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Antecedents of College Students' Continuance Behaviors in Online Fragmented Learning: An Empirical Analysis from the Extended ECM Perspective

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Abstract: With the popularity of mobile networks and intelligent terminals, online fragmented learning, as a new learning method, has become the mainstream way for college students to acquire knowledge and study independently. However, college students are prone to "accept-interruption" in online fragmented learning; thus, it is difficult for them to master a complete knowledge system and form a rigorous logic system, which is essential to ensure the effect of online fragmented learning. Therefore, this study investigates the antecedents of college students' continuance behaviors in online fragmented learning (CBOFL). Based on the expectation confirmation model (ECM), a theoretical model is developed to examine the factors influencing college students' CBOFL. Taking a total of 429 undergraduate students who have studied contest courses on the Chinese university massive open online courses (MOOCs) for research subjects, the mechanism underlying the determinants of college students' CBOFL is analyzed, and six hypotheses are tested by a structural equation modeling (SEM) technique with AMOS. The results indicate that confirmation positively impacts intrinsic learning motivation and satisfaction; intrinsic learning motivation, satisfaction, and teachers' influence all significantly positively affect college students' CBOFL. Additionally, the predicting powers of different factors on college students' CBOFL vary broadly; therein, satisfaction has the most significant effect. This study makes theoretical contributions to the quantitative research on college students' CBOFL and literature on the ECM. Still, it also has important practical significance in guiding college students' CBOFL and facilitating the sustainability of online fragmented learning.

Keywords: online fragmented learning; continuous learning behaviors; the extended ECM; college students; the Chinese university MOOC platform

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1. Introduction

With the rapid development of Internet technology and the popularity of mobile terminals, the traditional education industry is facing unprecedented shock and challenge. Thus, college students' learning methods and behaviors have dramatically changed [1]. Online learning, as a kind of new learning method born with the Internet, gets rid of the limitations of wired networks and fixed terminals and truly realizes the state of learning anytime and anywhere by breaking the traditional learning way of fixed space and time [2,3]. The convenience and flexibility of online learning spur college students always to make full use of their spare time to continuously acquire knowledge on the Internet platform and improve their ability to adapt to the increasingly fast-paced society. As a result, online learning content and time also show fragmentation characteristics [4]. In this context, online fragmented learning also emerges. The outbreak of the COVID-19 pandemic has dramatically propelled the development of online fragmented learning. So far, online fragmented learning is prevalent among college students and has become an essential method for acquiring knowledge and improving autonomy in learning and application skills [5,6]. However, college students are prone to the phenomenon of "accept-interruption" in online fragmented learning, which makes it difficult for them to form a complete knowledge system. Consequently, it may vastly reduce the effect of online learning. Therefore, ensuring the continuance of online fragmented learning has become a critical problem in scattered time and nonsystematic online learning.

Recent studies have paid attention to the determinants of online fragmented learning and its effect [4,6,7], but the research on the continuance behaviors in online fragmented learning is still relatively few. Although online fragmented learning, with the characteristics of high flexibility, strong pertinence, convenient learning, and high time efficiency, can make up for the deficiencies of traditional classroom-based learning and help students make better use of their fragmented time [5,6], the scattered and disorderly fragmented knowledge acquired by online fragmented learning lacks comprehensiveness and rigor [7,8]. Consequently, students must carry out continuance behaviors in online fragmented learning to master a complete knowledge system and rigorous logic system, thus improving their online learning efficiency and achieving better learning effects. Prior studies have suggested that online fragmented learning expands the functions of online learning and creates more possibilities. However, it is still necessary to learn all the content included in a certain knowledge point for a long time to form a complete knowledge system and thus ensure the effect of online learning [7]. Tang et al. [9] also believed that although online fragmented learning has specific operability and feasibility, it is still in its infancy and needs further improvement and optimization.

Therefore, this study investigates the factors affecting college students' continuance behaviors in online fragmented learning by analyzing the contest courses on the Chinese university MOOCs platform. Discipline contests, such as national college students' mathematical modeling competitions, various challenge cups, and innovation and entrepreneurship competitions, are a series of activities to stimulate students' abilities to combine theory with practice and work independently, aiming to cultivate students' innovative spirit, team cooperative spirit, and comprehensive ability by solving practical problems [10]. Under the student-centered educational concept, undergraduate education has emerged as the cornerstone of higher education in China. Thus, undergraduate discipline competitions have garnered significant attention as a pivotal approach to fostering their comprehensive abilities, teamworking spirit, and innovative awareness. At present, several kinds of discipline competitions are held every year. Therefore, college students have a lot of opportunities to participate in various discipline competitions during their school years. However, on the one hand, a discipline competition, as a comprehensive practice link, not only evaluates students' mastery of professional knowledge and their ability to apply this knowledge but also puts forward higher requirements for students' innovative capacity, potentially encompassing interdisciplinary and even multidisciplinary knowledge [11]. Therefore, compared with regular courses, contest courses should have new characteristics, such as tailoring the course design according to the actual requirements of the competition, teaching curriculum content involving the frontiers of subject development and industry standards, ensuring the participation of students from multiple grades and majors, and requiring professional guidance from teachers, etc. However, universities typically offer limited professional contest courses, resulting in a mismatch between the curriculum teaching and the guidance of discipline competitions [11,12]. Therefore, college students must spend extra time to learn contest knowledge independently. On the other hand, the learning time of college students is scattered and fragmented due to daily courses and social activities. In this case, college students can only use their spare time to study the contest knowledge in a fragmented manner [6]. Online platforms such as the Chinese university MOOCs provide abundant online courses by fully taking into account the fragmented learning features of college students. So far, the Chinese university MOOCs provide website and mobile app access so that students can view relevant content anytime and anywhere, which has become an essential approach for students to acquire knowledge and significantly promotes online fragmented learning. However, there are few studies on the Chinese university MOOCs and online fragmented learning among college students.

