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Student-instructor Interaction as Predictor of Student Engagement in Live Online Courses and Recorded Online Courses

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Abstract
This study investigates the predictive effects of student-instructor interaction on student engagement in both live online courses and recorded online courses. Drawing on Wubbels' Model of Interpersonal Instructor Behavior, eight types of student-instructor interaction were examined, including Directing, Helpful, Understanding, Compliant, Uncertain, Dissatisfied, Confrontational, and Imposing. The study employed stratified random sampling of 630 undergraduates from three Chinese universities and applied multiple regression analysis. This approach aims to address the gap that the Wubbles' Model has not been used to compare interaction effects across live and recorded scenarios, while clarifying the different predictive value of student-instructor interaction on engagement. Results showed that different forms of student-instructor interaction have distinct predictive effects on behavioral, emotional, and cognitive engagement across live online courses and recorded online courses. The findings extend the applicability of the interpersonal model in online education and offer practical implications for enhancing teaching strategies and training instructors to foster student engagement in diverse online learning environments.
Keywords: Student-Instructor Interaction, Student Engagement, Online Courses, Higher Education

Introduction
With the rapid advancement of educational technology, online courses have become increasingly prominent in higher education. They are widely regarded as an effective pathway for educational reform, attracting attention from administrators, instructors, and learners worldwide because of their speed in knowledge dissemination and flexible learning modes. As a country with the large population, China recognized the strategic value of online courses early on and actively supported their application, innovation, and sustainable development

through a range of educational policies (Jiang et al., 2023). By 2017, 73.5% of Chinese undergraduates had participated in online courses (SAMCC, 2017). Between 2021 and 2024, China consistently ranked first in the world for MOOC participation (MOE, 2024). However, in sharp contrast to the rapid expansion in course numbers, student engagement has not increased proportionately. A large-scale survey involving 334 universities found that only 19.48% of undergraduates, 34.09% of instructors, and 14.86% of administrators considered engagement in online courses to be high (Wu & Li, 2020). Student engagement refers to how students allocate their personal resources (e.g., effort, affect, and energy) during learning and the enthusiasm they show for learning activities (Peng, 2017). Engagement is directly linked to performance and achievement in online courses and has profound implications for students' knowledge acquisition and professional development (Wong et al., 2024). Conversely, low engagement negatively affects satisfaction with online learning and is positively correlated with dropout rates (Rajabalee & Santally, 2021; Álvarez-Pérez et al., 2024).

Previous research has highlighted interaction as a key factor influencing student engagement in online courses (Moore, 2016). Three major forms of interaction exist: student-student, student-instructor, and student-content interaction (Moore, 1989). Among these, student-instructor interaction plays a particularly crucial role, serving as a bridge to establish emotional connections between students and instructors (Miao et al., 2022). The absence of real-time contact in online learning often increases feelings of isolation and leads to burnout. High-quality student-instructor interaction provides essential emotional support, which can be transformed into sustained motivation (Sagayadevan & Jeyaraj, 2012; Odutayo et al., 2024). Furthermore, based on immediacy and sequencing of teaching, online courses can be categorized as live or recorded (Amiti, 2020). Live online courses (LOCs) involve real-time interaction between instructors and students, while recorded online courses (ROCs) allow learners to access pre-recorded content at their own pace, with interaction taking place asynchronously (Wang et al., 2021; Hadgu et al., 2016). Despite their differences, existing studies have not fully tested whether student-instructor interaction predicts engagement, nor whether this predictive effect differs between LOCs and ROCs. This gap not only limits the refinement of theories on online interaction and engagement. But also fails to provide targeted guidance for instructors designing interactions in different online course types. To address this gap, the present study investigates the predictive effects of student-instructor interaction on student engagement in both learning contexts among Chinese undergraduates. By identifying the different predictive patterns across live and recorded online courses, contributing to enrich the theoretical framework for online interaction and engagement. And offer empirical supporting for developing instructor's online teaching capabilities.

Literature Review

Theoretical Framework of Student-instructor Interaction

Student-instructor interaction has been defined in various ways. Some scholars describe it in terms of its purpose, such as achieving instructional goals or addressing learning difficulties (Sun, 2021), while others regard it as a bridge to maintain relationships and enhance emotional bonds (Asadzadeh et al., 2022). Another perspective distinguishes synchronous (real-time) from asynchronous (delayed) interaction (Berestok, 2021). Researchers have also examined the phenomenon from both instructor and student perspectives, focusing on teaching strategies or learning support (Kelton, 2022; Xie et al., 2023).

