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Investigation of the impact of cognitive load on EFL learners' satisfaction with MOOCs: the mediating role of expectation confirmation and perceived usefulness

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Abstract

MOOCs as a flexible form of online education, have gained increasing popularity among EFL learners. However, the impact of cognitive load on learners' satisfaction has not been thoroughly explored. This study, grounded in Cognitive Load Theory and Expectation Confirmation Theory, empirically investigates the effects of cognitive load, confirmation, and perceived usefulness on EFL learners' satisfaction with MOOCs. This study collected 293 valid questionnaire responses through an online survey, with data collection occurring from March 2024 to August 2024. The data were analyzed using Structural Equation Modeling (PLS-SEM). The results show that cognitive load significantly negatively affects EFL learners' confirmation (β = -0.391, $p < 0.001$), perceived usefulness (β = -0.808, $p < 0.001$), and satisfaction (β = -0.187, $p < 0.001$) with MOOCs. Confirmation positively influences learners' perceived usefulness (β = 0.763, $p < 0.001$) and satisfaction (β = 0.231, $p < 0.001$), perceived usefulness significantly positively influences learners' satisfaction (β = 0.571, $p < 0.001$). Additionally, confirmation (β = -0.090, $p < 0.001$) and perceived usefulness (β = -0.461, $p < 0.001$) partially mediate the relationship between cognitive load and satisfaction. The findings provide practical implications for MOOC platform designers in optimizing course content and reducing cognitive load to enhance learner satisfaction. Finally, the theoretical and practical significance of the study's results is discussed.

Keywords EFL learners, Cognitive load theory, Expectation confirmation theory, Satisfaction

Introduction

With the development of global online education, Massive Open Online Courses (MOOCs) have become an important platform for many EFL (English as a Foreign Language) learners to enhance their language skills and professional knowledge [1–3]. Compared to traditional classroom teaching, the flexibility and extensive course resources of MOOCs have attracted a large number of learners, especially during the global pandemic, when online learning became an indispensable mode of education [4, 5]. However, despite the convenience offered by MOOC platforms, some challenges have also surfaced, particularly regarding the cognitive load (CL) faced by learners during their use [6]. EFL learners, as a distinct group, face unique challenges in the MOOC learning process. They are not only required to overcome language barriers associated with foreign language learning but also to adapt to the technological complexities

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and self-directed learning demands of online education. These challenges result in a higher CL for EFL learners during their MOOC learning experience. Cognitive Load Theory (CLT) suggests that when the information load learners must process becomes too large, it can negatively affect learning outcomes [7]. EFL learners not only face the challenges of language learning but also need to adapt to the complexities of online learning, which results in a higher CL compared to native language learners. Furthermore, the success of MOOC platforms largely depends on learner satisfaction (SAT), and one of the key variables influencing this is the CL experienced during the learning process. Excessive CL may increase learner frustration and reduce their learning SAT [8, 9]. Therefore, exploring the impact of CL on the learning SAT of EFL learners in MOOCs is of significant theoretical and practical importance. Nevertheless, research on the relationship between CL and MOOCs SAT among EFL learners remains limited. In particular, how CL indirectly affects learners' SAT through other variables still requires further investigation.

In the field of information systems, Expectation Confirmation Theory (ECT) is often used to explain users' SAT with information systems [10]. This theory emphasizes that user SAT depends on whether their actual experience meets their prior expectations. When expectations are confirmed, SAT tends to be higher [11–13]. In the context of MOOC platforms, learners' expectations typically involve aspects such as course content quality, platform usability, technical support, and learning outcomes. If these expectations are confirmed, learners' perceived usefulness (PU) of the platform and SAT are significantly enhanced [14]. CL plays an essential role in this process. Research has shown that the level of CL directly influences users' confirmation (CON) and PU [15]. A high CL may cause learners' actual experience on MOOC platforms to fall short of expectations, negatively impacting their PU of the platform and subsequently lowering their SAT. This finding is particularly relevant for EFL learners, who face the dual challenges of language learning and processing a large amount of information while using MOOC platforms, thereby increasing their CL.

Although existing literature widely applies ECT and CLT to explain user behavior and learning SAT, particularly in the fields of education and information systems, the combined application of these two theories in the context of EFL learners using MOOC platforms remains a significant research gap. Current studies primarily focus on the application of single theories and lack a comprehensive understanding of how CL indirectly influences user SAT by affecting CON and PU. Specifically, in the unique context of MOOC platforms, the interaction between CL and CON has not been adequately explored. Therefore, addressing this research gap holds important theoretical and practical value.

This study aims to explore the learning experience of EFL learners on MOOC platforms by integrating ECT and CLT. Specifically, this research will analyze how CL, CON, and PU interact to influence learners' SAT. By deeply analyzing these relationships, this study can provide theoretical guidance for MOOC platform developers, assisting them in optimizing platform design and reducing learners' CL, thus enhancing user experience and learning outcomes. Additionally, it will offer practical guidance for educators, helping them better meet the needs of EFL learners and improve their learning experience on MOOC platforms.

