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Decoding MOOC Success: 7 Core Factors Shaping Chinese Students' Online Learning Behaviors

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Abstract

Purpose: This study sought to investigate the critical factors influencing undergraduate students' perceived usefulness of and continuance intention to use Chinese University MOOCs in Chongqing, China. The proposed conceptual framework illustrates causal relationships among seven variables: Perceived Ease of Use (PEU), Perceived Usefulness (PU), Cognitive Presence (CP), Teaching Presence (TP), Learning Engagement (LE), Satisfaction (SAT), and Continuance Intention (CI). **Research design, data and methodology:** This quantitative research gathered data from 500 undergraduates at Chongqing University through online surveys, using non-random sampling methods—specifically judgmental, quota, and convenience sampling. Data analysis employed AMOS to assess model fit, reliability, and construct validity. **Results:** Empirical findings revealed that Perceived Usefulness (PU, β=0.199), Satisfaction (SAT, β=0.167), Learning Engagement (LE, β=0.213), Cognitive Presence (CP, β=0.185), and Teaching Presence (TP, β=0.193) are key drivers of students' Continuance Intention (CI). Additionally, Perceived Ease of Use (PEU) exerts a significant positive impact on Perceived Usefulness (PU, β=0.365). All constructs demonstrated good reliability (Cronbach's $\alpha > 0.70$) and convergent validity (Average Variance Extracted, AVE > 0.50). **Conclusions:** Key findings highlighted direct impacts of relevant variables on usage intention, emphasizing system and interaction factors. The well-fitted model validated an integrated framework, enhancing understanding of MOOC usage.

Keywords: Perceived usefulness (PU), Satisfaction (SAT), Perceived ease of use (PEU), Learning engagement (LE), Continuance intention (CI), Cognitive presence (CP), Teaching presence (TP).

JEL classification: I20, I21, I23, I26, A22

1. Introduction

The term "MOOC," an acronym for Massive Open Online Course, was first proposed by Downes in 2008. Initially conceived as an educational approach focused on openness, social interaction, and network-based learning, its first practical application was in a course originally designed for just 25 on-campus students. Surprisingly, this course drew around 2,300 online participants—a phenomenon that underscored the extraordinary scalability of this new learning model.

In China, MOOCs play a crucial role in addressing the shortage of educational resources and have become a key pedagogical tool (Huang & Qi, 2025). The government actively encourages the integration of MOOCs into regular teaching, and many universities now offer a wide range of such courses. Within higher education, students can earn academic credits through MOOCs; however, their pass rates are lower compared to both traditional compulsory and elective courses. When it comes to average scores, MOOCs perform lower than electives but on par with compulsory courses. Multiple factors exert significant influence on students' MOOC performance, including learning behaviors, motivation, perceived value, learning environment, prior learning experience, and self-regulation. Notably, the learning environment—encompassing factors like study location and technical tools—has recently been identified as a newly relevant influencing element.

Chongqing University (CQU) is a leading comprehensive university directly under China's Ministry of Education. Spanning 12 academic disciplines, the university comprises 35 colleges and enrolls over 52,000 students,

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among whom more than 26,000 are postgraduates. CQU has been proactive in promoting MOOCs: it has collaborated with platforms such as Chinese University MOOCs and launched 16 MOOCs specifically for postgraduate students. During the COVID-19 pandemic, CQU's Graduate School offered 507 online courses, which attracted over 29,000 student enrollments. This initiative not only facilitated remote learning but also boosted postgraduates' adoption of MOOCs and other online resources. For this study, we focus on two postgraduate majors at CQU: Mechanical and Vehicle Engineering, and Electrical Engineering. These two majors hold a pivotal position within CQU's postgraduate programs, both in terms of student enrollment size and academic influence. Thus, investigating these two majors carries positive significance for advancing online education not only at CQU but also across the nation.