In addition, Wubbles & Levy (1993) analyzed instructors' interactive behavior from the perspective of students, drawing on interpersonal theory. They constructed the Model of Interpersonal Instructor Behavior by integrating the dimensions of Dominance–Submission and Cooperation–Opposition, and classified student-instructor interaction into eight categories. Later, this model was validated and applied in diverse cultural contexts. During its development, new labels were created to better fit the Chinese educational context, though the conceptual core remained unchanged (Sun et al., 2018). The eight categories are as follows: a. Directing (DR): characterized by medium-to-high communion and high agency, referring to instructors leading the class through explicit instructions, task allocation, and goal setting; b. Helpful (HF): defined by medium-to-high agency and high communion, referring to instructors actively providing assistance while avoiding excessive control; c. Understanding (UD): marked by medium-to-low agency and high communion, referring to instructors who mainly listen and show empathy, encouraging students to share their views; d. Compliant (CL): defined by low agency and medium-to-high communion, referring to instructors who set fewer rules and restrictions, allowing students greater autonomy; e. Uncertain (UC): characterized by low agency and medium-to-low communion, referring to instructors who neither guide nor respond actively, often resulting in classroom disorder; f. Dissatisfied (DS): marked by medium-to-low agency and medium-to-low communion, referring to instructors who express dissatisfaction with students' behavior or performance but take no constructive measures; g. Confrontational (CN): defined by medium-to-high agency and low communion, referring to instructors maintaining order through commands or punishments, yet lacking emotional support; h. Imposing (IM): characterized by high agency and medium-to-low communion, referring to instructors who emphasize rules and discipline, thereby severely limiting student autonomy.

Student Engagement in Online Courses

In educational psychology, there are two mainstream perspectives on student engagement. Schaufeli et al. (2002) defined it in terms of vigor, dedication, and absorption, focusing more on psychological aspects than on observable behavior. By contrast, Fredricks et al. (2004) conceptualized student engagement as comprising cognitive, behavioral, and emotional dimensions. Compared with the former, this definition takes students' perceptions of the external environment into account (Upadyaya & Salmela-Aro, 2013). As the present study focuses on how student-instructor interaction, as an external factor, influences student engagement, the framework proposed by Fredricks et al. (2004) was adopted. Specifically, behavioral engagement refers to students' observable learning behaviors in online courses; emotional engagement concerns the emotions and affective experiences that accompany online learning; and cognitive engagement relates to the thinking patterns and strategies students employ during learning. These three dimensions are interdependent and equally essential. Emotional engagement sustains behavioral engagement, while cognitive engagement shapes its depth. At the same time, active behavioral and cognitive engagement further reinforce emotional engagement (Redmond et al., 2018).

Student-instructor Interaction and Student Engagement

Research on face-to-face learning environments has already shown that student-instructor interaction exerts long-lasting effects on students' behavior, emotions, and cognition during task completion. First, such interaction helps students correct cognitive biases and address gaps in understanding, while instructors can guide them toward deeper thinking and the construction of knowledge frameworks (Zhu, 2006; Wang et al., 2014). Moreover, student-instructor interaction provides learning feedback, clarifies goals and requirements, and enhances students' willingness to learn, thereby promoting sustained engagement in the course (Nguyen et al., 2018). Finally, interaction strengthens emotional communication between instructors and students, exerting a direct influence on students' feelings (Archambault et al., 2017). For instance, instructors' positive emotions can readily influence students, fostering stronger motivation to learn. For these reasons, many scholars regard student-instructor interaction as a key intervention to enhance student engagement (e.g. Zapke et al., 2010).

In online courses, student-instructor interaction is often considered part of social interaction. It enables students to perceive instructors' care and support, which in turn enhances their interest in learning and motivates higher levels of engagement (Lu & Churchill, 2014). Empirical studies have confirmed the direct effect of such interaction on student engagement in online settings. Lang et al. (2022) found that student-instructor interaction positively predicted online engagement among university students, regardless of differences in academic performance, majors, or course types. Similarly, Javaid (2024) argued that student-instructor interaction significantly enhances students' motivation, learning enthusiasm, and participation.

