a specific technology would be helpful (Venkatesh et al., 2003). Family, friends, the moderator, and participants all exercise social influence in the setting of MOOCs to the point where other people feel compelled to utilize the MOOC platforms. Sometimes a student's choices about a course and platform are not solely their own. The choice of MOOCs is impacted by the user's peers or reference people, according to the literature currently in print (Mulik et al., 2019; Tseng et al., 2022). However, other research has indicated that behavioral intentions in MOOCs are not impacted by social influence (Mohan et al., 2020). According to existing research (Hsiao et al., 2016), social influence impact has an impact on user happiness.

### Confirmation

Users are more satisfied with the system when their expectations before accepting the e-learning system are met during real use of the system (Lee, 2010; Lin and Wang, 2012). In the context of MOOCs, students' confirmation of MOOCs refers to the fact that they have experienced the advantages of utilizing MOOCs in the way that was anticipated, which might enhance their happiness with MOOCs (Alraimi et al., 2015). Therefore, the study assumes that students' happiness with MOOCs may be influenced by the validation of their expectations for utilizing MOOCs.

### Perceived usefulness

High levels of system satisfaction should be anticipated if users regard the e-learning system to be beneficial (Lee, 2010; Lin and Wang, 2012). According to Chen et al. (2018), students will appreciate MOOCs more if they think them beneficial. Therefore, it is assumed in this study that students' perceptions of utility (PU) might affect how satisfied they are with MOOCs.

### Flow experience

Users' greater happiness with the systems may be positively impacted by the amount of intrinsic motivation that e-learning systems induce in them (Alraimi et al., 2015). As a result, this study proposes that students' experiences with the flow that MOOCs create may have an impact on how satisfied they are with MOOCs. As a result, we propose the following hypotheses:

### Satisfaction

Satisfaction is a reliable sign of persistence. Users will wish to keep using the e-learning system if they find it to be good (Larsen et al., 2009; Lee, 2010). Student satisfaction with MOOCs can have a





favorable impact on their intention to continue taking MOOCs (Chen et al., 2018). Therefore, it is hypothesized in this study that students' happiness with MOOCs may continually affect their desire to enroll in MOOCs.

### Continued Intention

Continued Intention is described as a user's decision to keep using a service after agreeing to its terms (Sun, Y., Bhattacherjee, 2009). While previous studies of IS/IT usage patterns considered information systems (IS) /information technology (IT) usage as the initial concept and placed less emphasis on evaluating outcomes of information systems (IS) /information technology (IT) usage, IS/IT success should be determined by its influence on performance (Sun et al., 2009; Chung et al., 2015; Tam and Oliveira, 2016), which leads to the assessment of information systems (IS) /information technology (IT) success being advised (Sun et al., 2009; Shih and Chen, 2013). Additionally, students' goal to use an online learning system to further their education has a favorable influence on how favorably they see the impact on learning (Lin and Wang, 2012; Chen et al, 2019).

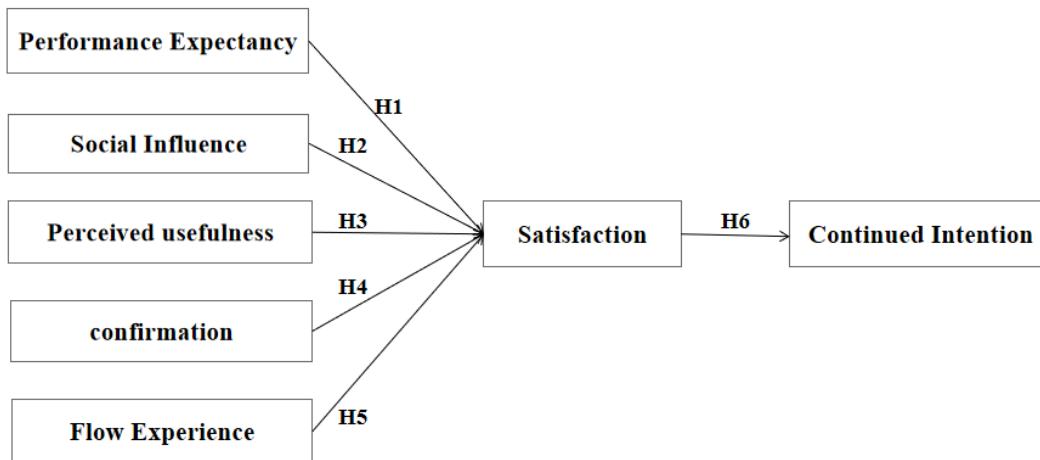
Therefore, the following hypotheses are put forth:

- H1:** Performance expectancy positively impacts satisfaction for MOOCs.
- H2:** Social influence positively impacts the satisfaction of MOOCs
- H3:** Perceived usefulness positively impacts satisfaction with MOOCs.
- H4:** Confirmation positively impacts satisfaction with MOOCs.
- H5:** Flow experience positively impacts satisfaction with MOOCs.
- H6:** Satisfaction positively impacts the continuance intention of MOOCs.

### Conceptual Framework

This research rigorously examines existing relevant theories and, based on this examination, refines them to propose a theoretical framework suitable for this study. Based on Venkatesh et al.'s (2003) Unified Theory of Acceptance and Use of Technology (UTAUT), four elements—performance expectancy, effort expectancy, social influence, and facilitating conditions directly influence both behavioral intention and usage behavior (Hoi, 2020). Subsequently, Dwivedi et al. (2019) introduced an enhanced UTAUT model. Introducing an additional individual construct, attitude, alongside the existing dimensions and their anticipated interrelationships. Given the acknowledged theoretical and empirical importance of attitude in determining technology acceptance, he considers it a vital inclusion previously absent in the model. Furthermore, attitude holds a pivotal role in their model, influencing student satisfaction and perceived learning outcomes. Building on this foundation, (Ikhsan et al., 2019) further established the connection between perceived learning outcomes and student satisfaction. Therefore, Figure 1 shows the conceptual framework of this study formed based on the previous theory (Venkatesh et al., 2003; Dwivedi et al., 2019; Alshare & Lane., 2011, and Ikhsan et al., 2019). The conceptual framework was devised in line with these elements, as depicted in Figure 1.





**Figure 1** Conceptual Framework

**Note:** Created by the Author

## Methodology

This research aims to determine the factors that impact satisfaction with and continued intention to use MOOCs among Chengdu undergraduate students at Xihua University (XHU) in Chengdu, China. This research has conducted the quantitative survey approach, which was the most effective research methodology for collecting students' attitude data and determining their psychological responses.

### Research Instrument

The primary tool used in this study was a quantitative questionnaire, structured into three main parts: a screening question, demographic details, and scale items evaluating various observed variables. First, a typical screening question was developed to recognize and evaluate people according to particular characteristics (Kennedy et al., 2011). The researcher used this screening tool to make sure the people who were chosen were suitable for further interviews. Basic facts about the participants, including gender, area of study, and pertinent university information, were sought after in the demographic section (Mertens, 2015; Lodhi et al., 2016). This data was collected using three distinct items: gender, academic year, and university affiliation. In addition, 27 scale items that were taken from previous research were used to evaluate the latent variables. The items for Confirmation, System Quality, Service Quality, Information Quality, Engagement, Satisfaction, and Behavioral Intention were among the five that were included in this. A five-point Likert scale was used to evaluate the items on this scale. Strong agreement with positive claims was indicated by a score of 5, while strong disagreement with negative statements was indicated by a score of 1 on this scale (Salkind, 2017).

### Validation of the Research Instrument

For the validity of the scale items, four experts with Ph.D. educational background, who hold at least an associate professor, and at least nine years of experience in education academic researchers were invited to conduct the item-objective congruence (IOC) assessment to examine the precise objectives recommended by the instrument developer for this investigation. The lowest score of the IOC assessment was 0.75 which indicates the entire scale items were regarding the satisfactory content validity.

In addition, the pilot test was conducted to evaluate the internal consistency reliability of the research instrument. Determined. According to several investigators (Hassan et al., 2006; Lavrakas, 2008), a respondent group of 10 to 30 members was acceptable for the pilot examination. Consequently, 40 students performed the pilot test, and the internal consistency reliability was evaluated by using Cronbach's Alpha



index. According to the results of the pilot test, the lowest Cronbach's Alpha of the constructs was 0.885, which indicated internal reliability of the scale items was at the ideal condition. The entire information is demonstrated in Table 1.