Most of the aforementioned influencing factors are derived from theoretical frameworks such as the Expectation-Confirmation Model (ECM) and the Stimulus-Organism-Response (SOR) model, along with other related theories. Against this backdrop, this research aims to deepen the exploration of comprehensive quality assessment in the context of MOOC continuance intention. By considering both the external and internal drivers that shape learners' willingness to keep using MOOCs, the study enables a more robust and rational analysis. This effort not only enriches existing knowledge about MOOC continuance intention but also provides a more holistic perspective for future research in this field. In doing so, it helps researchers better understand the complex interactions between various influencing factors and develop more effective strategies to enhance learners' long-term engagement with MOOCs.

2. Literature Review

2.1 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), developed by Davis et al. (1989), takes the Theory of Reasoned Action (TRA) as its theoretical foundation. Its core focus lies in users' perceptions of technology, aiming to explain and predict their acceptance of, and engagement with, technological tools.

At the heart of TAM are two key constructs. The first is perceived usefulness, which refers to users' belief that a given technology can enhance their performance in relevant tasks. The second is perceived ease of use, defined as users' belief that interacting with the technology requires little effort. Both constructs are shaped by a range of external factors, such as the design of the technology system itself, users' individual characteristics, the complexity of the tasks the technology is intended to support, relevant policies, and organizational structures.

Since its proposal, TAM has been widely adopted across multiple fields. In education, for example, it is used to evaluate the acceptance of online teaching platforms; in business, it helps assess how well enterprise resource planning systems are received by employees. By applying TAM, practitioners can better align technology with user needs, ultimately boosting user acceptance of technological tools (Davis et al., 1989).

2.2 Stimulus-Organism-Response (S-O-R) Model

The S-O-R model, first developed by Mehrabian and Russell (1974) within the field of environmental psychology, outlines a framework for understanding how external stimuli (S) initiate internal psychological processes in an organism (O), which then lead to behavioral responses (R). A key tenet of this model is its rejection of direct stimulus-response connections; instead, it emphasizes that external influences can only generate behaviors after being processed through an individual's cognitive and emotional states.

Initially, the S-O-R model was used to study physical environments—for instance, examining how the design of retail spaces affects consumer behavior. Over time, its application has expanded into other domains: in marketing, it helps analyze how consumers respond to advertising stimuli; in information systems, it is employed to explore user behavior on digital platforms.

When applied to the context of MOOCs, the model's components take on specific forms. Stimuli here include elements like gamification features (e.g., badges, progress trackers), opportunities for social interaction (e.g., peer discussions, instructor feedback), and core platform functions (e.g., navigation design, resource accessibility). The organism refers to learners' internal states, covering cognitive aspects (e.g., understanding of course content), affective factors (e.g., satisfaction with the learning experience), and motivational drivers (e.g., desire to achieve learning goals). Finally, the responses manifest as concrete behaviors—such as active participation in course activities—and learners' intentions to continue using the MOOC platform.

2.3 Expectation-Confirmation Theory (ECM)

First proposed by Oliver (1980) and later expanded by Bhattacherjee (2001), the Expectation-Confirmation Model (ECM) is designed to explain two key post-interaction phenomena: post-purchase (or post-use) satisfaction and continuance behavior. Its core framework revolves around five interrelated components: expectations (individuals' pre-use beliefs about a product or service), perceived performance (their evaluation of how the product/service performs after use), confirmation (the process of comparing pre-use expectations with post-use perceived performance), satisfaction (the emotional or evaluative response stemming from this confirmation), and loyalty (the inclination to continue using the product/service).

Originally rooted in consumer behavior research, the ECM has since been adapted to fields like information systems and e-learning. For example, in e-learning contexts, it has been used to study students' continuance use of electronic textbooks (Stone & Baker-Eveleth, 2013); in information systems, it has helped analyze users' sustained engagement with mobile messaging tools.

Within MOOC-related research, the ECM also plays a valuable role in explaining learners' continuance intentions. Studies in this area (Alraimi et al., 2015) have shown that factors like perceived usefulness of MOOCs, confirmation of initial expectations (e.g., whether the MOOC meets learners' anticipated learning goals), and overall satisfaction with the MOOC experience are key drivers of learners' willingness to keep engaging with MOOC platforms.