Table 1
Comparison of Student-Instructor Interaction between Live and Recorded Online Courses

	Live Online Courses (Synchronous)	Recorded Online Courses (Asynchronous)
Memory Traces	Transient speech is easy to disappear	Textual discussions can be preserved for a long time
Main interactive Form	Verbal expression: 1. Voice/video conversation 2. Chat box instant text Non-verbal expression: 1. Camera body language (e.g. nodding/gesture) 2. Quick reply with emoji	Verbal expression: 1. Structured text replies 2. Multimedia resource sharing Non-verbal expression: 1. Text layout design (e.g. bold/segmentation) 2. Quantitative feedback (e.g. likes/collections)
Typical Teaching Scenarios	1. Real-time classroom Q&A 2. Group collaboration whiteboard 3. Instant solution of emergencies	1. In-depth discussion of topics 2. Mutual evaluation and feedback of homework 3. Cross-time and space project collaboration

However, the dynamics differ between synchronous and asynchronous forms of online learning. In live-streamed courses, interaction occurs in real time and is therefore synchronous (Amiti, 2020). In contrast, in recorded courses, interaction is time-displaced and thus asynchronous (Zeng & Luo, 2024). The distinction between the two forms of interaction is considerable (see Table 1). In live-streamed courses, interaction is typically facilitated through real-time features such as voice connections or instant messages, whereas discussion forums serve as the primary platform for interaction in recorded courses. Chen and Teh (2022) found that passive students experienced higher levels of anxiety and were less willing to engage in synchronous interaction, while proactive students were more likely to initiate interaction and showed greater acceptance of asynchronous forms. Nevertheless, few studies have separately examined the effects of student-instructor interaction on student engagement in live-streamed versus recorded courses. Moreover, interaction is often treated as a single construct, without differentiating the specific types of interactive behavior and their influence on engagement.

To address this gap, the present study adopts the conceptualization of student-instructor interaction proposed by Sun & Wubbles (2018) and explores how eight categories of interactive behavior predict student engagement in both live and recorded online courses. This study therefore seeks to answer the following questions:

1. Which types of student-instructor interaction better predict behavioral engagement in LOCs?
2. Which types of student-instructor interaction better predict emotional engagement in LOCs?
3. Which types of student-instructor interaction better predict cognitive engagement in LOCs?
4. Which types of student-instructor interaction better predict behavioral engagement in ROCs?
5. Which types of student-instructor interaction better predict emotional engagement in ROCs?
6. Which types of student-instructor interaction better predict cognitive engagement in ROCs?

Methods

Participants

The participants in this study were full-time undergraduates from two public and one private university located in a city in China. To avoid disciplinary bias, the study focused on three majors offered across all three universities: Marketing, Electronic Information Engineering, and Chinese Language and Literature. All participants were required to have taken only one online course during the semester. Students enrolled in blended courses, international students, and part-time students were excluded. A stratified random sampling method was adopted, with stratification based on university, major, and course type, resulting in 18 sub-strata. Within each stratum, samples were randomly drawn with equal numbers assigned to each subgroup. Ultimately, 36 participants were selected from each sub-stratum, yielding 324 students in the live online courses (LOCs) group and 324 students in the recorded online courses (ROCs) group. After removing invalid cases that did not meet the inclusion criteria, a total of 630 undergraduates participated in this study. In the LOCs group, 153 participants were female (48.6%) and 162 were male (51.4%). In the ROCs group, 155 were female (49.2%) and 160 were male (50.8%).

Instruments

The Student Engagement in Distance Education

The Questionnaire of the Student Engagement in Distance Education was originally developed by Sun & Rueda (2012) and later translated into English by Liu et al. (2017). The instrument adopts a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), with higher scores indicating higher levels of student engagement. The questionnaire consists of

19 items, measuring behavioral engagement (e.g., I complete my assignments of online course on time), emotional engagement (e.g., I am interested in the activities conducted during online course), and cognitive engagement (e.g., When I read the online course materials, I ask myself questions to make sure I understand what it is about). The CFA results of Chinese version questionnaire were good (CFI = 0.95, TLI = 0.94, RMSEA = 0.07, SRMR = 0.06), the value of Cronbach's α was over 0.8 which showed good reliability.