Drawing on the literature on online fragmented learning and online continuous learning behaviors, we first adopt the ECM as the theoretical foundation to construct a research model to explore the antecedents of college students' CBOFL. Given that online fragmented learning is a kind of autonomous learning method, learners' intrinsic motivation impacts their continuous learning behaviors [13,14], which is crucial for sustainable learning outcomes [13]. Thus, combined with self-determination theory, we integrate intrinsic motivation learning into the ECM. In addition, we also introduce teachers' influence as an external variable to construct a research model. Then, we comprehensively analyze the determinants underlying college students' CBOFL and propose six hypotheses. Finally, using undergraduate students that have studied contest courses on the Chinese university MOOCs as the research object and 429 valid questionnaires collected from the sojump platform, a Chinese website similar to Qualtrics, we empirically test our predictions with the SEM technique with AMOS, and the results indicate that all hypotheses are supported. This study explores the influencing factors of college students' continuance behaviors in online fragmented learning from the perspective of the extended ECM and profoundly analyzes the mechanism of continuous behaviors in online fragmented learning, thus extending this line of literature on fragmented learning [6,14,15] and research on the ECM [16,17]. In addition, this study has important practical significance in guiding college students' CBOFL, which reinforces the practice of college students' continuous learning in the future and is beneficial for facilitating the sustainability of online learning. Meanwhile, it also provides policy suggestions for online platforms to optimize content and resources according to the characteristics of the fragmented learning behaviors of college students.

The remainder of this paper is organized as follows. A literature review is provided in the next section. Then, the research model is constructed, and hypotheses are developed. After that, we introduce the data collection, measurements of variables, and methodology. A section on descriptive statistics and empirical results follows this. Finally, we summarize the conclusions and provide suggestions.

2. Literature Review

2.1. Literature on Online Fragmented Learning and Its Factors

In the 1980s, studies on reading behavior focused on "fragmentation" and first proposed its concept. Fragmented learning usually refers to informal learning using fragmented time and fragmented resources [5,18], consisting of content-related and temporal aspects [19,20]. With the development of the mobile network and the popularization of mobile smart devices, online fragmented learning has become a new learning method [21]. Online fragmented learning breaks the restrictions of space and time. It makes knowledge more accessible, which enables students to use their spare time to learn anytime and anywhere according to their interests and objectives on various virtual learning platforms [21,22]. These features of flexibility and convenience not only provide opportunities for students to access high-quality educational resources from all over the world but also improve their abilities to learn independently, which is beneficial for them in establishing a lifelong learning system [5]. Online fragmented learning conforms to the development orientation of learning in the era of "Internet+", and an increasing number of students practice it. However, extant studies suggest that online fragmented learning is a "double-edged sword", because the content of online fragmented learning is incomplete and lacks summaries, and it is difficult for students to form a complete knowledge system [8]. Wang et al. [22] also indicate that fragmented learning only plays a supplemental role in formal learning for it may cause problems of distraction or lack of concentration.

Online fragmented learning as a recent phenomenon and the determinants that affect its efficiency and outcomes have been discussed in the existing literature. For example, Liang et al. [23] analyzed the features of fragmented learning behavior and considered learners' personalized learning needs to reorganize knowledge in online education. Yang et al. [5] investigated the factors influencing college students' online fragmented learning quality in four aspects: platform design, curriculum design, students' self-management, and hardware support. Song et al. [4] investigated the mediating role of the Internet on the influence of personal characteristics, learning motivation, learning, and resources' input on the learning effect. Yang [24] constructed the evaluation system for the fragmented learning effect and evaluated the impact of fragmented English learning in the mobile information environment through the integrated BPNN and genetic algorithm. Li et al. [6] found that learning motivation, self-efficacy, and fragmented time utilization influence college students' online fragmented learning effect significantly, while knowledge fragmentation has no significant impact. Recently, Zhou et al. [25] constructed a continuous intention model based on the SOR (Stimulus-Organism-Response) theory and investigated the factors influencing students' continuance intention using short videos (such as Douyin) for fragmented learning purposes.

2.2. Literature on the Determinants of Online Continuous Learning Behaviors

Existing studies have been conducted on students' online continuous learning behaviors from the perspectives of learning motivation, learning capability, self-efficacy, or attitudes [26,27]. Among these students' characteristics, motivation is the critical factor affecting willingness to continue learning. Prior studies have suggested that motivation is the driving force of learners' intrinsic behavior, which is the initial reason that affects the completion rate of MOOCs [28]. Greene et al. [29] indicated that students' expected investment in learning motivation, such as level of commitment, the expected number of hours, and the intention to obtain a certificate, are primarily related to the retention of MOOCs. Xie et al. [27] found that both intrinsic and extrinsic motivation significantly impact repeat learners in the connectionist MOOC "Internet + Education". Learning ability is also a critical determinant influencing the intention of continuance behaviors. De Freitas et al. [26] indicated that MOOC learners' learning ability dramatically impacts the quality of their course completion and learners with poor self-management ability are prone to have lower retention. Self-efficacy reflects the degree of effort in the realization of personal goals and can strengthen learners' determination to complete a task and, finally, affect their learning behaviors [30]. Additionally, Terras et al. [31] pointed out that digital literacy skills and self-regulation are also the key attributes of learners that can affect course completion rates in the context of MOOC-based learning. Meanwhile, attitude, learning styles, learning interests, and prior experience accumulation also influence learners' continuous learning intentions [32–34]. For example, Zhu et al. [35] found that college students' online learning attitudes have a significant impact on their continuous intention to undertake online courses. Wijaya et al. [34] indicated that attitudes can largely influence learners' continuous intention during this post-pandemic period.

In addition to personal characteristics, various online learning experiences also affect learners' continuous online learning behaviors in the future [35–37]. These studies have explored the significant relationships between students' flow experience, expectation confirmation, perceived usefulness, enjoyment, perceived ease of use, satisfaction with online learning, and their continuous intention to learn online [38]. For example, Guo et al. [36] investigated multiple government social media platforms drawing on the SOR theory, finding that individuals' online experiential states (i.e., flow experience and sense of belonging) positively affect their continuance intention. Huang et al. [37] indicated that course difficulty has a negative moderate effect on the relationship between course content vividness and students' intention to revisit. Joo et al. [39] demonstrated that satisfaction with the K-MOOCs significantly positively affects students' continuance intention to use them, and the perceived ease of use and the perceived usefulness indirectly affect the continuance intention to use K-MOOCs. Shanshan et al. [40] show that confirmation and perceived value can facilitate college students' experience and enhance trust and satisfaction, which significantly affects the continuous use of MOOCs. Additionally, based on the theory of exploring community, some scholars have examined the impact of teaching presence, social presence, and cognitive presence on students' continuance intention. Teaching presence refers to students' perception of teachers' presence, which directly impacts MOOC learning persistence [32]. Social presence, that is, social interaction in learning, enables MOOC learners to persist in learning, improving their grades and effectively reducing the dropout rate [29]. Other studies analyzed the factors influencing continuous learning intention from the platform's perspective and believe that the popularity and openness of the platform and course can significantly improve learners' intention to continue using MOOCs [41].