2.4 Perceived Usefulness

The idea of "perceived usefulness" centers on an individual's strong conviction that a specific system is capable of boosting their performance (Davis et al., 1989). For students, their willingness to embrace MOOCs often hinges on whether they perceive these platforms as meaningful contributors to their learning achievements (Wu & Chen, 2017). Expanding on this, Ma (2025) defined perceived usefulness in the context of MOOCs as learners' positive assessment of two core aspects: first, how effective MOOCs are in helping them enhance their existing knowledge and develop new skills; second, how much they recognize the practical value of MOOC platforms in supporting the achievement of their learning goals. In essence, this concept captures the degree to which learners see MOOCs as beneficial tools for reaching academic targets—whether that involves improving language skills, mastering specific course content, or other related learning outcomes.

Hypothesis 1: Perceived usefulness has significant impact on continuance intention.

2.5 Perceived Ease of Use

Davis et al. (1989) conceptualized perceived ease of use as a learner's psychological experience, one that reflects the level of compatibility between the user and electronic devices. At its core, this concept captures a user's expectations regarding how simple and intuitive a system will be to operate: a stronger sense of ease of use means an individual believes they can engage with the system smoothly, without devoting substantial effort to mastering its functions. Davis et al. further linked this notion to how people evaluate the amount of effort required to use a system—suggesting that when someone judges a system as easy to use, they anticipate putting in little effort during their interactions with it.

Such definitions underscore why this construct matters for understanding users' attitudes toward different systems. By taking users' perceptions of ease of use into account, designers can more effectively optimize systems to align with user expectations, which in turn boosts user acceptance and adoption. Complementing this view, Alshammari and Babu (2025) described perceived ease of use as a measure of a user's perception regarding how easy it is to utilize a specific technology. More precisely, they defined it as a user's impression of the simplicity and ease involved in interacting with that technology.

Hypothesis 2: Perceived ease of use has significant impact on perceived usefulness.

2.6 Satisfaction

Satisfaction holds a key position as a construct within the Expectation-Confirmation Model (ECM). Drawing on the principles of ECM, Bhattacherjee (2001) pointed out that two factors play a role in shaping users' intention to continue using an information system: first, users' contentment with their past experiences of using the system, and second, their expectations for using it after adoption.

In the specific context of this study, satisfaction refers to learners' comprehensive evaluation of their experiences with MOOC platforms—a judgment shaped by factors like cognitive load, whether their initial expectations of the platform are met, and their perception of the platform's usefulness. It embodies learners' positive or negative sentiments toward the entire MOOC learning process, encompassing their satisfaction with elements such as course design, the learning results they achieve, and the overall performance of the MOOC platform (Ma, 2025).

Hypothesis 3: Satisfaction exerts a substantial influence on continuance intention.

2.7 Learning Engagement

Under the context of advertising, adopted engagement was adopted and refined as a high-level degree of brand-consumer relevance and the development of an emotional link between the brand and the consumer (Rappaport, 2007). O'Brien and Toms (2008) applied the concept of engagement to computer-mediated communication, positing that engaged users exhibit effective involvement and motivation in their interactions with computer interfaces. Extending this to the e-learning context, Blasco-Arcas et al.

(2013) defined engagement as learners' emotional investment in the learning process, arising from their interactions with peers and instructors.

In e-learning settings, Blasco-Arcas et al. (2013) noted that engagement represents learners' emotional investment in the learning process—an investment that can be strengthened or weakened by their interactions with peers and instructors. Reschly and Christenson (2022), by contrast, conceptualized engagement as a form of learning motivation: it refers to the time and effort learners devote to their studies, all with the goal of achieving their intended educational objectives. Jiang and Peng (2025) offered a more action-oriented definition, describing learning engagement as the degree to which a student actively participates in learning activities. They emphasized that this engagement is marked by actions that are energized, purposeful, and sustained.