The Questionnaire on Instructor Interaction was constructed by Wubbels (1993) based on the Model for Interpersonal Instructor Behavior. This instrument has been widely used across multiple international contexts and was further developed by Sun et al. (2018) to create a Chinese version adapted to the local educational context. For the purposes of this study, some item descriptions were adjusted to fit the context of online courses without altering their original meaning. The questionnaire consists of 40 items, including: 5 items measuring Directing (e.g., This instructor shows good leadership with students), 5 items for Helpful (e.g., This instructor is reliable), 4 items for Understanding (e.g., This instructor is willing to listen to students' opinion), 7 items for Compliant (e.g., This instructor lets students have a lot of freedom in class), 4 items for Uncertain (e.g., This instructor has low requirements on discipline), 5 items for Dissatisfied (e.g., This instructor complains a lot), 5 items for Confrontational (e.g., This instructor is fearsome), and 5 items for Imposing (e.g., This instructor is extremely strict). The questionnaire uses a five-point Likert scale, where 1 represents strongly disagree and 5 represents strongly agree. Higher scores indicate a higher frequency of the interaction. The original questionnaire adopted two groups as samples, the Cronbach's α of each dimension ranged between 0.6 and 0.84. And the RMSEA ranged between 0.1 and 0.14, SRMR ranged between 0.04 and 0.08, TLI ranged between 0.85 and 0.92, CFI ranged between 0.95 and 0.97. All of above indicators meant the reliability and CFA results were acceptable.

Procedure

The questionnaire was distributed anonymously through the Wen Juan Xing platform. At the end of the first semester of the 2024–2025 academic year, the survey link was shared with all participants. They were instructed to recall the online course they had attended during the semester and to rate student-instructor interaction and student engagement in that course. Instructors who served as academic advisors at the participating universities assisted with distributing the questionnaire via email and WeChat groups. Finally, a data management procedure was established. Invalid responses were eliminated, including cases with multiple extreme values (exceeding three standard deviations), repetitive patterns, invariant answers, or those not meeting the sampling criteria. The remaining valid data were subjected to statistical analysis.

Data Analysis

All analyses were conducted using SPSS Version 27, with multiple regression employed to address the research questions. The alpha level was set at $p = 0.05$.

Results

Reliability and Multiple Collinearity

Before conducting multiple linear regression, it was necessary to ensure the reliability of the data and to examine whether multicollinearity existed among the independent variables. In this study, Cronbach's Alpha (α) and Variance Inflation Factor (VIF) analyses were employed to test reliability and multicollinearity. Generally, an alpha coefficient above 0.7 is considered to indicate acceptable reliability, while a VIF value below 5.0 suggests that serious multicollinearity is absent (Field, 2024).

Table 2
Cronbach' s Alpha (α) of Student Engagement and Its Dimensions

	BE	EE	CE	SE
LOCs	0.877	0.866	0.880	0.917
ROCs	0.897	0.838	0.857	0.933

Table 2 presents the Cronbach' s alpha values for student engagement (SE) and its three dimensions: Behavioral Engagement (BE), Emotional Engagement (EE), and Cognitive Engagement (CE) in both live online courses (LOCs) and recorded online courses (ROCs). All alpha values exceeded 0.7, indicating good reliability.

Table 3
Cronbach' s Alpha (α) of Student-instructor Interaction and Its Dimensions

	DR	HF	UD	CL	UC	DS	CF	IM	SII
LOCs	0.882	0.881	0.849	0.881	0.869	0.866	0.859	0.884	0.746
ROCs	0.881	0.876	0.839	0.886	0.863	0.856	0.856	0.865	0.741

As shown in Table 3, in LOCs the alpha values for student-instructor interaction (SII) and its dimensions: Directing (DR), Understanding (UD), Compliant (CL), Uncertain (UN), Dissatisfied (DS), Confrontational (CN), and Imposing (IM), ranged between 0.746 and 0.884. In ROCs, the alpha values ranged from 0.741 to 0.886. These results confirm that reliability requirements were met.

