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The Relationship between the Dissemination Mode of Live Courses on Online Education Platforms and Learners' Interactive Behavior: Taking "MOOC" as an Example

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Abstract: The bottleneck of existing research is that the deep interaction mechanism in the MOOC platform is imperfect, which makes it difficult to effectively promote learners' active participation and improve learning outcomes. This paper aims to deeply analyze how interactive design affects learners' engagement and learning outcomes by studying the relationship between the interactive mode of live courses in the MOOC platform and learners' interactive behavior. First, the Flanders Interaction Analysis System is used to code and quantify the teacher-student interaction behaviors in the live courses. Then, the interaction between teachers, teaching assistants, and "passers-by" in the live courses is observed in real time to capture the verbal communication and interaction methods in the classroom. Secondly, combining learner behavior data and learning feedback, regression analysis method is used to quantify the relationship between interactive behavior and learning effect, and to explore the correlation between learner behavior patterns and learning performance. Finally, the experiment takes multiple MOOC live courses as the subjects, and through comparative analysis of the impact of different interactive design strategies (such as interaction frequency, interaction form, interactive content, etc.) on learners' deep engagement, learning motivation and learning outcomes, puts forward effective interactive design optimization suggestions. Experimental data show that there is a significant positive correlation between deep interactive behavior in MOOC live courses and learners' participation and learning outcomes. The data also show that appropriate incentive mechanisms, such as interactive rewards and immediate feedback, can help further enhance learners' deep participation and enthusiasm.

1. Introduction

There is still a lack of research on the specific effects and influencing mechanisms of interactive behaviors in MOOC live courses, and the importance of interactive design in online education is becoming increasingly prominent. To this end, this paper takes MOOC live courses as the research background and discusses the impact of interactive design on learners' behavior, learning motivation and learning outcomes. Specifically, through designing experimental research and data analysis, this paper verifies the effectiveness of different interactive designs, and provides systematic suggestions for the optimization of MOOC interactive design from both theoretical and practical levels, in order to provide a reference for the construction and development of online education platforms.

First, the introduction section summarizes the interactive issues in MOOC teaching and their research significance; then, the related research section reviews the research progress in the field of online learning interactive behavior and learning effects at home and abroad; the research design is then introduced in detail in the research methods section, including variable settings, experimental grouping, and coding and analysis methods of interactive behaviors; in the results and discussion section, the impact of interactive design on learners' behaviors, motivations, and learning outcomes is demonstrated through data analysis and visualization, and an in-depth discussion is conducted; finally, the research findings are summarized and suggestions for optimizing the interactive design of MOOC live courses are put forward.

2. Related Works

Interaction and learning behavior in online learning environments have always been the focus of research. Many scholars have explored the impact of learners' behavior, motivation, self-efficacy and other factors on learning outcomes in online learning from different perspectives. The following are research results in related fields: Based on social cognitive theory, Khan et al. explored the impact of learner initiative on online interaction and social capital. The results showed that learners' active participation helps expand their social network through online interaction, thereby enhancing their social capital [1]. Keskin et al. aimed to develop a scale to measure the level of social anxiety in online learning environments. They conducted exploratory factor analysis, confirmatory factor analysis, and convergent and discriminant validity tests to design a social anxiety scale suitable for online learning environments [2]. Baba Rahim explored the moderating role of self-efficacy in the relationship between online teaching ability and student engagement. The data results showed that the relationship between online teaching ability and student engagement was moderated by self-efficacy [3]. Quadir et al. developed a blog learning platform called "Learner' s Digest Blog" (LDB) to promote interaction among learners, between learners and teachers, and between learners and content, thereby improving learning outcomes. The results showed that interaction between learners and interaction between learners and content had a significant impact on subjective learning outcomes[4]. Lee et al. developed a STEM (Science, Technology, Engineering, and Mathematics) learning behavior analysis system, which uses deep learning to evaluate learner behavior in STEM education and adopts the ICAP (Interactive, Constructive, Active, Passive) framework to map the behavior to help teachers better understand the learning process [5]. Yousef & Khatiry explored the application of behavioral and cognitive learning analytics dashboards. The results showed that behavioral dashboards are superior to cognitive dashboards in data evaluation, while cognitive dashboards are more advantageous in improving learning awareness, self-reflection, and learning process[6]. Lee et al. applied learning analysis methods (k-means clustering, data visualization) to analyze the behavioral patterns of 227 junior high school students in an interactive online algebra game, such as the number of questions completed, questions reset, questions retried, and the pause time before the first operation, and explored the relationship between these behaviors and the understanding of mathematical equations [7].