Beyond these broader definitions, there is also the specific concept of "online task engagement," which refers to learners' participation in online learning tasks (Mohtar & Md Yunus, 2022). Examples of such tasks include watching instructional videos, submitting assignments, and writing discussion posts—all of which can be measured through tracking data collected from learning management systems.

Hypothesis 4: Learning engagement has significant impact on continuance intention.

2.8 Cognitive Presence

Kanuka and Garrison (2004) first put forward the concept of cognitive presence, defining it as an individual's capacity to build meaning through ongoing communication. They stressed that this capacity plays a vital role in nurturing critical thinking and facilitating advanced learning—two core elements of in-depth educational experiences. In essence, cognitive presence covers the psychological processes learners rely on to engage in critical thinking: this includes exploring new concepts, working through questions related to course content, and constructing meaningful understanding via reflection and dialogue. Expanding on this, Putra et al. (2025) specified that cognitive presence manifests in concrete activities. These activities range from developing explanations or solutions to problems, drawing on various information sources to support learning, and deepening comprehension of foundational concepts by reflecting on course materials and participating in relevant discussions.

Hypothesis 5: Cognitive Presence has significant impact on continuance intention.

2.9 Teaching Presence

Akyol and Garrison (2008) proposed that teaching presence serves as an effective instructional strategy throughout the entire learning process. They argued that when educators actively exhibit their teaching presence, it can positively shape students' learning experiences and outcomes. This active display of teaching presence may take various forms: for instance, being readily available to offer guidance when students encounter difficulties, providing timely feedback on assignments or discussions, and proactively facilitating classroom interactions to keep learning on track. These actions collectively help create a more supportive learning environment—one that can deepen students' grasp of subject content, boost their learning motivation, and ultimately contribute to better academic performance.

Law et al. (2019) built on this perspective, further asserting that it is teachers' teaching presence that strengthens learners' cognitive presence and social presence. This insight suggests that a robust teaching presence does more than just enhance students' understanding and knowledge acquisition; it also fosters a stronger sense of connection among learners and encourages more active interaction within the learning community. Taken together, these studies consistently highlight the importance of teaching presence across different educational contexts, as well as its profound and far-reaching impact on the overall learning process.

Hypothesis 6: Teaching Presence has significant impact on continuance intention.

2.10 Continuance Intention

Joo et al. (2018) defined continuance intention as individuals' willingness to sustain their participation in a course. When students hold a strong inclination to keep using a learning platform, this inclination fuels their motivation to engage with the platform and makes them more likely to persist in their studies. In essence, this concept reflects the conscious choices people make about whether and how to engage with MOOCs.

2.11 Conceptual framework

This study's conceptual framework was developed through an integration of several established theoretical models. First, it leveraged the Technology Acceptance Model (TAM), a framework originally introduced by Davis et al. (1989). Central to TAM is the examination of how users adopt new technologies, with a specific focus on two core factors: perceived usefulness (PU)—the extent to which users believe a technology enhances their performance—and perceived ease of use (PEU)—the degree to which users find a technology free of effort.

In addition, the research incorporated the Stimulus-Organism-Response (S-O-R) model, first proposed by

Mehrabian and Russell (1974). This model argues that environmental stimuli (external triggers) shape an organism's (user's) internal psychological state, which in turn drives a behavioral response. A key emphasis of the S-O-R model is that external influences do not directly lead to behavior; instead, they must be processed through the user's cognitive and emotional states—including cognitive processing (CP), affective processing (TP), and emotional engagement (LEN)—before a response emerges.

The framework also integrated the Expectation-Confirmation Model (ECM), an extension of earlier work developed by Bhattacherjee (2001). This model is particularly valuable for explaining post-adoption behavior—that is, how users behave after initially adopting a technology. ECM links several interrelated components—pre-adoption expectations, perceived performance of the technology, confirmation of expectations (whether the technology meets user anticipations), post-adoption satisfaction (SAT), and continuance intention (CI, the willingness to keep using the technology)—to explain why users continue or discontinue using a technology.