Table 4
VIF Results of Independent Variable (Student-instructor Interaction)

	DR	HF	UD	CL	UC	DS	CF	IM
LOCs	1.995	1.857	1.843	1.871	1.846	1.872	1.768	2.013
ROCs	2.070	1.996	2.016	2.034	1.893	1.814	1.677	1.882

In both LOCs and ROCs, there were eight independent variables. In LOCs, the VIF values of all independent variables fell between 1.0 and 5.0, suggesting no serious multicollinearity. Similarly, in ROCs, all VIF values were below 5.0, indicating the absence of severe multicollinearity.

Multiple Regression Results in Online Courses

Table 5
Multiple Regression Results in LOCs

DV	**R^2**	**F**	**Predictors**	**β**	**t**	**p**
BE	0.294	17.373	Helpful	0.177	2.744	0.006
			Compliant	0.146	2.256	0.025
			Uncertain	-0.163	-2.527	0.012
EE	0.345	21.665	Directing	0.146	2.269	0.024
			Imposing	-0.135	-2.083	0.038
CE	0.354	22.552	Directing	0.154	2.403	0.017
			Uncertain	-0.156	-2.531	0.012
			Imposing	-0.158	-2.461	0.014

R1: Which types of student-instructor interaction better predict behavioral engagement in LOCs?

The results (Table 5) showed that Helpful, Compliant, and Uncertain interaction significantly predicted undergraduates' behavioral engagement in LOCs ($F_{(8, 306)} = 17.373$). Their linear combination explained 29.4% of the variance in behavioral engagement ($R^2 = 0.294$). Specifically, when Helpful interaction increased ($\beta = 0.177$, $t = 2.744$, $p < 0.01$), behavioral engagement rose by 0.177 units. When Compliant interaction increased ($\beta = 0.146$, $t = 2.256$, $p < 0.05$), behavioral engagement increased by 0.146 units. In contrast, when Uncertain interaction increased ($\beta = -0.163$, $t = -2.527$, $p < 0.05$), behavioral engagement decreased by 0.163 units. Thus, Helpful and Compliant interaction were positively associated with behavioral engagement, whereas Uncertain interaction showed a negative relationship. In other words, the more Helpful and Compliant behaviors instructors displayed, the more actively undergraduates engaged behaviorally, while frequent Uncertain behaviors reduced their behavioral engagement.

R2: Which types of student-instructor interaction better predict emotional engagement in LOCs?

As shown in Table 5, Directing and Imposing interaction were significant predictors of emotional engagement in LOCs ($F_{(8, 306)} = 21.665$). Together, they explained 34.5% of the variance ($R^2 = 0.345$). When Directing interaction increased ($\beta = 0.146$, $t = 2.744$, $p < 0.05$), emotional engagement rose by 0.146 units. Conversely, when Imposing interaction increased ($\beta = -0.135$, $t = -2.256$, $p < 0.05$), emotional engagement declined by 0.135 units. This indicates that Directing interaction was positively related to emotional engagement, while Imposing interaction was negatively related. In other words, undergraduates' emotional engagement deepened when instructors displayed more Directing behaviors, whereas frequent Imposing behaviors weakened their emotional engagement.

R3: Which types of student-instructor interaction better predict cognitive engagement in LOCs?

Table 5 shows that Directing, Uncertain, and Imposing interaction predicted cognitive engagement in LOCs ($F_{(8, 306)} = 22.552$). Together, they explained 35.4% of the variance ($R^2 = 0.354$). Specifically, when Directing interaction increased ($\beta = 0.154$, $t = 2.403$, $p < 0.05$), cognitive engagement rose by 0.154 units. In contrast, increases in Uncertain interaction ($\beta = -0.156$, $t = -2.531$, $p < 0.05$) and Imposing interaction ($\beta = -0.158$, $t = -2.461$, $p < 0.05$) reduced cognitive engagement by 0.156 and 0.158 units, respectively. This suggests that Directing interaction was positively associated with cognitive engagement, while Uncertain and Imposing interaction were negatively associated. In other words, instructors' Directing behaviors enhanced undergraduates'cognitive engagement, whereas Uncertain and Imposing behaviors diminished it.