2.3. Literature on Expectation Confirmation Model

The ECM is derived from the expectation confirmation theory (ECT) and the technology acceptance model (TAM). ECT is a theory in marking, putting forward that expectation and perceived performance can result in consumers' post-purchase satisfaction [42]. Consumers' confirmation of prior purchase experience is mediating in the above relationship. The TAM is a theory of information systems, and it uses perceived usefulness and perceived ease of use as core variables to determine users' continuous intention for information systems [43]. In 2001, Bhattacherjee [44] extended the ECM into the information systems discipline and posited that the users' continuous intention of using information systems is affected by confirmation, perceived usefulness, and satisfaction (as shown in Figure 1). Specifically, confirmation of prior information system use and post-adoption perceived usefulness affect users' continuance intention of the information system, and users' satisfaction partially mediates this effect.

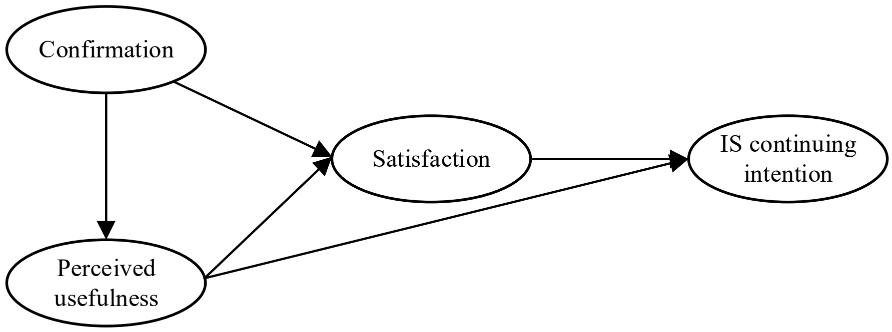

Figure 1. Bhattacherjee's ECM of information systems.

Since then, based on this model, many scholars have integrated the ECM with other models or external factors to explain the user's behavioral intention to continue using or learning. For example, Shiau et al. [45] integrated perceived enjoyment and user involvement into the continuous use model of information systems to better understand blogs' continuous use behavior. Turel et al. [46] found that trust can not only directly influence system use intentions but also has an indirect effect on the relationship with a system and its users through the promotion of social investment. Park [47] added switching costs to the ECM and demonstrated that personalization increases switching costs and satisfaction, which results in further use of SNSs. Zhao et al. [48] found that satisfaction, trust, performance expectancy, social influence, perceived task technology, and confirmation have direct or indirect positive impacts on the continuance behaviors of using FDAs during the COVID-19 pandemic period. Singh [17] employed an integrated model along with two additional constructs of perceived security and trust, indicating that satisfaction, trust, performance expectancy, and effort expectancy are critical antecedents of the continuance behaviors for mobile payment systems. Sasongko et al. [49] adopted the ECM to explain the continuance behaviors for using electronic money applications in Indonesia with significant factors involving perceived usefulness, satisfaction, and trust.

Scholars have also extended the ECM into online education and investigated the determinants of learners' continuance learning intentions/behaviors. For example, Lee [50] empirically found that satisfaction, attitude, subjective norm, perceived usefulness, and perceived behavior significantly influence users' intentions to continue using E-learning platforms. The satisfaction effect is the most significant. Chow et al. [51] indicated that both the learning process and course directly affect learners' satisfaction and continuance behavioral intention, but tutor interaction and peer interaction have no significant impact. Alraimi et al. [41] demonstrated that perceived openness, perceived reputation, perceived usefulness, and user satisfaction are the determinants that substantially influence learners' continuance intention of MOOCs. Zhou [16] found that knowledge outcome, social influence, performance proficiency, and three ECM factors, including confirmation with the prior learning experience, perceived usefulness, and satisfaction with the prior learning experience, have different predicting powers on learners' continuance behavioral intention in MOOCs for online collaborative learning.

From the extant literature mentioned above, it can be found that scholars have extensively studied the influencing factors of online fragmented learning and online continuous learning behaviors and also extended the ECM into the education field, yielding substantial findings. However, certain limitations persist. First, although prior studies have investigated the determinants of the effect or outcome of online fragmented learning from aspects of learners' characteristics, features of courses, and platforms [5,6,23,24], the antecedents of continuance behaviors in online fragmented learning have been largely ignored. Recently, fewer studies have begun to focus on the factors influencing students' continuance intention for fragmented learning purposes [25]. Still, it has not been studied in the context of online fragmented learning concerning courses of discipline contests. Second, existing scholars have explored the impacts of personal characteristics [26,27], learning experience [35–37]., and the presence of teaching, social, and cognitive factors [29,32] on the behaviors in online continuous learning and suggested that both motivation and satisfaction have the most significant impacts, and they usually appear as mediating variables. However, it remains unclear whether college students' intrinsic learning motivation and satisfaction with online fragmented learning also play an essential role in their continuous behaviors to undertake online fragmented learning. At the same time, most of the studies focus on the continuance of learning behaviors in the context of MOOCs, but few scholars empirically explore factors of college students' continuous learning behaviors in online fragmented learning. Third, extant studies have added new constructs to the original ECM, such as social influence [48], subjective norm [50], trust [46], self-efficacy, switching cost [47], perceived security [17], reputation [41], or peer interaction [51], etc., and further extended this model into mobile learning, E-learning, and online learning. However, the ECM has not been extended into studies on continuous online fragmented learning.

3. Research Model and Hypotheses

3.1. Hypothesis

3.1.1. Confirmation

According to self-determination theory, motivation contains intrinsic and extrinsic motivation [44,52]. However, the original ECM has mainly emphasized the influence of confirmation on learners' extrinsic motivation, such as perceived usefulness [53,54], primarily ignoring the impact of confirmation on intrinsic motivation. As mentioned above, online fragmented learning is a self-independent learning approach, and its behavior is driven mainly by the learner's intrinsic learning motivation [6]. During this process, confirmation can act as a role concerning the supportive condition in catalyzing and improving intrinsic learning motivation. Hence, it is reasonable to believe that confirmation can significantly influence intrinsic motivation for studying in online fragmented learning. This influence association also can be explained by the cognitive dissonance theory [44,55]. For instance, in the context of discipline contests, if college students with high initial intrinsic motivation to learn contest knowledge through the online fragmented learning approach, but their initial expectations are disconfirmed in the actual fragmented learning process, they will modify their initial perceptions to be consistent with reality. Thus, disconfirmation will weaken college students' intrinsic learning motivation; in turn, confirmation will strengthen their intrinsic learning motivation. In addition, when the expectation is effectively confirmed, college students will also be satisfied with the prior experience of online fragmented learning. Previous studies have fully demonstrated that confirmation has a significant positive impact on learning satisfaction, respectively [56,57]. Therefore, we propose the following hypotheses:

H1. *College students' confirmation significantly positivelyaffects their intrinsic learning motivation in online fragmented learning.*

H2. *College students' confirmation significantly positivelyaffects their satisfaction with online fragmented learning.*

3.1.2. Intrinsic Learning Motivation

Motivation is a core concept in social psychology, mainly manifested as a person's effort to pursue or achieve a specific goal [58]. In other words, motivation is the force that drives someone to do something. Intrinsic motivation refers to the engagement in an activity driven solely by genuine interest or enjoyment derived from performing it without any discernible external incentives [52]. Intrinsic learning motivation reflects a student's intrinsic tendency to actively learn knowledge, strengthen their abilities, and try to achieve academic goals or achievements [30]. Previous scholars have indicated that learning motivation positively influences online learning satisfaction and continuous behavioral intention. For instance, Rahman et al. [59] found that learning motivation not only directly affects online learning satisfaction but also significantly mediates the relationships between instructor–learner interaction, learner–learner interaction, Internet self-efficacyand online learning satisfaction. Xie et al. [27] found that motivation significantly affects the repeat learners of MOOCs. Therefore, when college students participate in discipline contests, if they have a stronger intrinsic learning motivation, they are more likely to make appropriate plans and make full use of the fragmented time to study independently. The high degree of autonomy and the effective utilization of fragmented time are more likely to improve students' learning efficiency and effectiveness [6,60]. Such positive feedback will, in turn, improve students' learning satisfaction [59] and increase the possibility of continuing to adopt fragmented learning methods in the future [27]. Hence, we propose the following hypotheses:

H3. *College students' intrinsic learning motivation significantly positively influences their satisfaction with online fragmented learning.*

H4. *College students' intrinsic learning motivation significantly positively affects their CBOFL.*

3.1.3. Satisfaction

Satisfaction is "a positive emotional state after a job performance evaluation is completed" [61]. According to expectation confirmation theory, continuance behavior is mainly determined by satisfaction with prior information system use [44]. In online education, previous research has also found that learning satisfaction is one of the most essential predictors among the influencing factors of continuous learning behaviors [39] and is widely used as a mediating factor [40,41]. In our study, satisfaction is defined as a favorable evaluation of college students' online fragmented learning after their knowledge requirements concerning discipline contests are met through this learning method. When college students fragmentally study contest courses on the Chinese university MOOCs, they may be satisfied with the learning process, resulting in positive emotions and attitudes, which can further encourage them continue to adopt the method of online fragmented learning; on the contrary, they will give up such learning approach and choose another one to acquire contest knowledge. Therefore, students' satisfaction directly determines their behaviors to continue online fragmented learning in the future. Consequently, we propose the following hypothesis:

H5. *The satisfaction college students gain in online fragmented learning significantly positively affects their CBOFL.*

3.1.4. Teachers' Influence

Existing studies have suggested that the opinions and suggestions of people around a person can be critical in making decisions [62]. Social influence is employed to assess the extent to which individuals perceive themselves as being influenced by their social group, which is a powerful indicator of individuals' continuance intention of using information systems [16,63]. Social influence contains two parts: external and interpersonal influences. Therein, college teachers are an essential component of college students' interpersonal influences, which can guide their thoughts and behaviors [62]. Therefore, it can be believed that teachers can positively impact college students' learning behaviors. Specifically, in the process of discipline competition, teachers are more inclined to possess a comprehensive understanding of the frontiers of subject development and industry standards, and this knowledge can effectively guide topic selection, monitor progress, and facilitate problem-solving. At the same time, college students need to interact with teachers for advice and suggestions to alleviate potential uncertainty and anxiety when they face difficulties during the period of discipline contests [64]. Hence, teachers can significantly influence students' continuous learning behaviors, thus serving as an external facilitating condition for college students' continuance behaviors in online fragmented learning. Therefore, we propose the following hypothesis:

H6. *Teachers' influence significantly positively affects college students' CBOFL.*

3.2. Model Specification

According to the proposed hypotheses and the ECM, this study develops a theoretical framework to investigate the mechanism influencing college students' CBOFL. Existing studies on continuous behavioral intention for information systems suggest that users' initial acceptance intention cannot determine their final continuous use behaviors [55,65]. Therefore, our study focuses on continuance behaviors, a sequence of repeated online fragmented learning. According to self-determination theory [53,54], motivation encompasses two distinct forms: intrinsic and extrinsic. Intrinsic motivation is the main driving force in individuals' behavior, which has a positive impact on sustainability learning [13] and can lead to better satisfaction and persistence. In the context of the discipline competition, students with intrinsic learning motivation fragmentally learn contest knowledge mainly based on their interests and different goals, such as scholarships and the opportunities to be recommended for graduate study without examination, etc. Specifically, when students have intrinsic solid learning motivation, they actively fragmentally learn contest knowledge and professional skills in their spare time. Thus, the influence of intrinsic motivation on college students' CBOFL may be more pronounced than extrinsic motivation (i.e., perceived usefulness) in the fragmented learning process [55]. Therefore, we use intrinsic learning motivation as a replacement for perceived usefulness in the original ECM. Additionally, as competition tutors, teachers possessing a comprehensive understanding of the competitions have an important impact on college students' continuous learning behaviors. Previous studies also suggest that the continuous behaviors of college students are also affected by the external environment, such as teachers' influence [62]. Overall, taking the ECM as a theoretical foundation and combining it with self-determination theory, this study integrates the intrinsic learning motivation of college students and teachers' influence as an external variable into the ECM and constructs a theoretical research model. In this model, first, confirmation is proposed to positively influence college students' intrinsic learning motivation and satisfaction obtained in online fragmented learning, and then intrinsic learning motivation is proposed to positively affect college students' satisfaction; meanwhile, both learning motivation and satisfaction are posited to directly affect college students' CBOFL. Finally, teachers' influence is posited to have a positive impact on college students' CBOFL.