Martin & Borup combined the research of educational technology, educational psychology and learning science to propose a new perspective to redefine online learner engagement, emphasizing the cognitive, emotional and behavioral dimensions of learner engagement and the influence of their environment [8]. Barut Tugtekin & Dursun aimed to develop and validate a single-use instructional materials motivation scale for the Turkish context. Through a two-stage validation with 1,654 students, they discovered that the 14 items on the scale had good fit and high reliability (Cronbach's α=0.95). The findings demonstrated that while interactive video materials increased external cognitive strain, animation and interactive video materials did not significantly increase cognitive burden [9]. Toscu et al. investigated the interaction in university-level online English as a Foreign Language (EFL) courses. Through the analysis of recordings of seven different teachers' online EFL sessions, they discovered that teachers interacted with students more frequently and spoke more continuously in online classrooms [10]. Lai et al. analyzed the interaction patterns in online English classes in universities and found that there was more interaction between teachers and students than between students, and that teachers spoke more continuously while students' speeches were usually briefer. They also pointed out that group activities were less than individual activities, classroom content was mainly teaching-oriented, and teachers' language was highly disciplined [11]. Spain et al. explored the use of reinforcement learning to provide learners with personalized adaptive tutoring and optimize cognitive engagement based on an interactive, constructive, active, and passive framework [12]. Lan et al. aimed to explore whether online communities combined with contractual learning can enhance students' learning motivation, promote self-regulated learning, and improve academic performance [13]. Existing research mainly focuses on certain single dimensions (such as learner behavior, interaction patterns, learning motivation, etc.), and lacks comprehensive cross-dimensional analysis.

3. Methods

3.1 Problems in Current Research

Through a detailed analysis of relevant research fields at home and abroad, it can be found that many scholars have made meaningful progress in this field, and their research results have provided impetus for the development of this direction. However, there are still some deficiencies in learning behavior analysis, fatigue state analysis and performance prediction in multi-objective learning environments.

The diversity of online learning platforms (such as XuetangX, China University MOOC, etc.) and their course designs and activities leads to large differences in the course activities engaged in by learners on different platforms. These differences may have a certain impact on subsequent research. Therefore, this topic proposes a more suitable solution to this problem, which is to conduct a quantitative analysis of the course behaviors generated by learners when interacting with the system. At the same time, the behavioral indicators based on learner behavior data used in existing research fail to reasonably and effectively reflect the learner's behavioral state and cannot fully reflect the learner's learning input, behavioral preferences and other characteristics.

3.2 MOOC

Massive Open Online Course (MOOC) is a massive open online course that provides open and free educational resources to learners around the world through the Internet. The characteristics of MOOC include rich course content, flexible learning methods, a wide range of participants, and autonomous learning progress. As a powerful supplement to the traditional education model, MOOC breaks through the limitations of time and space and provides learners with a personalized learning experience. However, the teaching effectiveness of MOOC depends largely on the initiative and participation of learners, which poses new challenges to course design and teaching methods.

3.3 Research Process

3.3.1 Coding and verification of teacher-student interaction behaviors

First, the coding system of iFIAS was improved and perfected according to actual needs. The coding system includes teacher speech, learner speech, silent speech and technical speech. The live broadcast model breaks through the traditional teaching method of "one person speaking", and the subjects interacting with it are also expanded to real native Chinese speakers (such as passers-by). During the teaching process, passers-by play a key role. With the help of the main teacher and the teaching assistant, they communicate with learners about a certain topic or issue, play the role of a teacher, and practice dialogue with learners. At the same time, they can also share some of the work of the main teacher and the teaching assistant to enhance the authenticity of classroom communication. Due to the influence of factors such as region, occupation, age, etc., there are certain differences in pronunciation, intonation, speaking speed, and word choice among the speakers. Therefore, the corpus of this study can make teaching more authentic, more natural, more open, and more uncertain. This paper divides "teacher speech" into three types: lecturers, teaching assistants, and conversations with passers-by.