Table 6
Multiple Regression Results in ROCs

DV	R^2	F	Predictors	β	t	p
BE	0.505	41.096	Directing	0.227	3.972	0.000
			Understanding	0.142	2.523	0.012
			Compliant	0.193	3.408	0.001
			Uncertain	-0.156	-2.531	0.012
EE	0.481	35.410	Directing	0.175	2.961	0.003
			Understanding	0.168	2.872	0.004
			Compliant	0.140	2.386	0.018
			Uncertain	-0.146	-2.580	0.010
CE	0.478	36.946	Directing	0.119	2.024	0.044
			Understanding	0.120	2.065	0.040
			Compliant	0.149	2.555	0.011
			Uncertain	-0.198	-3.526	0.000
			Confrontational	-0.113	-2.144	0.033

R4: Which types of student-instructor interaction better predict behavioral engagement in ROCs?

The results (Table 6) revealed that Directing, Understanding, Compliant, and Uncertain interaction significantly predicted behavioral engagement in ROCs ($F_{(8, 306)} = 41.096$). Their combined effect explained 50.5% of the variance ($R^2 = 0.505$). Specifically, Directing interaction (β = 0.227, t = 3.972, $p < 0.01$), Understanding (β = 0.142, t = 2.523, $p < 0.05$), and Compliant interaction (β = 0.193, t = 3.408, $p < 0.01$) were positively related to behavioral engagement, while Uncertain interaction (β = -0.156, t = -2.531, $p < 0.05$) was negatively related. This indicates that more Directing, Understanding, and Compliant behaviors encouraged higher behavioral engagement, whereas frequent Uncertain behaviors reduced it.

R5: Which types of student-instructor interaction better predict emotional engagement in ROCs?

Regarding emotional engagement in ROCs (Table 6), Directing, Understanding, Compliant, and Uncertain interaction were significant predictors ($F_{(8, 306)} = 35.410$). Together, they explained 48.1% of the variance ($R^2 = 0.481$). Increases in Directing (β = 0.175, t = 2.961, $p < 0.01$), Understanding (β = 0.168, t = 2.872, $p < 0.01$), and Compliant interaction (β = 0.140, t = 2.386, $p < 0.05$) enhanced emotional engagement. In contrast, when Uncertain interaction increased (β = -0.146, t = -2.580, p = 0.01), emotional engagement declined. This indicates that Directing, Understanding, and Compliant interaction were positively related to emotional engagement, while Uncertain interaction was negatively associated.

R6: Which types of student-instructor interaction better predict cognitive engagement in ROCs?

As shown in Table 6, Directing, Understanding, Compliant, Uncertain, and Confrontational interaction predicted cognitive engagement in ROCs ($F_{(8, 306)} = 36.963$). Together, they explained 47.8% of the variance ($R^2 = 0.478$). Specifically, increases in Directing (β = 0.119, t = 2.024, $p < 0.05$), Understanding (β = 0.120, t = 2.065, $p < 0.05$), and Compliant interaction (β = 0.149, t = 2.555, $p < 0.05$) were positively associated with cognitive engagement. In contrast, increases in Uncertain (β = -0.198, t = -3.526, $p < 0.01$) and Confrontational interaction (β = -

0.113, $t = -2.144$, $p < 0.05$) reduced cognitive engagement. This suggests that Directing, Understanding, and Compliant interaction were significantly and positively associated with cognitive engagement, while Uncertain and Confrontational interaction were negatively related.

Discussion

The findings revealed that student–instructor interaction exerted predictive effects on student engagement in both live online courses (LOCs) and recorded online courses (ROCs). In LOCs, for behavioral engagement, instructors' helpful and compliant interaction behaviors were positive predictors, whereas uncertain interaction was a negative predictor. For emotional engagement, instructors' directing interaction behavior had a positive predictive effect, while uncertain and imposing interaction behaviors exerted negative predictive effects. For cognitive engagement, instructors' directing interaction behavior was a positive predictor, whereas uncertain and imposing interaction behaviors were negative predictors. In ROCs, across behavioral, emotional, and cognitive engagement, directing, understanding, and compliant interaction behaviors consistently showed positive predictive effects; meanwhile, uncertain interaction behaviors demonstrated pervasive negative predictive effects across all three dimensions of engagement. Additionally, confrontational interaction behavior was found to negatively predict cognitive engagement only.