Literature review

CLT

CLT was proposed by Sweller [7] in the 1980s to explain how humans process and store information during learning. This theory suggests that when learners experience excessive CL, their learning outcomes are negatively affected. CL is affected by three primary factors: the learner's prior experience, the inherent characteristics of the learning materials, and the organization and presentation of the materials. CL can be categorized into three types based on its sources: intrinsic CL, extraneous CL, and germane CL [16]. CLT has been widely applied in the field of education, including in scientific teaching systems [17], digital learning platforms [18], and video-based instruction [19]. Existing research suggests that by optimizing instructional design and reducing unnecessary CL, students' learning efficiency and SAT can be improved. However, most existing studies focus on traditional teaching environments and rarely address the CL of EFL learners on MOOC platforms. Therefore, this study will explore the impact of CL on the MOOC experience of EFL learners, particularly its influence on CON, PU, and SAT.

ECT

ECT was proposed by Oliver [20] in 1980 and is primarily used to explain consumer behavior and SAT. According to this theory, consumers form certain expectations before purchasing goods or services, and after the actual experience, they compare their perceptions with these expectations, leading to confirmation or disconfirmation. If the actual experience meets or exceeds expectations, consumers feel satisfied; if the experience falls short, they feel dissatisfied [11–13]. ECT is also applicable in the field of information systems, with research focusing on users' continued use intentions and SAT with information systems [21].

In previous studies, ECT has been widely applied to explore users' continuation intentions in various

domains, including e-learning systems [22, 23], MOOCs [14], e-government services [24], and mobile applications [25]. These studies demonstrate the broad applicability and strong explanatory power of ECT across different fields. By understanding the relationship between users' initial expectations and actual experiences, developers and managers can better meet user needs and improve user SAT [26, 27]. However, the application of ECT on MOOC platforms is often integrated with Flow Theory [28], the Information system success model (ISSM) [29], and the Technology Acceptance Model [30] for a comprehensive explanation. However, research on the interaction between ECT and CLT remains relatively limited. By combining ECT and CLT, this study aims to explore how CL, through its influence on CON and PU, jointly affects learners' SAT in the context of EFL learners using MOOCs. Through this theoretical framework, we hope to provide more comprehensive and practical theoretical guidance for the optimization of MOOC platforms.

EFL learners' SAT with MOOCs

Existing research has placed significant emphasis on EFL learners' SAT with MOOCs. Gu, et al. [29] using an integrated theoretical framework of the D&M ISS model and the Expectation Confirmation Model (ECM), found that when users' expectations are confirmed, their SAT with MOOC platforms increases significantly, as does their intention to continue using the platform. However, many studies have not fully considered the language background and cultural differences of EFL learners, nor how these factors influence learner SAT. Research by Alyoussef [31] suggests that Task-Technology Fit significantly affects learner SAT, yet there is limited discussion on strategies for optimizing MOOC platform design. Additionally, while factors such as PU [32], motivation [33], emotional engagement [34], and system quality [35] also impact learner SAT, the role of CL has not been adequately explored. This study, combining CLT and ECT, aims to investigate the SAT of EFL learners in MOOCs, analyzing how CL influences learners' overall SAT through CON and PU.

Research hypotheses

CL and SAT

CL generally refers to the mental effort required to process information when completing a specific task [7]. Complex or difficult-to-use products or services can increase CL, negatively impacting user SAT and experience [36, 37]. In the context of online learning, CL affects students' SAT with learning platforms, particularly in relation to CON and PU. Studies have shown a significant negative correlation between CL and SAT, meaning that higher CL leads to lower SAT [15]. For instance, Huang [38] examined the effects of self-efficacy, PU, and CL on student SAT in blended learning environments and found that CL significantly negatively affects students' learning SAT. For EFL learners, the impact of CL is equally significant. During English learning, learners may need to simultaneously manage new vocabulary, grammar structures, and the four language skills of listening, speaking, reading, and writing, all of which increase CL and, in turn, reduce SAT [39]. However, some studies have reached different conclusions. For example, Woo, et al. [37] discussed the impact of CL on the SAT with the learning process when EFL learners use GPT for English writing. The results showed that while students experienced higher CL during collaborative tasks, they still expressed overall SAT with the learning process. According to CLT, excessive CL can diminish the learning experience. By further exploring the impact mechanism of CL on the SAT of EFL learners using MOOCs, this study will contribute to a deeper understanding of the cognitive challenges learners face when using online learning platforms and provide empirical support for the design and optimization of MOOC platforms.