Based on those mentioned above, the following model (as shown in Figure 2) is constructed:

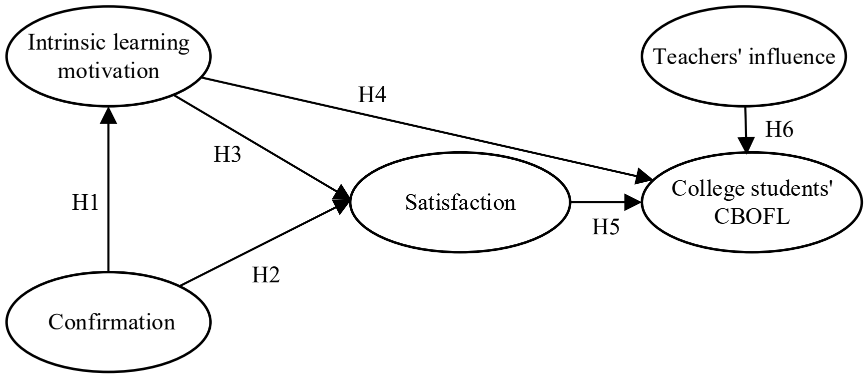

Figure 2. The extended ECM for college students' CBOFL.

4. Methodology

4.1. Constructs and Scales

Based on the research model and hypotheses proposed above, a set of scientific and reasonable questionnaires of college students' continuance behaviors in online fragmented learning of contest courses on the Chinese university MOOCs was designed. This questionnaire contains the demographic information of the survey participants and the measurement scales for crucial variables, including confirmation (CF), intrinsic learning motivation (ILM), satisfaction (SF), teachers' influence (TI), and college students' continuance behaviors in online fragmented learning (CBOFL). Table 1 shows all the variable measurement items and definitions. The options for each item included in this scale were designed in the form of a five-point Likert scale, where 1 means "strongly disagree", 2 means "basically disagree", 3 means "hard to say", 4 means "basically agree", and 5 means "strongly agree", and each respondent could only select 1 score for each item.

Table 1. Constructs, items, and sources.

Variable	Items	Resources
Confirmation (CF)	CF1: I gained an experience that exceeded my expectations through the fragmented learning of contest courses on the Chinese university MOOCs. CF2: I gained more knowledge than expected through the fragmented learning of contest courses on the Chinese university MOOCs. CF3: My expectations have been met through the fragmented learning of contest courses on the Chinese university MOOCs.	Bhattacherjee [44] Bhattacherjee et al. [66] Dai et al. [67] Hu et al. [57]
Intrinsic learning motivation (ILM)	ILM1: I want to use fragmentation time to learn contest knowledge on the Chinese university MOOCs. ILM2: I hope to improve my level of competition through the fragmented learning of contest courses on the Chinese university MOOCs. ILM3: I hope to acquire relevant knowledge through the fragmented learning of contest courses on the Chinese university MOOCs and apply them in practice. ILM4: I hope to finish my homework without supervision and achieve a good learning effect.	Rafiola et al. [30] Xie et al. [27]

Table 1. *Cont.*

Variable	Items	Resources
Satisfaction (SF)	SF1: I am satisfied with learning contest courses and acquiring knowledge on the Chinese university MOOCs. SF2: I am happy with the process of learning contest courses and acquiring knowledge on the Chinese university MOOCs. SF3: I enjoy the process of learning contest courses and acquiring knowledge on the Chinese university MOOCs. SF4: I am satisfied with my experience learning contest courses on the Chinese university MOOCs.	Bhattacherjee [44] Hu et al. [57] Dai et al. [67]
Teachers' influence (TI)	TI1: Teachers' experience of fragmented learning contest courses on the Chinese university MOOCs will affect my willingness to use it. TI2: Teachers' advice will affect my willingness to participate in fragmented learning contest courses on the Chinese University MOOCs. TI3: I will try to use it if teachers suggest that it's an excellent way to learn contest courses by fragmented learning on the Chinese university MOOCs.	Venkatesh et al. [68] Liu et al. [62]
College students' continuance behaviors of online fragmented learning (CBOFL)	CBOFL1: In the past month, I have often learned contest courses in a fragmented manner on the Chinese university MOOCs. CBOFL2: In the past month, I have learned contest courses in a fragmented manner on the Chinese university MOOCs almost every week. CBOFL3: In the past month, I have learned contest courses in a fragmented manner on the Chinese university MOOCs with a relatively high frequency. CBOFL4: In the past month, I have devoted a lot of time to learning contest courses in a fragmented manner on the Chinese university MOOCs.	Bhattacherjee et al. [66]

4.2. Data Collection

Currently, most Chinese colleges have formulated the classification or level of discipline competitions based on their educational level and discipline situation. The classification basis is mainly determined by organizers, and these classifications contain A, B, and C competitions at international, national, provincial, and university levels. College students can participate in competitions for different disciplines according to their abilities and interests. Undergraduate education is the main body of higher education in China, and discipline competitions of undergraduate students also receive the most attention. Therefore, this study only focuses on undergraduate students' continuance behaviors in online fragmented learning by empirically analyzing the contest courses on the Chinese university MOOCs. We conducted an online survey through sojump.com, accessed on 10 February 2024. After completing the pre-survey and verifying its reliability, we distributed questionnaires to undergraduate students who have studied contest courses on the Chinese university MOOCs platform. We informed them that all data collected are only used for academic research, and the privacy information of all participants will be well protected. To ensure the appropriateness of data collected, we took further precautions as follows: First, to check whether the college student had actual experience with fragmented learning contest courses on the Chinese university MOOCs or not, we added the question "Have you used or are you currently using a Chinese university MOOC platform to study contest courses in a fragmented manner?" Second, each IP address was allowed to appear only once. Third, the records were deleted if the answer time is too short or if all the answers were consistent. Under the assurance of these processes, 429 valid samples were finally collected. Among these samples, the proportions of males and females are 36.4% and 63.6%, respectively, and the percentage of students in their first year only accounts for 6.5%, indicating that students participating in discipline competitions are senior undergraduates.

5. Results

5.1. Reliability and Validity Tests

This study uses convergent and discriminant validity to test the scale's reliability and validity; the former is tested by explorative factor analysis, and the latter is tested by confirmative factor analysis. We use SPSS 26.0 and AMOS 24.0 to conduct all the analyses. The value of the Bartlett sphericity test is 0.906, and the statistic of the KMO (Kaiser–Meyer–Olkin) test is 4111.143, which is significant at a 1% level, indicating that the questionnaire data collected meet the requirements of factor analysis and are suitable for analyzing the influence relationship between variables [69].

5.2. Explorative Factor Analysis

In the results of the explorative factor analysis, the cumulative variance of the first five factors reaches 68.72%. As shown in Table 2, all the item loadings are greater than the values in their irrespective factors. The factor loading of each item is greater than 0.5, indicating that the convergent validity of this scale constructed in our study is good [70]. These results suggest that this scale can be used to measure and analyze the determinants of college students' CBOFL.