3.3.2 Setting teaching content

With "Obstetrics and Gynecology Nursing" as the main teaching content, "pregnant women" as the research object, and life cycle health management as the guiding ideology, an educational resource library based on "health and nursing" as the core content was constructed and developed. This course is divided into five parts: basic knowledge of the anatomy and physiology of women's reproductive organs, pregnancy physiology, pregnancy health care and nursing, factors affecting fertility, and nursing for natural childbirth. The course lasts for 8 weeks. According to the teaching characteristics of MOOCs, the course content is divided into 32 segments, and the average length of each video is (13±5) minutes. The recording methods include video recording of lectures in the studio and video recording of live demonstrations. In addition, this course also provides classroom exchange forums, unit quizzes, homework and the latest literature reading.

3.3.3 Flanders interactive analysis system

In the introduction of the Flanders system, four parts are explained, including the concept of the Flanders system, the current status of research at home and abroad, the demonstration advantages of the system, and the composition of the system. Based on the perspective of teacher-student behavior, this system analyzes the impact of interactive behaviors in the classroom on students and establishes a behavioral chart between teachers and students. In order to better reflect students' classroom interaction behaviors, observers are required to record the interaction behaviors between students within a certain period of time (3 seconds) (every 3 seconds). The precise time unit improves the accuracy of the system in recording classroom interaction behaviors, and records them in the form of code for statistical analysis.

4. Results and Discussion

4.1 Experimental Design and Grouping

In order to study the impact of interactive design on learner behavior and learning outcomes, this study adopted a controlled experimental design. The experimental subjects were learners in multiple

MOOC live courses, and they were divided into the following groups according to different interactive design strategies:

High interaction group: The interaction frequency is high, teachers and teaching assistants actively participate in course discussions and respond to learners' questions in a timely manner, and adopt real-time feedback and interactive reward mechanisms.

Low interaction group: The interaction frequency is low, mainly one-way explanation by the teacher, learners have few questions and discussions, and feedback is delayed.

Control group: The interaction design is consistent with the standard course, and there is no obvious adjustment in the frequency and form of teacher-student interaction in the classroom.

The number of learners in each group was equal, and a preliminary survey was conducted before the experiment to ensure that the initial levels of learners in each group were similar. The experiment lasted for 8 weeks, the same as the course. Learners in each group participated in the course through an online platform. The course content and activity arrangement were exactly the same, with the only difference being the interactive design.

4.2 Data Collection and Analysis

Before the experiment began, baseline measurements of learning motivation and academic performance were first taken for the 10 students in each group. Subsequently, an interactive design intervention is carried out for a period of time (such as a course learning cycle), during which data such as the students' interaction frequency and participation in learning activities are continuously collected. After the intervention, post-measurements were conducted on the five participants in each group to assess changes in their learning motivation, academic performance, and other aspects, providing a basis for data comparison and analysis.

In order to better understand the impact of interactive design on students' learning outcomes, this paper analyzed the experimental data of the high-interaction group, low-interaction group and control group, and evaluated the changes in learning motivation, self-efficacy, academic performance and other aspects. Next, we will analyze the impact of different interactive designs on students' learning motivation, academic performance and other learning effect indicators through specific data presentation.