**Table 1** Results of Internal Consistency Reliability Evaluation of the Pilot Test

Constructs	No. of Items	Cronbach's Alpha
Perceived Ease of Use	5	0.945
Perceived Usefulness	5	0.889
Attitude	4	0.885
Performance Expectancy	4	0.946
Effort Expectancy	4	0.894
Social Influence	4	0.965
Satisfaction	5	0.957

**Note:** Constructed by the Author

### Data Collection and Analysis

Following the content validity and internal consistency reliability assessment preceding the full-scale data collection, the content validity and internal consistency reliability were evaluated, and then the electronic questionnaire was sent to 500 science and engineering undergraduates at Xihua University. The researchers utilized the statistical programs JAMOVI and AMOS to investigate the information. The researchers also conducted confirmatory factor analysis (CFA) to evaluate the factor loading, t-value, composite reliability (CR), average variance extracted (AVE), and discriminant validity. The structural equation model (SEM) was subsequently employed to investigate the outcomes of the hypotheses as well as the direct, indirect, and overall effects of the correlations between the latent variables.

### Population and Sample Size

The target population of the survey is science and engineering undergraduates from Xihua University in Chengdu China. Hair, et al. (2013) suggested a minimum sample size of 200–500 participants for the difficult methodological approach in the structural equation model. So, from a population of 1982 students, 500 students were chosen as the final sample size after screening and quota selection.

### Sampling Strategy

The sample was chosen from 1982 undergraduates from the target four crucial public universities in Sichuan Province of China with two-month online education at the initial stage. Afterward, 500 respondents were selected from the 12 divisions utilizing quota selection as the final stage sample. After collecting the questionnaires, 487 were considered valid and 13 invalid data.

**Table 2** Sample Units and Sample Size

Four Main subjects	Undergraduate Year	Judgmental Size Total=1982	Proportional Size Total=500
Computer science and Technology	Year 2,3, and Year 4	483	105
Mechanical Manufacturing and Automation	Year 2,3, and Year 4	512	126





Four Main subjects	Undergraduate Year	Judgmental Size Total=1982	Proportional Size Total=500
Electric Engineering	Year 2,3, and Year 4	496	158
Materials Science and Engineering	Year 2,3, and Year 4	491	111

**Note:** Created by the Author

## Results and Discussion

### Demographic Information

The comprehensive demographic characteristic information of 478 respondents is summarized in Table 3. Male students constituted 65.27% of all participants, while female respondents comprised 34.73% of students, Computer science and Technology major accounts for 29.08%, Mechanical Manufacturing and Automation for 22.18%, Electric Engineering for 25.73%, Materials Science and Engineering for 23.01%. According to the participants' academic year, 41% were sophomores, 36% were juniors, and 23% were seniors.

**Table 3** Demographic Profile

Demographic Information (n=598)		Frequency	Percentage
Gender	Male	312	65.27%
	Female	166	34.73%
Four Main subjects	Computer Science and Technology	139	29.08%
	Mechanical Manufacturing and Automation	106	22.18%
Grade	Electric Engineering	123	25.73%
	Materials Science and Engineering	110	23.01%
Grade	Sophomore	200	41.84%
	Junior	163	34.10%
	Senior	115	24.06%

**Note:** Constructed by the Author

### Confirmatory Factor Analysis (CFA)

Confirmatory factor analysis (CFA) was used to determine whether the scale items' constituent and loading counts matched expectations based on theories or presumptions. The outcome of the factor loading and acceptable values for each observed variable illustrated the goodness of fit of the research matrix (Hair et al., 2010). Additionally, as presented in Table 4, all of the applicable thresholds for the absolute fit indicators, such as CMIN/DF, GFI, AGFI, and RMSEA, as well as the incremental fit measurements as CFI, NFI, and TLI match the requirements. As a result, all the goodness of fit metrics used in the CFA evaluation were valid.

**Table 4** Goodness of Fit for Confirmatory Factor Analysis

Index	Criterion	Source	Practical Values
CMIN/DF	< 5.00	Hair et al. (2010)	2.047
GFI	> 0.85	Bagozzi & Yi (1988)	0.897
AGFI	> 0.80	Sica & Ghisi (2007)	0.861
RMSEA	< 0.08	Pedroso et al. (2016)	0.071





Index	Criterion	Source	Practical Values
CFI	> 0.90	Bentler (1990)	0.951
NFI	> 0.90	Bentler & Bonnet (1980)	0.936
TLI	> 0.90	Bentler & Bonnet (1980)	0.939