Table 2. Rotated factor loading matrix for explorative factor analysis.

Items	Factor1 CF	Factor2 ILM	Factor3 SF	Factor4 TI	Factor5 CBOFL
CF1	0.767				
CF2	0.692				
CF3	0.725				
ILM1		0.687			
ILM2		0.743			
ILM3		0.696			
ILM4		0.762			
SF1			0.748		
SF2			0.725		
SF3			0.692		
SF4			0.679		
TI1				0.726	
TI2				0.802	
TI3				0.608	
CBOFL1					0.669
CBOFL2					0.718
CBOFL3					0.751
CBOFL4					0.734

5.3. Confirmative Factor Analysis

The Cronbach's alpha is 0.896, indicating that the reliability of this questionnaire is good enough and the data are appropriate for factor analysis. Table 3 demonstrates the results of the confirmative factor analysis. The values of the composite reliability (CR) of each dimension are greater than 0.7, and the values of the average variance extraction (AVE) for each dimension are greater than 0.5 [70], indicating that this questionnaire has good convergent validity.

Table 3. Confirmative factor analysis and test results.

Variables	Items	Std. Factor Loading	CR	AVE
CF	CF1 CF2 CF3	0.759 0.693 0.821	0.803	0.577
ILM	ILM1 ILM2 ILM3 ILM4	0.701 0.773 0.679 0.792	0.826	0.544
SF	SF1 SF2 SF3 SF4	0.768 0.731 0.760 0.743	0.838	0.563
TI	TI1 TI2 TI3	0.713 0.661 0.782	0.763	0.519
CBOFL	CBOFL1 CBOFL2 CBOFL3 CBOFL4	0.801 0.786 0.734 0.702	0.842	0.573

The judgment of discriminant validity can be carried out by comparing the square root of the AVE value and variables with the absolute value of the correlation coefficient between variables. If the square root of the AVE values is greater than the correlation values, then discriminant validity is high [70]. As shown in Table 4, the values of the AVE square root are on the dialog line, while the values of correlations between different variables are on the non-dialog line. From these results in Table 4, it can be found that the correlation values between any two variables are less than the square root of the AVE values, indicating that our questionnaire meets the requirements for discriminant validity.

Table 4. Discriminant validity test results.

Variable	CF	ILM	SF	TI	CBOFL
CF	**0.760**				
ILM	0.448	**0.738**			
SF	0.624	0.634	**0.750**		
TI	0.355	0.536	0.497	**0.720**	
CBOFL	0.639	0.598	0.641	0.496	**0.757**

Note: The diagonal numbers in bold are the values of the square root of the AVE.

5.4. Hypotheses Testing

5.4.1. Fitness Indices

The fitness should be tested when a structural equation model is built [16]. According to previous studies, the χ^2/df should range from 1 to 3, and the reasonable level of RMSEA is less than 0.08 [71]. Additionally, the values of GFI, CFI, and NFI should be greater than 0.9 [72]. As indicated in Table 5, the value of χ^2/df is 2.759, the value of RMSEA is 0.064, and the values of CFI, GFI, and NFI, are 0.944, 0.924, and 0.915, indicating that all these fitness indices are at an acceptable level. Therefore, the structural model has good fitness.

Table 5. Fitness test of the model.

Indicators	χ^2	df	χ^2/df	RMSEA	CFI	GFI	NFI
	353.197	128	2.759	0.064	0.944	0.924	0.915

5.4.2. Regression Results

Figure 3 is the structural equation model with standardized coefficients of the determinants of college students' CBOFL, and Table 6 is the results of the structural model assessment. From Figure 3 and Table 6, it can be found that the significance level of each path in the research model is relatively good, and except for the path CBOFL ← TI, which is significant at the level of 5%, all other paths are significant at the level of 1%. First, confirmation has a significant positive effect on intrinsic learning motivation ($\beta = 0.445$, $p < 0.01$) and satisfaction ($\beta = 0.558$, $p < 0.01$); thus, H1 and H2 are tested. Second, intrinsic learning motivation significantly positively affects satisfaction ($\beta = 0.525$, $p < 0.01$) and college students' CBOFL ($\beta = 0.166$, $p < 0.01$); hence, H3 and H4 are supported. Third, the relationship between satisfaction and college students' CBOFL is significant and positive ($\beta = 0.734$, $p < 0.01$); therefore, H5 is held. Fourth, the influence of teachers on college students' CBOFL is significantly positive ($\beta = 0.214$, $p < 0.05$); consequently, H6 is verified. In addition, in terms of the degree of impact, satisfaction has the most significant effect on college students' CBOFL, and there are large differences in the degree of influence among other variables.

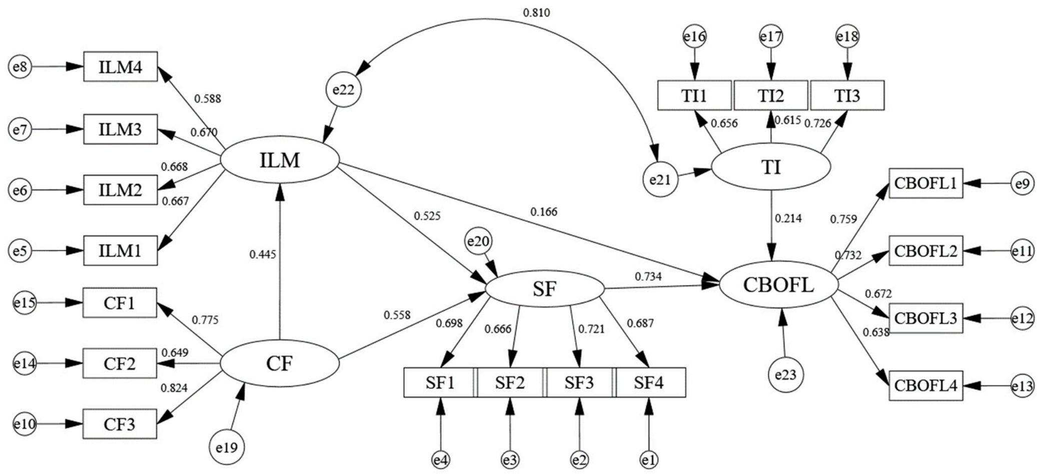

Figure 3. Structure equation model of the standardized coefficients for college students' CBOFL.