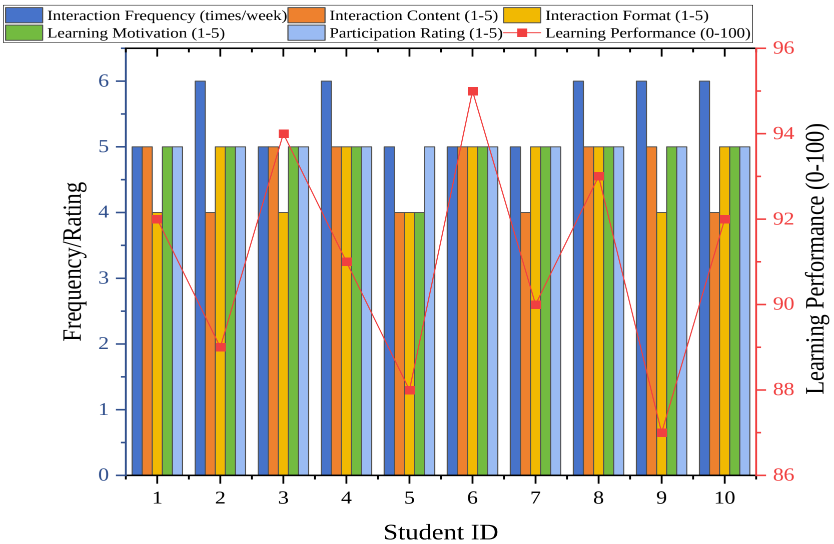

Figure 1. Learning frequency and performance of the high interaction group

In the experimental data, learners in the high-interaction group show significantly higher engagement. Specifically, the average weekly interaction frequency of the high-interaction group is 5 times, the ratings of interaction form and content are generally high (all between 4 and 5 points), and the engagement score reaches the highest value of 5. The students in the high-interaction group show active participation in discussions, asking questions, and receiving feedback, indicating that they are more proactive and interactive in the course, which is closely related to their higher academic performance and learning motivation. In terms of academic performance, the students in the high-interaction group perform best overall, with an average score of more than 90 points. High-interaction design effectively stimulates students' learning motivation and interest through frequent interactions, rich interactive forms and content, thereby improving their academic performance. The study found that the increase in interaction frequency and content is positively correlated with learning performance. In particular, when the interaction frequency reaches more than 5 times, the students' learning performance is generally higher than 80 points, and most students' scores are above 85 points, as shown in Figure 1.

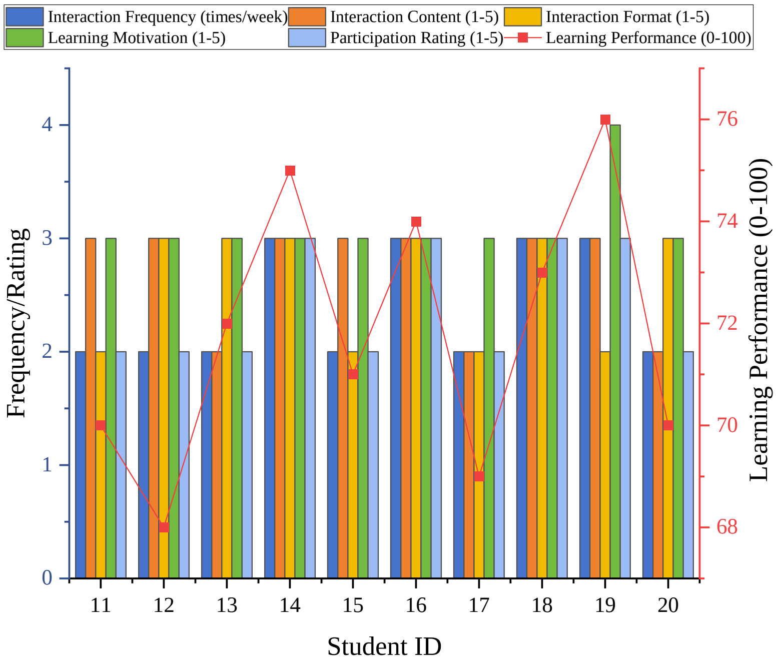

Figure 2. Study frequency and performance of the low interaction group

In contrast, the low-interaction group has significantly lower participation. The interaction frequency of the low-interaction group is only 2-3 times per week, the interaction form and content are rated low (mostly 2-3 points), and the participation rating is generally low (2-3 points). The specific data is shown in Figure 2. These students are usually limited to passively accepting teaching content and lack active classroom participation. These differences may be the main reason for the generally lower academic performance and learning motivation of students in the low-interaction group. Students in the low-interaction group generally have lower grades, with an average score of between 70 and 75 points. The low frequency of interaction and simple interaction design (for example, the scores of interaction content and form are generally below 3 points) lead to insufficient learning motivation of students, thus affecting their learning performance. The poor learning performance is closely related to the limitations of low-interaction design, indicating that a low-interaction learning environment is difficult to effectively stimulate students' learning interest and improve their learning performance.