**Note:** Constructed by the Author

**Table 5** Confirmatory Factor Analysis Result, Composite Reliability (CR), and Average Variance Extracted (AVE)

Latent Variables	Source of Questionnaire	Item Amount	Cronbach's Alpha	Factors Loading	CR	AVE
PE	Shah & Khanna, (2024).	3	0.913	0.864-0.904	0.91	0.778
SI	Shah & Khanna, (2024).	3	0.886	0.816-0.882	0.90	0.754
PU	Chen (2022).	3	0.921	0.882-0.901	0.92	0.796
CON	Chen (2022).	3	0.912	0.925	0.81	0.783
FE	Chen (2022).	3	0.854	0.601-0.872	0.89	0.607
SAT	Shah & Khanna, (2024).	4	0.887	0.845-0.871	0.89	0.682
CI	Chen (2022).	3	0.903	0.809-0.905	0.90	0.761

The statistical summary in Table 5 revealed Cronbach's alpha value exceeding 0.70, comprehensive reliability (CR) surpassing 0.60, and average variance extracted (AVE) exceeding 0.50. Consequently, these outcomes validated both the convergent and discriminant validity of the CFA results.

**Table 6** Discriminant Validity

	PE	SI	PU	FE	SAT	CON	CI
PE	0.778						
SI	0.736	0.754					
PU	0.736	0.698	0.796				
FE	0.701	0.684	0.692	0.607			
SAT	0.664	0.694	0.653	0.738	0.682		
CON	0.722	0.714	0.747	0.618	0.733	0.783	
CI	0.691	0.734	0.717	0.687	0.802	0.671	0.761

**Note:** Constructed by the Author

### Structural Equation Model (SEM)

In this study, the CFA assessment was followed by the structural equation model (SEM) verification. To evaluate whether or not the suggested causality explanation fits, a specific set of linear coefficients is evaluated using the SEM technique. Furthermore, SEM examines the relationship of causation between the characteristics in the provided matrix and modifies the coefficient to take judgmental or dishonesty bias





into account (Rattanaburi, 2021). After being adjusted using AMOS version 24, Table 6 demonstrates that the total values of CMIN/DF, GFI, AGFI, CFI, NFI, TLI, and RMSEA were all beyond the allowed limits. The findings demonstrate the validity of the SEM's goodness of fit.

**Table 7** Goodness of Fit for Structural Equation Modeling

Index	Criterion	Source	Practical Values
CMIN/DF	< 5.00	Hair et al. (2010)	2.015
GFI	> 0.85	Bagozzi & Yi (1988)	0.894
AGFI	> 0.80	Sica & Ghisi (2007)	0.861
RMSEA	< 0.08	Pedroso et al. (2016)	0.071
CFI	> 0.90	Bentler (1990)	0.950
		Bentler & Bonnet (1980)	0.935
NFI	> 0.90	Bentler & Bonnet (1980)	0.940
TLI	> 0.90		

**Note:** Constructed by the Author

### Hypothesis Testing Results

According to the outcomes shown in Table 8, continued intention exhibited a direct, significant effect on satisfaction, resulting in the strongest impact effects in this quantitative approach, a standardized path coefficient ( $\beta$ ) of 0.955 (t-value = 21.232\*\*\*). Flow experience provides the second powerful considerable interaction effect on satisfaction with  $\beta$  at 0.415 (t-value of 5.730\*\*\*).

Additionally, perceived usefulness significantly influenced satisfaction with the  $\beta$  at 0.395 (t-value at 5.093\*\*\*), while perceived ease of use markedly impacted confirmation with the  $\beta$  at 0.325 (t-value at 4.785\*\*\*), as well as a social influence which significantly influenced satisfaction with  $\beta$  at 0.287 (t-value at 3.521\*\*\*). Consequently, performance expectancy exhibited the least significant influence on satisfaction in this quantifiable investigation, with 0.170 (t-value at 0.069\*).

**Table 8** Hypothesis Result of the Structural Equation Modeling

Hypothesis	Paths	Standardized Path Coefficient ( $\beta$ )	S.E.	T-Value	Test Result
H1	SAT←PE	0.170	0.069	2.258*	Supported
H2	SAT←SI	0.287	0.088	3.521***	Supported
H3	SAT←PU	0.395	0.074	5.093***	Supported
H4	SAT←CON	0.325	0.062	4.785***	Supported
H5	SAT←FE	0.415	0.078	5.730***	Supported
H6	CI←SAT	0.955	0.046	21.232***	Supported

**Note:** \*\*\* p<0.001, \*\* p<0.01, \* p<0.05

**Note:** Constructed by the Author

According to the results in Table 8, In the structural pathway, the standardized route coefficient value is 0.170. H1 revealed that the relevant data supports the influence of performance expectation on satisfaction, which supports this statement, which was the weakest effect point in this academic research, but the relatively low range of coefficient indicates that this may not be the most important factor affecting student satisfaction.