Table 6. Hypotheses testing results of college students' CBOFL.

Hypotheses	Path	Std. Regression Weights	S.E.	t	*p*	Results
H1	ILM ← CF	0.445	0.045	7.800	***	Support
H2	SF ← CF	0.558	0.050	9.952	***	Support
H3	SF ← ILM	0.525	0.068	8.432	***	Support
H4	CBOFL ← ILM	0.166	0.046	3.935	***	Support
H5	CBOFL ← SF	0.734	0.082	10.170	***	Support
H6	CBOFL ← TI	0.214	0.102	2.252	0.024 **	Support

Note: *** indicates a significance level of 1%; ** indicates a significance level of 5%.

6. Discussions and Conclusions

6.1. Discussions

This study verifies the research model of college students' CBOFL from the extended ECM perspective with questionnaire data analysis. This model has the following innovations. First, compared with prior studies constructing a theoretical research model based on the ECM [17,48,50,51], this study combines self-determination theory and integrates intrinsic learning motivation in the ECM by highlighting the self-independent learning characteristics of online fragmented learning. In addition to considering the impact of factors in the original ECM, we also took into account the influence of external factors. By doing this way, it can expand the explanatory power and scope of application of the ECM in the field of online fragmented learning. Second, this research model investigates the antecedents of college students' CBOFL and their mechanisms, extending the stream of literature on online fragmented learning [4,6,24,25]. The results can provide an academic reference for guiding the promotion of college students' CBOFL and the formation of their online fragmented learning habits in the future. From the empirical results, we find the following:

Confirmation has a significant positive impact on college students' satisfaction and learning motivation. As for the relationship between confirmation and satisfaction, it is consistent with the hypothesis in the original ECM [43,44]. It indicates that when the expected benefits of fragmentally learning contest courses on the Chinese university MOOCs are realized, that is, the expectation has been confirmed, college students will be satisfied with the prior experience of online fragmented learning. However, disconfirmation (the perception of performance falling short of expectations) signifies a failure to meet the anticipated outcome, and there will be less satisfaction. In addition, the association between confirmation and learning motivation is consistent with previous studies [55,56]. It shows that college students may experience cognitive dissonance if their initial intrinsic motivations to learning contest knowledge are not confirmed during the actual process of online fragmented learning. Rational students may try to remedy this dissonance by modifying their initial perceptions to be more consistent with reality. As a result, college students' intrinsic learning motivation will be decreased, and on the contrary, confirmation will reinforce intrinsic learning motivation.

Intrinsic learning motivation significantly positively influences satisfaction and college students' CBOFL. It demonstrates that, in our extended model, intrinsic learning motivation can contribute to whether a college student would be satisfied with the prior experience of online fragmented learning and be inclined to repeatedly adopt this learning approach. Intrinsic learning motivation as an intrinsic tendency can ensure the sustainability of learning [73] and can serve as a pivotal catalyst for fostering college students' autonomous learning, enhancing their concentration and enthusiasm towards continuous learning [30,56]. Therefore, intrinsic learning motivation cannot be ignored when investigating continuous online fragmented learning behaviors. When designing an online contest course, intrinsic motivation, rather than extrinsic motivation (i.e., perceived usefulness), will also be a new factor that should be focused on, which is critical to facilitate the sustainable development of online learning. Thus, the extended ECM could provide a better understanding of college students' continuous fragmented learning behaviors than the original ECM.

Satisfaction and teachers' influence positively affect college students' CBOFL. Regarding the relationship between satisfaction and college students' CBOFL, it is also consistent with the hypothesis in the original ECM [43,44], and satisfaction has the most significant impact. It indicates that college students' CBOFL is mainly determined by satisfaction. Suppose college students believe that fragmented learning contest courses via the Chinese university MOOCs can improve their knowledge scope, help them to acquire the necessary knowledge, and satisfy them with prior experience. In that case, these positive feelings will make them choose to continue to learn in a fragmented manner. Concerning the relationship between teacher influence and college students' CBOFL, the result aligns with the positive outcomes reported in previous studies [16,48]. Teachers can guide discipline contests and help students organize fragmented knowledge more effectively, which makes it easier to form a complete and comprehensive knowledge structure. Therefore, when teachers encourage students to carry out continuous online fragmented learning behaviors, this will arouse students' confidence in continuous online fragmented learning.

6.2. Conclusions

This study holds that the influence mechanism of college students' CBOFL is that, before implementing behaviors of online fragmented learning, college students have certain expectations. After implementing behaviors of online fragmented learning, college students will evaluate whether their expectations can be achieved. The confirmed expectation will further influence their intrinsic learning motivation and learning satisfaction. Finally, college students consider continuance behaviors in online fragmented learning together through intrinsic learning motivation and satisfaction. At the same time, the teachers' influence is an important external variable [16,48], emphasizing that external factors also play a critical role in college students' CBOFL. Based on the ECM, considering the influence of intrinsic motivation and introducing the external variables of teachers' influence, this study explores the influencing factors of college students' CBOFL by taking the contest courses on the Chinese university MOOCs as an example. Using 429 valid samples and adopting the SME technique with AMOS, the six hypotheses proposed before are tested. Based on the above analysis, the following conclusions can be drawn. First, all hypotheses proposed before are supported, and college students' satisfaction with their contest courses learning on the Chinese university MOOCs is related to two critical factors, i.e., their confirmation and intrinsic learning motivation. Second, the predicting powers of different factors on college students' CBOFL are largely distinct, and satisfaction has the most significant effect. Third, the extension of the ECM in this study is successful, and the constructed research model is verified.

6.3. Theoretical Contributions

This study makes the following significant theoretical contributions. First, prior studies have integrated the ECM with other models or factors, i.e., social influence, subjective norm, trust, self-efficacy, switching cost, perceived security, reputation, or peer interaction, etc., and further extended this model into the field of mobile learning, E-learning, and online learning to explain the learners' behaviors to continue using or learning [16,41,45,49]. This study enriches this line of the literature by integrating intrinsic motivation and teachers' influence into the ECM and extending the research of online fragmented learning in the context of the Chinese university MOOCs. Due to fragmented learning belonging to a kind of self-directed learning method, intrinsic learning motivation is an important factor driving continuous behaviors [28,29]. In addition, teachers' influence is an important external factor that can significantly affect college students' continuous behaviors [51,66]. Therefore, we consider the influence of college students' learning motivation and integrate teachers' influence into the ECM as an extension. The empirical results show that all the hypotheses are supported, indicating that the extension of the ECM is successful, thereby expanding the explanatory power and scope of application of the ECM.