CON and PU

According to ECT, an individual's PU is influenced by CON. When the user experience exceeds expectations, their PU of the technology typically increases, as the positive experience reinforces their favorable evaluation of the technology [20, 40]. For example, Lee, et al. [32] using the ECM, investigated factors influencing university students' continued use of MOOCs and found that CON significantly and positively affects PU and SAT. Specifically, when students' learning experiences with MOOCs exceed their expectations, they perceive the platform as more helpful for their learning, thereby increasing their overall SAT with the MOOC. Additionally, Gu, et al. [29] employing an integrated model of the D&M ISS and ECT, studied factors influencing users' continued use of MOOCs. The study showed that when students' expectations are confirmed, their PU of the MOOC platform significantly increases. This suggests that the gap between students' expectations regarding course content, teaching quality, and technical support, and their actual experiences, directly affects their evaluation of MOOCs and their willingness to continue using the platform. Therefore, this study hypothesizes that EFL learners' PU of MOOCs platforms may also be adjusted by their CON.

The mediating role of CON and PU

Existing studies have demonstrated that CL negatively impacts individuals' perceptions and CON. According to ECT, PU is a key measure of users' evaluation of system usability, and it is also one of the main reasons people choose to use certain technologies. CON refers to the degree of consistency between users' expectations of an

information system and its actual performance [20]. Wu, et al. [41] in their study on students' continuous learning intention in STEAM education, found that CL negatively affects PU in the cognitive domain. Although this study provides an important perspective on understanding the role of CL, its sample is limited to a STEAM education context, making it difficult to directly apply to the EFL learner population, especially in the specific environment of MOOCs platforms. Additionally, research based on ECT and CLT on students' SAT with online collaborative learning has shown that high CL significantly reduces both PU and CON, further lowering SAT [15]. These studies indicate that CL has a significant impact on learners' PU and CON. However, they often overlook the specific language challenges and cultural background differences faced by EFL learners, limiting the applicability of their findings to different groups. Therefore, while these studies provide valuable insights into the role of CL, they lack in-depth exploration of how specific learning groups, such as EFL learners, are affected by CL. This study fills this gap by integrating ECT and CLT. We argue that EFL learners' PU and CON when using MOOC platforms are largely influenced by their cognitive state and the level of CL. Thus, this study will explore how CL, by affecting CON and PU, subsequently influences EFL learners' learning SAT. Through this integrated perspective, we aim to offer new theoretical guidance for the optimization of MOOC platforms, particularly in alleviating CL and improving learner SAT and learning outcomes.

CON reflects users' perceptions of the consistency between their expectations of an information system and its actual performance [42]. ECT posits that, similar to consumer environments, when students' expectations of a MOOC platform are confirmed, it enhances their positive perceptions of the platform and increases SAT [43]. For example, Zhang, et al. [21] used ECT and the ISSM to investigate key predictors of students' continued use of online learning systems and found that system CON significantly positively affected student SAT. However, other studies have reached different conclusions. Li, et al. [26] incorporated the Theory of Planned Behavior into the ECM to examine students continued intention to use online learning during the COVID-19 pandemic. The results showed that CON did not have a direct effect on SAT, but it was positively correlated with PU and perceived enjoyment. PU is a key determinant in users' assessment of system usability and is one of the primary reasons people adopt certain technologies [42]. Users are generally more satisfied with systems they perceive as providing concrete benefits in practical use, as PU often influences SAT. For instance, Joo, et al. [44] based on the Technology Acceptance Model (TAM), examined factors affecting university students' continued use intention of MOOCs and found that PU significantly positively impacts SAT, which in turn influences their intention to continue using the system. Similarly, a meta-analysis has shown that increasing individuals' positive perceptions of MOOCs and the PU of the platform can enhance learners' SAT and willingness to continue using the platform [45]. These studies indicate that CON and PU significantly impact MOOC learners' SAT. However, they largely overlook the role of CL in these relationships, particularly for EFL learners, where CL may play a more prominent role. To address this research gap, this study will combine ECT and CLT to explore how CL, CON, and PU interact to influence the MOOC SAT of EFL learners. Additionally, this research aims to provide a new perspective for optimizing MOOC platform design to better meet the specific needs of EFL learners.

Theoretical framework and research hypotheses

Based on relevant literature and previous empirical studies, this research proposes the theoretical framework shown in Fig. 1 (a hypothesized model of the relationships between variables). Based on this framework, the following research hypotheses are proposed:

H1 CL significantly negatively affects the SAT of the MOOC platform for EFL learners.

H2 CON significantly positively affects the PU of the MOOC platform for EFL learners.

H3 CL significantly negatively affects the CON of the MOOC platform for EFL learners.

H4 CL significantly negatively affects the PU of the MOOC platform for EFL learners.

H5 CON significantly positively affects SAT with the MOOC platform for EFL learners.

H6 PU significantly positively affects SAT with the MOOC platform for EFL learners.

H7 CON significantly mediates the relationship between CL and SAT among EFL learners.

H8 PU significantly mediates the relationship between CL and SAT among EFL learners.

Methods

Research design

After determining the content of the questionnaire, the study first hired professional translators to translate the questionnaire into Chinese, and used back-translation techniques to ensure the accuracy of the translation.