In H2, social influence has a positive impact on MOOCs satisfaction, and the standard coefficient value is 0.287. Although the influence of this factor is not as good as perceived usefulness or flow experience, it is still significant. This means that social influence can improve student satisfaction.

In H3, confirmation has a significant positive impact on MOOC satisfaction, and the standard coefficient value is 0.395, which means that the performance of information systems and technologies is in line with students' expectations.

In H4, the analysis demonstrated that one of the primary characteristics of satisfaction is perceived usefulness, with a standardized path coefficient of 0.395. Agarwal and Prasad (1999) suggest that attitudes

toward using a specific available technology were influenced by perceived usefulness. The perceived usefulness of the assessment generally had a considerable impact on students' sentiments regarding a particular instructional approach (Nagy, 2018).

In H5, has determined that flow experience was significantly associated with satisfaction, as demonstrated by a statistical score of 0.415 on the standard coefficient of the active influence, and the second strongest effect point on satisfaction in this research. Users' greater happiness with the systems may be positively impacted by the amount of intrinsic motivation that e-learning systems induce in them.

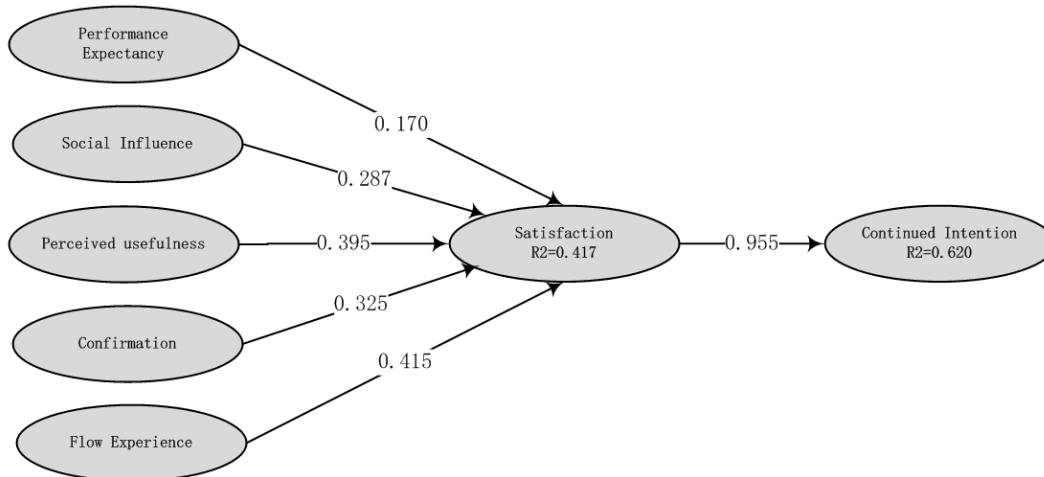
In H6, The final hypothesis emphasizes the relationship between satisfaction and continuous use, and the standard coefficient value is 0.955, which is the highest, which means that students who are satisfied with MOOCs are more likely to continue to use it and recommend it to other students. This connection emphasizes the importance of maintaining high user satisfaction to ensure continuous use and positive word of mouth.

### Direct, Indirect, and Total Effects

The conceptual framework of this research included five independent variables, one mediator, and one dependent variable. Figure 2 summarizes the path diagram analysis.

The model explains approximately 41.7% of the variance in Satisfaction, as denoted by an R<sup>2</sup> value of 0.417. The model accounts for about 62% of the variance in continued Intention, represented by an R<sup>2</sup> value of 0.620. Engagement has a direct and significant positive effect on satisfaction, meaning that as engagement with MOOCs increases, satisfaction levels also rise. Moreover, four variables had an indirectly considerable impact on satisfaction: performance expectancy, social influence, confirmation, and flow experience, with influence effect points of 0.170\*\*\*, 0.287\*\*\*, 0.395\*\*\*, and 0.415\*\*\* correspondingly.