By synthesizing these three theoretical models and adapting their core constructs to the unique context of the current investigation, the researchers developed a distinct, context-specific conceptual framework. The detailed relationships between the constructs of this framework—including how TAM's PU/PEU, S-O-R's cognitive/emotional states, and ECM's satisfaction/continuance intention interact—are visually illustrated in Figure 1, which serves as a guide for the study's analytical approach.

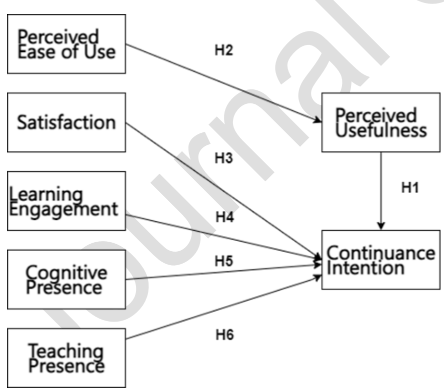

Figure 1: Conceptual framework

The aim of this study is to explore the critical factors of Chinese University MOOCs that significantly influence postgraduate students' perceived usefulness (PU) and continuance intention (CI) to use such platforms in Chongqing, China. The variables examined in this paper include: Learning Engagement (LEN), Cognitive Presence (CP), Satisfaction (SAT), Perceived Ease of Use (PEU), and Teaching Presence (TP).

3. Research methodology

3.1 Population and Samples

This study adopted a descriptive research design, utilizing a questionnaire to conduct quantitative analysis of the factors influencing undergraduate students' continuance intention and perceived usefulness regarding the use of Chinese University MOOCs in Chongqing, China. The questionnaire was structured into three distinct sections: first, screening questions to ensure participants met the study's eligibility criteria; second, a set of items measured on a 5-point Likert scale (where 1 = "strongly disagree" and 5 = "strongly agree"), which assessed seven core variables to test the study's six hypotheses; and third, demographic questions capturing information such as gender, age, and academic grade. Prior to large-scale distribution, a pilot test was administered to 50 participants to refine the instrument. Additionally, the questionnaire underwent expert review, where it met the required standards for the Item-Objective Consistency Index (IOC), confirming the alignment between each question and its intended research objective.

As shown in the calculation results presented in Figure 2, the questionnaire included 27 items corresponding to seven variables. For the structural equation modeling (SEM) analysis, the study set an expected effect size of 0.2. Based on this parameter, the minimum number of questionnaires to be distributed was calculated as 425. However, considering that the minimum sample size required to validate the model's mechanism in SEM is 100—a threshold to ensure the model's statistical stability—the researchers opted to distribute at least 500 questionnaires in total to secure an adequate and robust dataset for analysis.

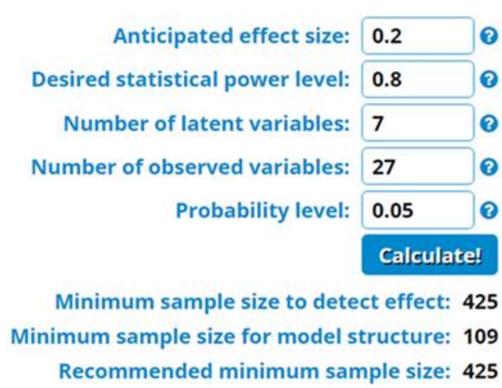

Figure 2: Sample Size Calculator for Structural Equation Models
Note: Soper, D. (2006).

3.2 Population and Sample Size

Using non-probability methods (judgmental and quota sampling), the study selected undergraduate students from Chongqing University, China, and distributed questionnaires via an online platform. Table 1 details the specific sampling.

Table 1: Population and sample size of Chongqing University

Two Majors	Population Size	Proportional Sample Size
Mechanical and Vehicle Engineering	1615	259
Electrical Engineering	1503	241
Total	3118	500

Source: The data comes from Chongqing university population statistics in 2023. http://study.cqu.edu.cn/index/lxsq/yxjs.htm

The study distributed 523 questionnaires to target population and collect 500 suitable data. The researcher measured the proportional sample size distributed to each university based on the population size of the two majors and the size of each group to collect 500 valid questionnaires. Specifically, the researchers finally received 259 valid questionnaires from undergraduates majoring in Mechanical and Vehicle Engineering, and 241 valid questionnaires from undergraduates majoring in Electrical Engineering.