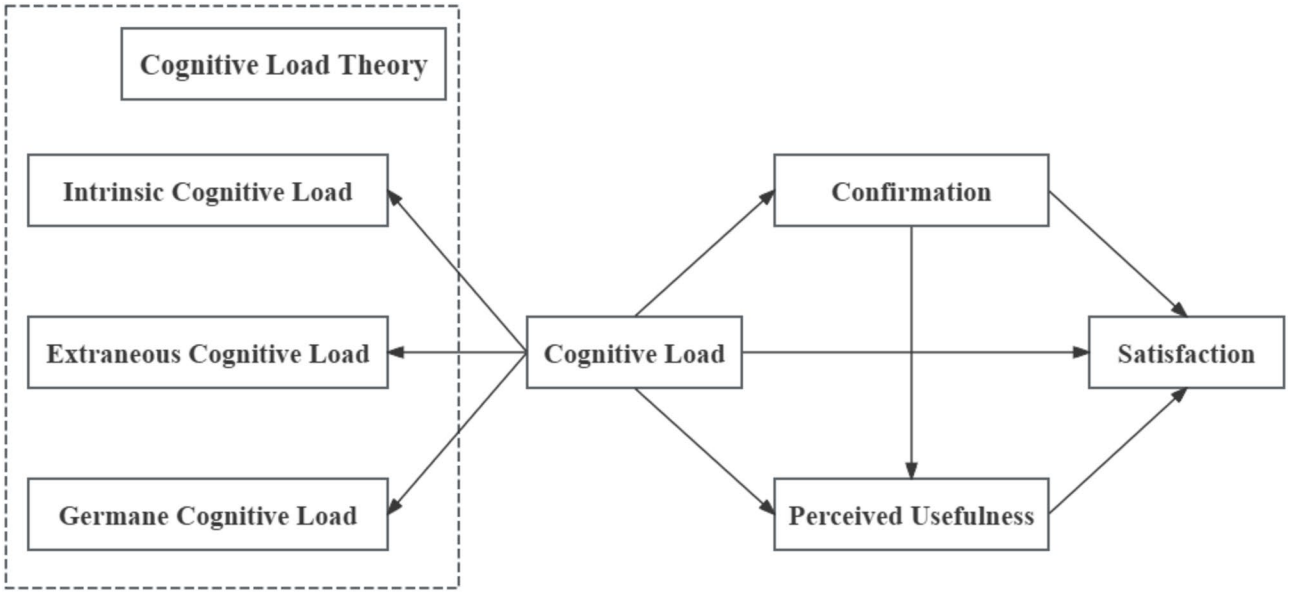

Fig. 1 Theoretical Model

Table 1 Demographic information of the sample

Demographic Characteristics	Category	Quantity	Percentage (%)
Gender	Male	126	24.91
	Female	380	75.09
Age	Below 18 years old	86	17.00
	19–22 years old	414	81.81
	23 years and above	6	1.19
Grade	Freshman	97	19.17
	Sophomore	237	46.84
	Junior	172	33.99
	Senior	0	0

Once the translation was completed, data collection was carried out through the Questionnaire Star platform, and the questionnaires were distributed and collected using random sampling methods. The research team first established initial communication with the school administration and coordinated with counselors, who introduced the purpose and significance of the survey to students during class meetings. Subsequently, participants were randomly selected from each class's student roster using computer-generated random numbers to ensure the randomness and representativeness of the sample. Once participants were selected, the counselors shared the questionnaire link in the class group and emphasized the voluntary nature of participation and privacy protection measures. This approach respected the students' willingness and ensured the quality and reliability of the data, providing a solid foundation for subsequent analysis.

Participants and data collection

From March 2024 to August 2024, this study collected data through the online questionnaire platform Questionnaire Star (www.Sojump.com), using random sampling to select participants from universities in Henan Province. A total of 519 questionnaires were distributed, and after data cleaning, 293 valid responses remained. The data cleaning criteria were as follows: non-EFL learners; students who had not used MOOCs for learning; questionnaires with more than 20% missing responses; and questionnaires where over 80% of the answers were extreme (completely agree or completely disagree). Such response patterns could introduce significant bias, known as floor or ceiling effects, which could impact the accuracy of data analysis. The specific demographic data are shown in Table 1: 73 males (24.91%) and 220 females (75.09%); the majority of participants were aged between 18 and 23, with 240 individuals (81.81%); the majority were in the second year (137 participants, 46.76%) and third year (100 participants, 34.13%) of their university studies. All participants voluntarily participated in this study and signed written informed consent. The research process adhered to the ethical principles outlined in the Declaration of Helsinki.