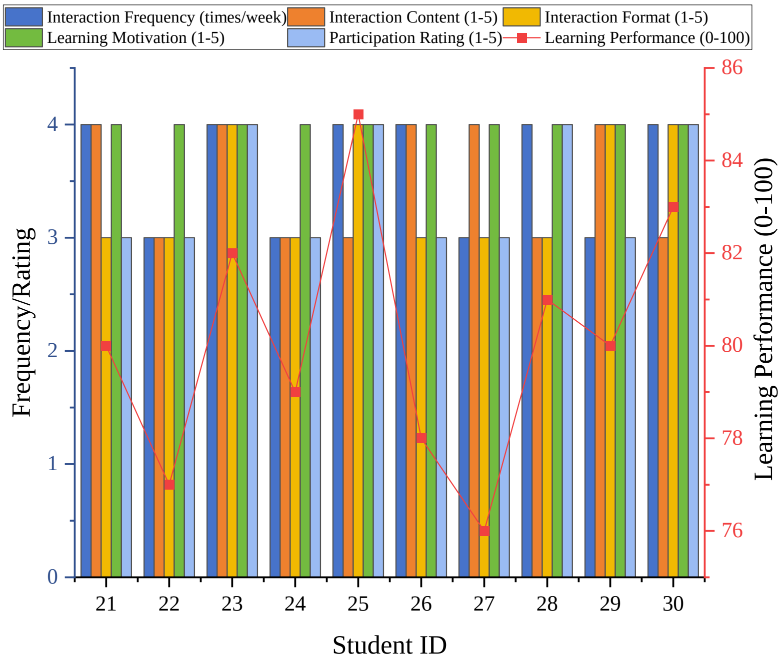

Figure 3. Interaction frequency and learning performance of the control group

The interaction frequency, interaction form and content scores of the students in the control group are between those of the high interaction group and the low interaction group, and the participation scores are mostly between 3 and 4 points. This shows that in the absence of deep interaction design, appropriate standard interaction design can trigger a certain degree of student participation, but there is still a large gap compared with the high interaction group. The scores of the students in the control group are between those in the high-interaction group and the low-interaction group, with an average score of 77-85 points. The specific data are shown in Figure 3. The interaction design of the control group is moderate, which can moderately stimulate students' learning motivation. However, due to the limitations of interaction frequency and content, the learning performance is still lower than that of the high-interaction group. Nevertheless, the learning performance of students in the control group is significantly higher than that in the low-interaction group, indicating that moderate interaction design can still have a positive impact on students' learning performance.

From the learning motivation change data in Table 1, it can be seen that the learning motivation of the students in the high interaction group has significantly improved. The learning motivation change scores of all students in the high interaction group are above 1 point, and the student with the largest change (A04) reaches 1.7 points, and the smallest is 1.1 points. This shows that high-interaction design (such as frequent interaction, rich interactive content and form) has a significant effect on promoting learning motivation. In contrast, the changes in learning motivation of students in the low-interaction group are relatively limited, with most changes ranging from 0.2 to 0.4 points, indicating that low-interaction design has failed to effectively stimulate students' learning motivation. This may be because the low-interaction group lacks sufficient interaction frequency and diverse interaction forms, resulting in lower motivation and participation of trainees in the learning process. The change in learning motivation of the control group is between that of the high interaction group and the low interaction group, and the learning motivation change scores of most students are between 0.5 and 0.7 points. The self-efficacy change scores of the high-interaction group are generally between 0.9 and 1.3 points, with the highest change of 1.1

points for the student (A01) and the lowest change of 0.9 points for the student (A02). The self-efficacy change of the low-interaction group is smaller, with most students changing between 0.2 and 0.3 points.

Table 1. Changes in learning motivation and self-efficacy before and after measurement

Group	Student ID	Pre-test Learning Motivation Score	Post-test Learning Motivation Score	Pre-test Self-efficacy Score	Post-test Self-efficacy Score
High Interaction Group	A01	3.2	4.8	3.5	4.6
High Interaction Group	A02	3.5	4.6	3.6	4.5
High Interaction Group	A03	3.1	4.5	3.2	4.4
High Interaction Group	A04	3	4.7	3.4	4.7
High Interaction Group	A05	3.4	4.9	3.3	4.6
Low Interaction Group	B01	3.3	3.5	3.4	3.6
Low Interaction Group	B02	3	3.3	3.2	3.5
Low Interaction Group	B03	3.2	3.6	3.1	3.3
Low Interaction Group	B04	3.1	3.4	3.3	3.5
Low Interaction Group	B05	3	3.2	3.2	3.4
Control Group	C01	3.4	4	3.5	4
Control Group	C02	3.3	3.9	3.4	3.9
Control Group	C03	3.5	4.2	3.6	4.1
Control Group	C04	3.2	3.8	3.3	3.8
Control Group	C05	3.4	4.1	3.4	3.9