Depending on this research goal and the study, when designing the sampling procedure, the author adopted multistage sampling including Purposive Sampling, Stratification Random Sampling, as well as Purposive and Convenient Sampling for this study. Respondents included 84 females (16.8%) and 416 males (83.2%). Among them, 205 undergraduates (41%) had at least one semester of Chinese University MOOC experience, and 295 (59%) had two or more semesters. Detailed demographic data are presented in Table 2.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Student Status	undergraduate	500	100%
Gender	female	84	16.8%
	male	416	83.2%
Chinese University MOOC Experience	One semester	205	41%
	Two or above	295	59%

Source: Created by the author

3.3 Research Instrument

3.3.1 Sampling Strategy

Depending on this research goal and the study, when designing the sampling procedure, the author adopted multistage sampling including Purposive Sampling, Stratification Random Sampling, as well as Purposive and Convenient Sampling for this study. The researcher measured the proportional sample size based on the population size of the two majors and the size of 500 questionnaires. The researcher received 259 questionnaires from the undergraduate students whose major is Mechanical and Vehicle Engineering and 241 questionnaires from undergraduate students majoring in the Electrical Engineering. All the students involved are the users of the Chinese University MOOC. The set of data provided feedback on factors impacting undergraduate students' perceived usefulness and continuance intention to use Chinese University MOOC in Chongqing, China.

3.3.2 Confirmatory Factor Analysis (CFA)

To assess the seven variables included in the conceptual framework, confirmatory factor analysis was employed. The analysis outcomes identified significant scale items for each variable, accompanied by satisfactory factor loadings, thereby validating a favorable model fit.

3.3.3 Structural Equation Model (SEM)

Hair et al. (2013) recommended that the Chi-square/degrees-of-freedom (CMIN/DF) ratio for model fit measures was less than 3.00. Sica and Ghisi (2007) suggested, AGFI and TLI were both greater than 0.80 and Hu and Bentler (1999) proposed that NFI should be greater than 0.80. Bentler (1990) suggested that the CFI was greater than 0.80. Kline (2016) suggested that the GLI was greater than 0.85. Pedroso et al. (2016) recommended an RMSEA value below 0.08 as indicative of an adequate model fit.

In this study, structural equation modeling (SEM) was performed using SPSS AMOS, with iterative refinements made to the model. The fit indices from the analysis confirmed a well-fitted model.

4. Results and Discussion

As presented in Table 3, all the fit indices met or surpassed the acceptable thresholds. This indicates that the structural equation model (or the relevant statistical model) under assessment aligns exceptionally well with the data. These values suggest that the model effectively depicts the relationships among the variables in the dataset.

Table 3: Goodness of Fit for Confirmatory Factor Analysis (CFA)

Fit Index	Acceptable Criteria	Values
CMIN/df	$<$ 3.00 (Hair et al., 2013)	1.042
GFI	$\geq$ 0.85 (Kline, 2016)	0.957
AGFI	$\geq$ 0.80 (Sica & Ghisi, 2007)	0.946
NFI	$\geq$ 0.80 (Hu & Bentler, 1999)	0.954
CFI	$\geq$ 0.80 (Bentler, 1990)	0.998
TLI	$\geq$ 0.80 (Sica & Ghisi, 2007)	0.998

Fit Index	Acceptable Criteria	Values
RMSEA	< 0.08 (Pedroso et al., 2016)	0.009

Source: Created by the author

In this study, structural equation modeling (SEM) was performed using SPSS AMOS, with iterative refinements made to the model. The fit indices from the analysis confirmed a well-fitted model, with CMIN/df at 2.912, TLI of 0.898, GFI at 0.852, AGFI at 0.824, NFI at 0.866, CFI at 0.907, and an RMSEA value of 0.062 (refer to Table 4 for details).