Table 2 Construct reliability and validity

Constructs	Items	Outer loadings	Cronbach' α	CR	AVE
CL	CL 1	0.740	0.953	0.958	0.605
	CL 2	0.795			
	CL 3	0.753			
	CL 4	0.805			
	CL 5	0.817			
	CL 6	0.853			
	CL 7	0.840			
	CL 8	0.794			
	CL 9	0.836			
	CL 10	0.807			
	CL 11	0.802			
	CL 12	0.773			
	CL 13	0.749			
	CL 14	0.790			
	CL 15	0.761			
	CL 16	0.791			
CON	CON 1	0.928	0.922	0.951	0.865
	CON 2	0.949			
	CON 3	0.913			
PU	PU 1	0.943	0.934	0.958	0.884
	PU 2	0.946			
	PU 3	0.932			
SAT	SAT 1	0.945	0.939	0.961	0.891
	SAT 2	0.947			
	SAT 3	0.939			

Table 3 Discriminant validity (Cross-loadings Criterion)

	CL	CON	PU	SAT
CL 1	**0.740**	-0.330	-0.338	-0.343
CL 2	**0.795**	-0.506	-0.504	-0.510
CL 3	**0.753**	-0.453	-0.413	-0.426
CL 4	**0.805**	-0.582	-0.528	-0.565
CL 5	**0.817**	-0.576	-0.577	-0.581
CL 6	**0.853**	-0.604	-0.610	-0.608
CL 7	**0.840**	-0.553	-0.551	-0.559
CL 8	**0.794**	-0.503	-0.481	-0.524
CL 9	**0.836**	-0.518	-0.515	-0.526
CL 10	**0.807**	-0.544	-0.531	-0.542
CL 11	**0.802**	-0.528	-0.506	-0.538
CL 12	**0.773**	-0.465	-0.452	-0.477
CL 13	**0.749**	-0.770	-0.678	-0.694
CL 14	**0.790**	-0.782	-0.701	-0.719
CL 15	**0.761**	-0.808	-0.716	-0.723
CL 16	**0.791**	-0.756	-0.623	-0.819
CON 1	-0.730	**0.928**	0.785	0.796
CON 2	-0.721	**0.949**	0.811	0.836
CON 3	-0.669	**0.913**	0.825	0.833
PU 1	-0.687	0.815	**0.943**	0.854
PU 2	-0.660	0.813	**0.946**	0.884
PU 3	-0.676	0 820	**0 932**	0.865
SAT 1	-0.683	0.839	0 875	**0.945**
SAT 2	-0.712	0.831	0.877	**0.947**
SAT 3	-0.691	0.831	0.860	**0.939**

Measurement tools

The questionnaire comprised two sections: one for collecting demographic information and the other for measuring the constructs examined in this study. To evaluate these constructs, validated scales were employed. CL was assessed using the multidimensional CL scale by Andersen and Makransky [46], which includes three dimensions: intrinsic, extraneous, and germane CL. The scale consists of 16 items, and after removing those with an external load lower than 0.708, 15 items remained. The Cronbach's α was 0.953, indicating good reliability. The scales for PU, CON, and SAT were adapted from Lu, et al. [47], drawing on previous work by Davis [48], Gerlach, et al. [49], and Alraimi, et al. [50]. Each of the three scales contains three items, with the Cronbach's α for the three scales being 0.934, 0.922, and 0.939, respectively, demonstrating good validity.

Statistical analysis

This study utilized Partial Least Squares Structural Equation Modeling (PLS-SEM) to assess both the measurement and structural models. PLS-SEM provides several benefits, including its suitability as a prediction-focused data analysis approach [51]. Secondly, it performs well with small sample sizes and even under conditions of non-normal data distribution [51]. Thirdly, it is suitable for more complex models [52]. In this study, although PLS-SEM has several advantages, it also has some limitations. First, while PLS-SEM is effective with small sample sizes, smaller samples may affect the stability and generalizability of the results. Second, PLS-SEM is more suited for explanatory analysis rather than causal inference, so caution is needed when interpreting causal relationships. Despite these potential limitations, this study argues that PLS-SEM remains suitable for the objectives and data characteristics of this research.

Results

Structural equation model analysis

Reliability was assessed using the outer loadings of items and the composite reliability of scales, both of which should exceed 0.70. As shown in Table 2, all outer loadings and composite reliability values meet this threshold, demonstrating high reliability. Validity was evaluated through convergent and discriminant validity. Convergent validity, assessed by the Average Variance Extracted (AVE), exceeded the required 0.5 [51]. Discriminant validity was verified using the Fornell-Larcker criterion [53]) and the cross-loading approach. All indicators showed higher outer loadings on their associated constructs compared to their cross-loadings (Table 3), and the correlations between constructs were lower than the square root of the AVE (Table 4). These findings confirm strong discriminant validity for the constructs.

Table 4 Discriminant validity (Fornell-Larcker Criterion)

	PU	CON	SAT	CL
PU	**0.940**			
CON	0.868	**0.930**		
SAT	0.923	0.883	**0.944**	
CL	-0.717	-0.759	-0.737	**0.778**

Table 5 VIF

	PU	CON	SAT	CL
PU		2.059	2.190	
CON			2.804	
SAT				
CL	1.000	2.059	2.440	

Structural model

In analyzing the structural model for this study, several indicators can be used, including the significance testing of path coefficient estimates and the coefficient of determination (R^2). These indicators help assess the reliability and explanatory power of the model.