In this quantitative analysis, satisfaction was the initial mediator variable, with R<sup>2</sup> at 0.417 demonstrating that continued intention accounts for 41.7% percent of the variance in perceived ease of use. Additionally, there was a 0.203\*\*\* direct correlation between satisfaction and continued intention. Furthermore, the direct influence points for performance expectancy, social influence, confirmation, and flow experience were 0.170\*\*\*, 0.287\*\*\*, 0.395\*\*\*, and 0.415\*\*\* respectively.



**Figure 2** Path Diagram Analysis  
 Note: \*\*\* p<0.001, \*\* p<0.01, \* p<0.05

**Note:** Constructed by the Author

### Conclusions

This research aimed to determine which factors had a significant impact on science and engineering major undergraduate students' satisfaction regarding MOOCs at Xihua University in Chengdu China. The conceptual framework showed the six hypotheses to validate the interaction between performance



expectancy, social influence, confirmation, and flow experience. To determine any interaction among these variables, 487 undergraduate students with experience using MOOCs participated in answering the survey questionnaire. Confirmatory Factor Analysis (CFA) was utilized to determine whether the data fit the specified theory-derived measurement model. Likewise, Structural Equation Modeling (SEM) was utilized to evaluate the relationships between observed and latent variables that influence satisfaction and to test hypotheses.

According to the findings of this research, satisfaction has the greatest significant direct interaction on continued intention, flow experience generated the most powerful influence on satisfaction. Moreover, perceived usefulness, confirmation, and performance expectancy significantly impacted satisfaction, with a lower standardized path coefficient.

Synthesize the conclusion as the new knowledge by setting the mind-mapping

With the main aim of understanding and predicting learners' intention of engaging in MOOCs, this study was embarked on to investigate the significant determinants of their continuance usage intention in this online platform. Based on the research results, the continuance usage intention is determined by perceived usefulness, social influence, confirmation, flow experience, and performance expectancy. The identification of these influencing and motivating key factors will help providers take the necessary measures to improve the completion rate of MOOCs, a unique online self-learning mode in the education industry of China.

### Recommendations for Practice

Based on the results of this quantitative investigation, the researcher offered the following practical recommendations for subsequent used MOOCs. First, in this study, flow experience is the construction impacting students' satisfaction with MOOCs. It can be seen that many students choose MOOCs because the process experience in use influences them. Therefore, the teaching unit of the university should fully develop and implement a positive social atmosphere for online learning to encourage more students to accept this learning platform.

Secondly, students believe that using an e-learning platform would increase their happiness and be helpful. In this study, four latent factors influence students' happiness, with the flow experience having the most impact. As a result, in the future, teaching practices should concentrate on minimizing the technical barriers to online learning for students. This can be achieved by further streamlining the online learning platform's program design and offering relevant tutorial materials and manual support so that students can comprehend that the platform's various learning functions are far more straightforward, understandable, and practical than traditional classroom instruction. As a result, this suggestion will significantly improve students' favorable perception of using the MOOCs platform.

Additionally, the MOOC providers should give learners the most essential yet significant courses, taught by trained instructors of a higher caliber. These classes guarantee the learners' satisfaction and long-term dedication. These courses should also be customized for diverse learner groups with varying requirements and skill levels. To meet their unique learning objectives, academic aspirations, and professional growth, various learner groups will be able to select the most engaging and appropriate courses on their own. As a result, participants in MOOCs will react by rating the courses as more beneficial. Through MOOC platforms, they could develop a lifetime enthusiasm for learning and become lifelong learners.

Ultimately, to enhance students' satisfaction and continuance intention of MOOCs, instructors and course designers may stimulate interactions between students and course contents via using interactive multimedia tools (e.g. text, audio, graphics, images, animation, sounds, video, or graphic representations) provided by MOOCs to promote students' learning effectiveness.

### Limitations and the Further Exploration.

This research is mainly aimed at science and engineering undergraduates at Xihua University, Chengdu, China. This particular population may not represent all MOOC users, so the universality of the research results will be limited. In addition, the conceptual framework only includes six latent variables. Given the limited scope of this study, further research can extend the samples of this study to the respondents of other universities and make cross-school comparisons to enhance the integrity of this study. Finally, the results of this study are based on cross-sectional data, and further research can use longitudinal analysis to consider the changes in students' willingness to continue intention MOOCs over time.





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