Table 4: Goodness of Fit for Structural Equation Model (SEM)

Fit Index	Acceptable Criteria	Values
CMIN/df	< 3.00 (Hair et al., 2013)	2.912
GFI	≥ 0.85 (Kline, 2016)	0.852
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.824
NFI	≥ 0.80 (Hu & Bentler, 1999)	0.866
CFI	≥ 0.80 (Bentler, 1990)	0.907
TLI	≥ 0.80 (Sica & Ghisi, 2007)	0.898
RMSEA	< 0.08 (Pedroso et al., 2016)	0.062

Source: Created by the autho

Table 5: 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 U sefulness (PU)	Davis et al. (1989)	4	0.853	0.757-0.793	0.853	0.593
Satisfaction (SAT)	Bhattacherjee (2001)	4	0.847	0.745-0.776	0.847	0.581
Learning E ngagement (LEN)	Rappaport (2007)	4	0.875	0.790-0.804	0.875	0.636
Continuance I ntention (CI)	Joo et al. (2018)	4	0.860	0.755-0.802	0.859	0.606
Perceived Ease of Use (PEU)	Davis et al. (1989)	3	0.824	0.761-0.795	0.824	0.610
Cognitive P resence (CP)	Kanuka and Garrison (2004)	4	0.860	0.765-0.794	0.897	0.605
Teaching Presence (TP)	Shea et al. (2006)	4	0.858	0.751-0.823	0.893	0.603

Source: Created by the author

The statistical data in Table 5 indicates that all variables exhibit strong internal consistency, as shown by Cronbach's Alpha values exceeding the benchmark of 0.7. Most variables display factor loadings within the acceptable range, signifying that the items in each scale correspond well to the theoretical constructs they aim to measure. The high Composite Reliability values for all variables suggest excellent convergent validity. Additionally, the Average Variance Extracted for each variable is above 0.5, further confirming the constructs' ability to explain the variance in their respective indicators.

Table 6: Discriminant Validity Factor Correlations

Variable	PU	SAT	LEN	CI	PEU	CP	TP
PU	**0.770**						
SAT	0.374	**0.762**					
LEN	0.364	0.403	**0.797**				
CI	0.368	0.365	0.395	**0.778**			
PEU	0.303	0.271	0.322	0.362	**0.781**		
CP	0.359	0.356	0.430	0.379	0.358	**0.778**	
TP	0.420	0.404	0.386	0.391	0.318	0.433	**0.777**

Note: Diagonal values are the square roots of variables' AVE.

Source: Created by the author

As shown in Table 6, for all variables therein, the square root of their respective Average Variance Extracted (AVE) values exceeds their correlations with other variables. This suggests that each construct is distinct, indicating that the constructs in this study possess good discriminant validity. This is crucial for ensuring that the measured constructs are separate entities and do not inappropriately overlap.

Table 6: Hypothesis Result of the Structural Model

Hypotheses	Paths	Standardized Path Coefficients (β)	S.E.	T-Value	Tests Result
H1	CI<---PU	0.199	0.044	3.920***	Supported
H2	PU<---PEU	0.365	0.055	6.710***	Supported
H3	CI<---SAT	0.167	0.045	3.304***	Supported
H4	CI<---LEN	0.213	0.040	4.234***	Supported
H5	CI<---CP	0.185	0.044	3.667***	Supported
H6	CI<---TP	0.193	0.041	3.837***	Supported

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

Table 6 shows that all six hypotheses were supported. Specifically, the structural path coefficients revealed:

H1: Perceived Usefulness (PU) → Continuance Intention (CI), β = 0.199

H2: Perceived Ease of Use (PEU) → PU, β = 0.365

H3: Satisfaction (SAT) → CI, β = 0.167

H4: Learning Engagement (LEN) → CI, β = 0.213

H5: Cognitive Presence (CP) → CI, β = 0.185

H6: Teaching Presence (TP) → CI, β = 0.193

These results confirm each hypothesized variable as a significant driver of its respective outcome, with PEU exerting the strongest influence on PU and LEN having the highest direct effect on CI.