Collinearity test

First, the variance inflation factor (VIF) values of the latent constructs were used to evaluate potential multicollinearity issues within the model. All VIF values for the latent constructs ranged from 1.000 to 2.804, which are well below the critical threshold of 3.3, indicating that multicollinearity is not a concern in the results [51]. The low VIF values indicate weak correlations between the latent constructs, and they do not significantly affect the stability and reliability of the results. Therefore, this study is confident that the research findings are not disturbed by multicollinearity. Furthermore, the VIF values in Table 5 further demonstrate that multicollinearity issues do not impact the results of this study.

Path hypotheses

The outcomes of the hypothesis testing are presented in Table 6. The findings indicate that CL has a significant negative effect on CON ($\beta = -0.282$, $p = 0.000$), PU ($\beta = -0.717$, $p = 0.000$), and SAT ($\beta = -0.187$, $p = 0.000$). Therefore, H1, H3, and H4 are supported. PU has a significant positive effect on both CON ($\beta = 0.666$, $p = 0.000$) and SAT ($\beta = 0.616$, $p = 0.000$), supporting H2 and H6. Additionally, CON has a significant positive effect on SAT ($\beta = 0.295$, $p = 0.000$), supporting H5. The path coefficient of the research model is shown in Fig. 2.

Explanatory power and predictive relevance

The R^2 and Stone-Geisser Q^2 values demonstrate the model's explanatory power and predictive relevance. Table 7 shows that the R^2 value for SAT indicates that predictors account for 88.1% of its variance, reflecting strong explanatory power. Furthermore, all Q^2 values

Table 6 Results of the structural model relationship significance

Hypothesis	β	2.50%	97.50%	t	*p*	Results
CL → SAT	-0.187	-0.154	-0.005	9.174***	0.000	Supported
CON → PU	0.763	0.643	0.853	14.218***	0.000	Supported
CL → CON	-0.391	-0.525	-0.277	6.234***	0.000	Supported
CL → PU	-0.808	-0.792	-0.646	38.537***	0.000	Supported
CON → SAT	0.231	0.186	0.426	3.770***	0.000	Supported
PU → SAT	0.571	0.481	0.720	9.146***	0.000	Supported

Note. ***$p < 0.001$; **$p < 0.01$; * $p < 0.05$

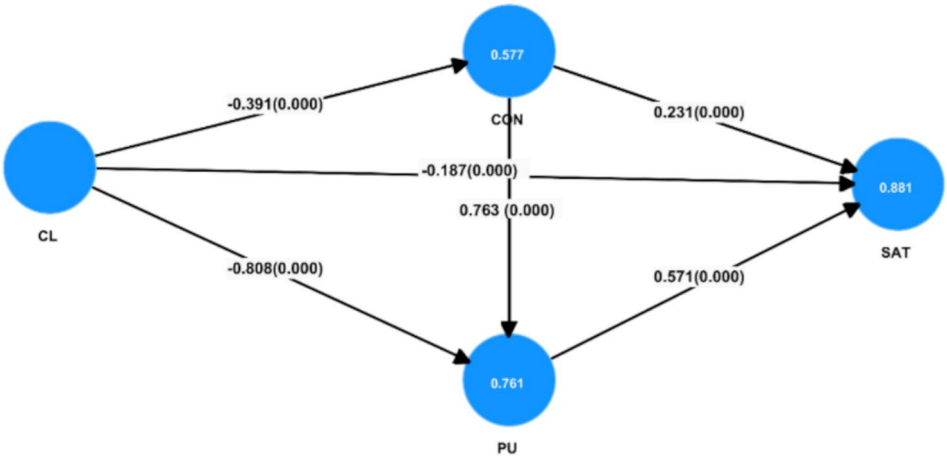

Fig. 2 Path Coefficients of the Research Model

Table 7 Model explanatory power and predictive relevance

	R^2	$R^2_{Adjusted}$	Q^2
PU	0.514	0.513	0.715
CON	0.792	0.790	0.682
SAT	0.881	0.880	0.727

exceed zero, confirming the model's high predictive relevance [51].

Mediation effect analysis

To assess the mediating roles of CON and PU in the relationship between CL and SAT, a mediation analysis was conducted. The study employed a PLS-SEM-based mediation analysis method, using bootstrapping to test the significance of both the direct and indirect effects [54], as well as the sign of the product of effects, to determine the type and magnitude of the mediation effect. Table 8 presents the results of the mediation analysis, showing that CON and PU act as mediators in the relationship between CL and SAT. Further analysis of the direct effects was conducted to evaluate the nature and size of the mediation by CON and PU. As shown in Table 6, CL has a direct and significant effect on EFL learners' SAT with using MOOCs, indicating that CON and PU partially mediate the relationship between CL and SAT. Specifically, although CON and PU play a mediating role in this relationship, CL still has a significant direct impact on SAT. This indicates that the mediating effect does not completely replace the direct effect of CL on SAT, thus the study observes a partial mediation effect.