Second, previous studies have explored the determinants of the efficiency and outcomes of online fragmented learning, such as learners' personalized learning needs [23], platform design, curriculum design, students' self-management and hardware support [5], learning motivation and resources' learning input [4], self-efficacy, fragmented time utilization, and knowledge fragmentation [6]. However, these studies have not investigated the factors influencing continuance behaviors in online fragmented learning. Thus, this study extends this stream of the literature by exploring the antecedents of college students' CBOFL in the context of MOOCs from an extended ECM perspective. The empirical results indicate that different determinants have different predicting powers, and satisfaction is the first powerful indicator of college students' continuance behaviors in online fragmented learning, followed by teachers' influence and learning motivation. This study also complementsprior studies that have only emphasized that satisfaction or perceived reputation has the most significant impact on learners' continuance behaviors [41,50].

6.4. Practical Implications

Online fragmented learning is a new phenomenon that emerged with the development of Internet technology and the digital era [5,8]. For college students, online fragmented learning has become a mainstream trend, an indispensable part of their learning life, and the key to cultivating their lifelong learning ability. However, online fragmented learning is a double-edged sword, and college students should give full play to its advantages and overcome its disadvantages so that they can update their knowledge structure and keep up to date with the times through continuous online fragmented learning [8]. Therefore, according to the conclusions, this study puts forward suggestions from three aspects of learning motivation: teachers' guidance role, platform course quality to promote college students' CBOFL, and the facilitation of the sustainable development of online learning.

First, boost students' intrinsic learning motivation and enhance their enthusiasm for online fragmented learning.

(1) Precisely clarify learning objectives. The discipline competition is a team project that ultimately achieves the team goal through the efforts of each member [12]. Thus, it is imperative to clearly define both the team goal and each member's learning task, such as striving for outstanding achievements or attaining a specific ranking, which enables each student to engage wholeheartedly in various learning activities related to the contests. Doing this will facilitate their professional skill improvement and elevate their overall proficiency level, thereby stimulating intrinsic motivation to attain their desired goals effectively.

(2) Breaking down the learning task. The composition of team members often encompasses students from diverse disciplinary backgrounds, resulting in significant variations in their abilities and interests. Thus, teams should break down the overall learning task into manageable parts and develop reasonable plans. The task should be assigned to each student based on their strengths and abilities, thus improving their learning interests. Finally, teams need to transform individual contributions from "zero deposit" into a collective withdrawal that accumulates into comprehensive competition works [6]. In addition, each member should make a detailed timetable and schedule tasks to improve efficiency and quality in online fragmented learning.

(3) Attach the importance of collaborative teamwork and cooperation in online fragmented learning. It can be fostered to lead toward collective progress through ideological collisions, mutual learning experiences, and communication inspiration among members. The interactive reconstruction of fragmented knowledge can promote comprehension of competition-related content while providing a sense of achievement that ultimately enhances intrinsic motivation for online fragmented learning [7].

Second, give full play to the guiding role of teachers and improve students' self-confidence.

(1) Grasp the topic selection of the contests. It is imperative for college teachers to actively engage in the guidance activities of contests and provide students with direction in selecting their projects. Given that the participants are primarily senior students, who may lack a comprehensive understanding of cutting-edge developments within their discipline and practical challenges before completing their professional courses, teachers should guide the topic selection when college students prepare to take part in a contest [10].

(2) Strengthen the supervision of learning progress and improve students' ability to manage fragmented time. Once the fundamental content or direction of the project has been determined, students should be encouraged to conduct independent and thorough research on the topic during their spare time by utilizing online fragmented learning methods. In this process, teachers can stimulate critical thinking through questioning techniques and prompt students to search for and learn relevant knowledge about specific problems using online fragmented learning resources [62].

(3) Help college students build the knowledge system and form a complete theoretical framework. Teachers need to assist students in screening, integrating, and recon-

structing acquired knowledge while assisting students in establishing a complete system that aligns with technical schemes proposed for their projects throughout the process of online fragmented learning. In addition, teachers should provide emotional support for college students and alleviate their anxieties about online fragmented learning, thus, finally, enhancing their learning confidence.

Third, optimize the design of contest courses to improve college students' expectations and learning satisfaction.

(1) Focus on the practicability of the contest course content. In the process of learning competition courses, students are more inclined to enroll in courses that offer practical applications for competitions, thereby helping them translate theoretical knowledge into practice. Therefore, the online learning platforms should provide more practical contest courses and provide more effective information screening and resource acquisition strategies so that students can easily find relevant content [16]. Simultaneously, attention should be given to the level of difficulty and engagement factor of the course content to improve college students' expectations and enhance their satisfaction.
(2) Utilize emerging technologies to develop personalized learning plans. Online platforms can deploy AI algorithms on applications to adjust content dynamically based on students' learning objectives, pace of learning, and the relevance of their existing knowledge. To do so, college students can also benefit from a highly personalized learning experience that enhances their overall satisfaction with online fragmented learning, which guarantees their continuous behaviors in online fragmented learning.
(3) Provide evaluation of learning outcomes. After learning specific contest knowledge, college students can use the evaluation system to practice and test their knowledge mastery. It not only facilitates students' reflection and summarization but also enables the evaluation of knowledge coherence and comprehensibility, thereby establishing a personalized learning system, which improves their learning effects in the whole process of online fragmented learning.

6.5. Limitations and Future Research

This study also has several shortcomings that might provide ideas for future research. First, our study adopts the ECM as the theoretical foundation to explore the influencing mechanism of college students' CBOFL and uses questionnaires to collect data and the SEM to conduct an empirical analysis. However, this study does not further investigate the effect of college students' CBOFL. In future studies, scholars can examine how factors in the ECM, intrinsic learning motivation, and CBOFL affect the effect of college students' CBOFL. In this way, we can better explore the factors that affect the ultimate learning outcomes in continuous online fragmented learning, which helps students achieve better-fragmented learning performance. Thus, it can better promote research on online fragmented learning, as well as the sustainability of online learning. Second, we focus on the Chinese university MOOCs platform when investigating college students' CBOFL. When college students participate in discipline competitions, they can not only fragmentally learn contest knowledge from Chinese university MOOCs platforms but also acquire relevant knowledge from other online platforms, such as Bilibili and Douyin. Therefore, future research can analyze and compare the differences concerning college students' CBOFL among different platforms. By conducting in this manner, we can explore which platform is more effective in fostering continuous fragmented learning behaviors among college students and offer insights for other platforms.

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