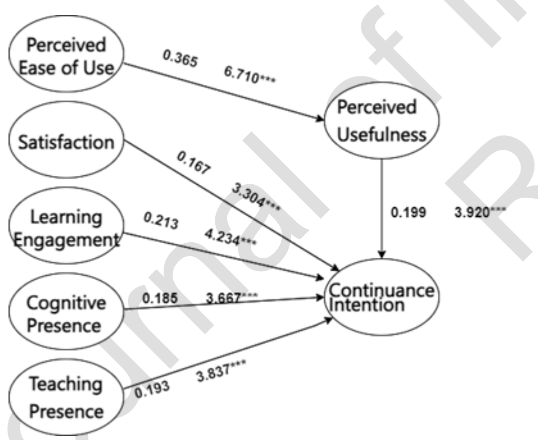

Figure 3: Path Diagram Analysis
Note: Created by the Author

5. Conclusions and Recommendation

5.1 Conclusion

This study empirically investigates the factors shaping undergraduate students' perceived usefulness (PU) and continuance intention (CI) to use Chinese University MOOCs, focusing on two engineering majors (Mechanical and Vehicle Engineering, Electrical Engineering) at Chongqing University. By integrating three theoretical frameworks—the Technology Acceptance Model (TAM), Stimulus-Organism-Response (S-O-R) model, and Expectation-Confirmation Theory (ECM)—the research tests six hypotheses across seven core variables, providing both empirical and theoretical insights into MOOC usage behavior.

SEM results supported all six hypotheses, revealing nuanced relationships between variables. First, Perceived Ease of Use (PEU) emerged as the strongest predictor of Perceived Usefulness (PU) (β = 0.365, t = 6.710***), aligning with TAM's core assertion that usability shapes perceived value. This finding is particularly salient for engineering undergraduates, who often prioritize efficiency when balancing MOOCs with lab work and coursework—an intuitive platform reduces cognitive load, making students more likely to recognize MOOCs as useful.

Notably, the integrated theoretical framework (TAM + S-O-R + ECM) achieved excellent model fit (CFA: CMIN/df = 1.042, CFI = 0.998, RMSEA = 0.009; SEM: CMIN/df = 2.912, CFI = 0.907, RMSEA = 0.062), validating its utility for explaining undergraduate MOOC behavior. Unlike studies that rely on a single theory, this framework captures both individual perceptions (TAM) and contextual interactions (S-O-R, ECM), offering a more comprehensive lens.

A key theoretical contribution lies in clarifying the relative importance of variables: while prior research often groups factors broadly (e.g., "engagement" or "presence"), this study quantifies their unique effects—for example, LE's stronger impact on CI compared to SAT suggests that active participation matters more for long-term usage than general contentment. Practically, this implies that MOOC providers should prioritize engagement-driven features over passive satisfaction boosters (e.g., aesthetic platform design).

No unexpected findings or non-significant relationships emerged, which may reflect the homogeneity of the sample (engineering undergraduates at a single university) or the robustness of the theoretical framework. However, the consistency of results with hypotheses reinforces the model's predictive power for this specific population.

5.2 Recommendation

To enhance undergraduates' continuance intention toward Chinese University MOOCs, several targeted actions are recommended. First, optimize platform usability for engineering students by adding discipline - specific navigation, integrating engineering software links, and developing a mobile app with offline access to reduce operational friction. Second, design engagement - driven activities like project - based modules, gamified quizzes, and real - world case studies with discussion forums to boost learning engagement. Third, strengthen Teaching and Cognitive Presence through structured teaching support (e.g., live Q&A sessions), guided cognitive exercises, and clear learning objectives aligned with engineering competencies. Fourth, link MOOC content to academic and career value by aligning with university credits, offering industry - recognized certificates, providing personalized content recommendations, and conducting regular satisfaction surveys to address issues promptly.

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