Discussion

This study aimed to explore the impact of MOOCs usage on university students' SAT based on CLT and the mediating roles of CON and PU. Through a comprehensive review of the existing literature, we hypothesized that the management of CL in a MOOCs environment has a significant influence on students' learning SAT, with CON and PU playing crucial mediating roles in this relationship. The findings support these hypotheses, demonstrating that CL significantly reduces EFL learners' SAT in MOOCs learning. Additionally, CON and PU were found to mediate the relationship between CL and learning SAT. The following sections will discuss these findings in detail.

CL has a significant negative effect on EFL learners' SAT with using MOOCs. This finding is consistent with Huang [38] study, which indicated that CL negatively affects students' SAT with learning platforms. According to CLT, the task complexity and additional language processing burdens faced by EFL learners increase their CL, which in turn affects their learning experience and SAT. MOOC courses are typically content-rich and have high self-learning requirements, and EFL learners need additional cognitive resources to process language comprehension and course content in a non-native language environment. This significantly increases their CL. Higher CL weakens learners' positive experiences, leading to feelings of confusion, anxiety, or fatigue, which reduces their overall SAT [55]. When the complexity of learning tasks exceeds the learner's cognitive abilities, they may feel confused, anxious, or fatigued, leading to a decline in SAT with both the learning process and the platform [56]. It is worth noting that this study only focuses on the overall CL's impact on EFL learners' SAT with MOOCs and does not explore intrinsic CL, extraneous CL, or germane CL. Therefore, future research could further investigate the specific impact of these three different types of CL on learners' SAT. By distinguishing the effects of these three types of loads, the research can provide more detailed optimization recommendations for MOOC platform design, aimed at alleviating EFL learners' CL and enhancing their learning experience and SAT.

CON has a significant positive impact on EFL learners' PU with using MOOCs. This finding aligns with the study by Lee, et al. [32], which showed that CON positively influences students' PU of MOOCs. When EFL learners' actual experiences with MOOCs match or exceed their prior expectations, they perceive the courses as meeting or fulfilling their learning needs [57]. CON leads learners to have a higher appreciation for the effectiveness of course content, the practicality of tools, and the overall learning experience, thereby enhancing their perception of the usefulness of MOOCs. This result is consistent with ECT, as an increase in CON enhances learners' perceived value of the course, thereby strengthening their positive evaluation of the learning platform. However, although this study further clarifies the positive impact of CON on PU, we did not deeply explore the potential feedback effect between CON and PU. Specifically, learners' expectations of the platform may change as their PU of the platform increases, and this interaction may further affect their SAT. Therefore, future research could consider incorporating a longitudinal design to explore the dynamic relationship between CON and PU,

Table 8 Mediation analysis

Relationships	Indirect effects	t	*p*	Direct effects	t	*p*	Mediation type
CL → CON → SAT	-0.083	4.180	0.000	-0.187	9.174	0.000	CPM
CL → PU → SAT	-0.442	9.811	0.000	-0.187	9.174	0.000	CPM

Note: CPM stands for Complementary Partial Mediation

and further examine how CL, based on CLT, influences this process.

This study found that CL significantly negatively impacts EFL learners' SAT, with CON and PU serving as partial mediators. This aligns with Cheng, et al. [15], who found that higher CL reduces college students' CON and PU, lowering SAT with MOOCs. Specifically, higher CL impairs CON and PU, which in turn reduces SAT. CL typically results from excessive information, poor course design, or insufficient prior knowledge, making it difficult for learners to process and absorb course content, thus reducing CON and SAT with the platform [14]. Additionally, CL lowers PU, as students may view the learning method as ineffective when dealing with complex or confusing information [58]. As CON and PU decrease, learners' SAT with the platform also declines, as they feel the platform fails to effectively enhance their knowledge and skills, affecting their overall learning experience [59]. These findings support the integration of CLT and ECT. However, the study also shows that CL impacts ($\beta = -0.808$, $p<0.001$) more than CON ($\beta = -0.391$, $p<0.001$). CLT suggests that when the cognitive demands of a task exceed a learner's capacity, confusion or anxiety may arise, impairing information processing [7]. In MOOCs, where learners must self-regulate their learning and manage large amounts of information, this leads to reduced PU of the platform, as learners may perceive it as lacking adequate support. In contrast, CON is less affected by CL, as it is influenced by learners' actual experiences with the platform. Although CL plays a role, CON is also shaped by other factors like course design and teaching quality. This study's sample, limited to EFL learners from three Chinese universities with gender imbalance, restricts the generalizability of the results. Future research should expand the sample size and achieve gender balance to enhance generalizability. Additionally, future studies should investigate the interaction between CL, CON, and PU in different learning contexts to explore how optimizing instructional design can reduce CL and improve SAT.