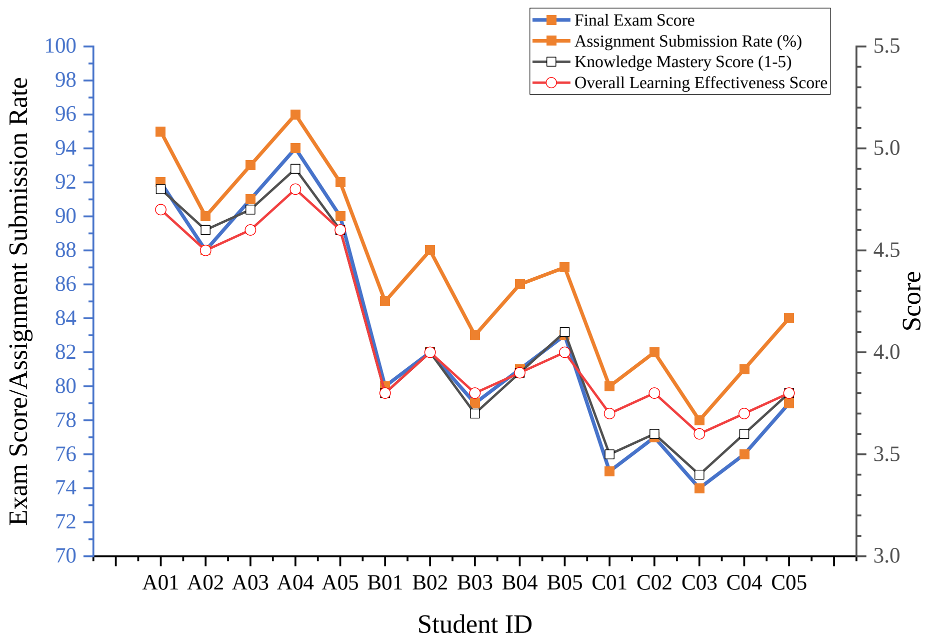

Figure 4. Final exam results and knowledge mastery scores

The students in the high-interaction group perform well in all learning effect indicators. In terms of final exam scores, all students in the high-interaction group score no less than 88 points, demonstrating their strong ability in academic assessment. In terms of homework submission rate, almost all students in the high-interaction group reach over 90%, indicating that they are highly involved in the course and completed their tasks well. In terms of knowledge mastery, students in the high interaction group generally score higher, with most students scoring between 4.6 and 4.9, indicating that they have a high level of understanding and mastery of the course content. In contrast, the low-interaction group has lower final exam scores, homework submission rates, and knowledge mastery than the high-interaction group. Final exam scores generally range from 79 to 83 points, homework submission rates range from 83% to 87%, and knowledge mastery scores range from 3.7 to 4.1 (as shown in Figure 4). Although the learners in the control group participate in some course activities, their overall learning effect is significantly inferior to that of the high-interaction group and the low-interaction group.

5. Conclusion

In recent years, MOOC has been widely promoted in colleges and universities and favored by learners due to their advantages such as resource sharing, learning autonomy, course openness, and learning collaboration. However, most MOOC currently still adopts the method of instructors pre-recording course videos and uploading them to the platform, and learners watching and learning on their own. This model has changed the interactive mode of traditional classroom teaching to a certain extent, weakened the instant communication between teachers and students, students and students, and affected the teaching effect of MOOC. In order to alleviate the above problems, many MOOC platforms have gradually introduced interactive functions, such as real-time discussion areas, online Q&A and study groups, to improve the current situation of insufficient interaction and improve the learning quality of learners. This paper takes MOOC live courses as the research background, and explores the impact of different interactive designs on learners' behavior, learning motivation and learning outcomes through designing experiments and data analysis. First, the interactive design significantly improves learners' behavioral activity. By introducing interactive methods such as real-time Q&A and group discussions, learners show more participation and higher learning investment. Secondly, interactive design enhances learners' learning motivation. Positive interactive experience not only stimulates learning interest but also prompts learners to maintain a higher level of concentration during the learning process. Finally, interactive design has a positive impact on learning outcomes. The diverse forms of interaction helped learners to understand the course content more deeply and significantly improved their learning performance. However, this study also has certain limitations, such as insufficient investigation of the long-term effects of interactive design and the need for further verification of its applicability among different learner groups. Future research can focus on a wider range of course types, personalized interaction strategies and their long-term mechanisms to promote the further development of MOOC teaching.

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