Implications and limitations

Implications

This study, based on CLT and ECT, investigates the impact of MOOCs usage on college students' SAT, with a particular focus on the mediating roles of CON and PU. The theoretical contributions of this study are as follows: First, it highlights the central role of CL management in enhancing student SAT, expanding the application of CLT in online education environments, especially its impact on EFL learners. Second, it reveals how CON and PU mediate the relationship between CL and SAT, offering new insights into the interplay between CL, CON, and PU. Finally, the study emphasizes the importance of learners' expectations in the learning process and their influence on SAT. Learners' CON of their expectations significantly affects their PU of the MOOC platform and overall SAT. In summary, this research not only extends the application of CLT but also provides new theoretical insights for the field of educational technology, particularly in enhancing the learning experience and SAT of EFL learners by managing CL and CON. Future research could explore other learner groups and online platforms within this framework.

From a practical perspective, this study provides valuable guidance for MOOC platform designers, aiding in the optimization of course design to improve college students' learning SAT. Specifically, it is recommended that MOOC platform designers structure course content with clear titles and subtitles, while incorporating charts, videos, and other visual aids to simplify information presentation and reduce CL. Furthermore, enhancing course interactivity is crucial. Platform designers can foster student engagement and motivation through real-time Q&A sessions, discussion forums, and group assignments. To further support the learning process, platforms should offer online tutoring and feedback systems, addressing student queries and providing personalized feedback, as well as supplementary learning resources such as preparatory materials, review guides, and extracurricular reading to help students better grasp the course content. Through these strategies, MOOCs can significantly improve students' learning experience and SAT, making online learning more effective and enjoyable.

Limitations and future research directions

This study has several limitations. Firstly, the sample was drawn only from EFL learners at three universities. Although the sample included learners from different academic disciplines, it may not fully represent EFL learners from other regions or educational backgrounds, limiting the generalizability of the findings. Future research could expand the sample size to include a broader range of EFL learners from diverse regions and educational backgrounds, particularly incorporating students with varying language proficiency levels and cultural contexts, in order to enhance the generalizability and applicability of the findings. Specifically, researchers could conduct cross-regional and cross-cultural comparative studies to explore the CL and SAT of EFL learners from different backgrounds, providing a comprehensive evaluation of the effectiveness of MOOCs. Secondly, this study utilized cross-sectional data for analysis, which cannot adequately capture the dynamic changes and long-term effects of CL, CON, and PU on SAT. Future research should adopt a longitudinal design to track changes in learners' CL and SAT over time while using MOOCs, analyzing the trajectory of these variables

at different time points. For example, researchers could collect data at regular intervals to better capture changes during the learning process and reveal long-term effects. Third, this study relied on self-reported questionnaire data, which may be subject to participant bias and social desirability effects, potentially impacting the accuracy of the data. Although measures such as ensuring participant anonymity and confidentiality were taken to reduce social desirability effects, self-report data may still be biased. Future studies could combine multiple data collection methods, such as incorporating behavioral data or using system logs from the learning platform to objectively measure learners' behaviors and engagement, thereby reducing the bias in self-report data. Additionally, using physiological or behavioral data (e.g., eye-tracking, click-rate analysis) to assess learners' CL could further enhance the objectivity and accuracy of the research findings. Lastly, this study did not deeply explore the specific characteristics of MOOC platforms (e.g., platform design, interactive features) that may influence CL and SAT, potentially overlooking the critical role of platform features in enhancing user experience. Future research should also focus on the characteristics of MOOC platforms, particularly the interactive design, feedback mechanisms, and technical support, analyzing how these factors influence learners' CL and SAT. For instance, researchers could adopt experimental designs to compare the effects of different platform designs on learner experience or conduct multiple case studies to explore the strengths and weaknesses of various platforms in meeting learners' needs, offering more targeted recommendations for platform optimization.

Conclusion

This study empirically analyzed the effects of CL, CON, and PU on EFL learners' SAT with MOOC platforms, extending the application of CLT and ECT in the field of online education. All hypotheses in this study were supported. Firstly, we found that CL has a significant negative impact on CON, PU, and SAT, while CON and PU have significant positive effects on learners' SAT. Secondly, CON and PU were found to partially mediate the relationship between CL and SAT, indicating that CL can influence EFL learners' SAT both directly and indirectly through these mediators. The results suggest that effectively managing learners' CL, enhancing the PU of the platform, and ensuring that the learning experience meets learners' expectations are crucial for improving their SAT with MOOCs. Furthermore, the study reveals the profound impact of CL on the MOOC learning experience, particularly through the mediating roles of CON and PU, which indirectly affect learners' SAT. These findings provide practical insights for MOOC platform developers and educators, offering suggestions for optimizing platform design and instructional strategies.

Author contributions
Lingling Ma completed all aspects of the study, including writing the main manuscript text, preparing all tables and figures, conducting the data analysis, participating in the survey, performing the on-site investigation, organizing and managing the data, and reviewing the manuscript.

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Data availability
The data that support the findings of this study are available on request from the corresponding author.

Declarations

Ethics approval and consent to participate
The researchers confirms that all research was performed in accordance with relevant guidelines/regulations applicable when human participants are involved (e.g., Declaration of Helsinki or similar). This study was approved by the Ethics Committee of Xuchang University. The participants received oral and written information and provided written informed consent before participating in the study.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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