Based on the results, this study found that certain student–instructor interaction behaviors demonstrated cross-situational consistency in predicting student engagement. First, uncertain interaction behaviors consistently served as negative predictors in both LOCs and ROCs. Such behaviors often manifest as ambiguous instructional language, inconsistent task requirements, or instructors' inability to respond accurately to students' questions. From the perspective of self-determination theory, uncertain interaction behaviors fail to meet undergraduates' needs for autonomy, competence, and relatedness (Chiu, 2022). Ambiguous rules undermine students' ability to plan their learning process independently (autonomy frustration). When instructors avoid answering questions, it signals neglect, which weakens students' trust in instructors (relatedness frustration). Moreover, uncertainty in instructor interaction disrupts students' self-assessment of competence (competence frustration). When these three fundamental needs are unmet, students' overall engagement is inevitably diminished. Secondly, directing interaction behaviors consistently emerged as positive predictors in both types of online courses, aligning with prior research on instructor leadership in online education (e.g. Hazzam & Wilkins, 2023). Online courses often grant students substantial autonomy, allowing them to arrange their own learning environment, pace, and schedule. However, students who lack self-discipline or planning skills are prone to procrastination and feelings of helplessness. In such cases, instructors' guiding behaviors provide structural support, clarify learning objectives, and stimulate higher levels of engagement (Kranzow, 2013).

Meanwhile, some interaction behaviors demonstrated situational specificity in predicting student engagement. Helpful interaction behavior positively predicted engagement only in LOCs, possibly because student–instructor interaction in live settings occurs in real time. Although previous studies have confirmed the importance of instructor support for student engagement in online courses (Muir et al., 2022), such support is particularly effective in live environments where instructors can address problems immediately. In ROCs, where instructor–student communication is asynchronous, personalized support is limited. Conversely, understanding interaction behavior exerted a unique positive effect in ROCs. In the absence of real-time feedback, instructors who thoroughly understand students' needs can anticipate potential difficulties when recording teaching videos and provide proactive support, which significantly enhances engagement. In contrast, confrontational interaction behaviors significantly predicted engagement only in ROCs. This may be attributed to the asynchronous nature of recorded courses. While confrontation during live sessions can be mitigated through immediate communication, the lack of real-time interaction in ROCs prolongs negative emotions, amplifying their detrimental impact on student engagement (Fidan & Koçak Usluel, 2024).

It is also noteworthy that imposing interaction behaviors demonstrated different predictive patterns across contexts. In LOCs, they negatively predicted emotional engagement, whereas in ROCs they negatively predicted cognitive engagement. In live settings, imposing behaviors disrupt learning processes and elicit negative emotions. By contrast, in recorded setting, such behaviors threaten students' autonomy, reducing their willingness to engage in deep learning and consequently lowering cognitive engagement (Zaky, 2024).

Implication

This study applied Wubbels' s model, originally developed for face-to-face classrooms, to the context of online courses and verified its predictive role of student–instructor interaction on student engagement. The results not only confirmed the adaptability of the model to online education but also revealed context-specific patterns that traditional offline classrooms cannot fully capture, thereby extending the theoretical boundaries. Furthermore, this study clarified the specific impacts of student–instructor interaction on the three dimensions of student engagement across different contexts, providing empirical support for refining both interaction theory and engagement theory. By identifying the predictive factors of student engagement in greater detail, it also enriched empirical research on the determinants of engagement.

The findings also provide practical implications for improving both live and recorded online courses as well as for cultivating instructors' interactional competencies. For LOCs, instructors should increase the frequency of directing and compliant interaction behaviors. Specifically, they may provide directive guidance before, during, and at the conclusion of live sessions, while allowing sufficient time for Q&A to support students' sense of autonomy. At the same time, instructors should strictly limit imposing and uncertain interaction behaviors, avoiding unexplained requirements or ambiguous expressions. For ROCs, instructors should thoroughly understand students' needs and characteristics prior to recording instructional videos. Anticipating potential learning barriers and embedding understanding and directing interaction behaviors directly into the videos can substantially foster engagement. Additionally, instructors can set up Q&A forums or offer social media channels for communication to reduce the occurrence of confrontational interactions. Given that online courses are characterized by a lack of temporal and spatial co-presence between students and instructors, higher demands are placed on instructors' interactional skills. Therefore, universities should provide targeted training to enhance instructors' ability to manage student–instructor interaction across different online learning contexts.

Limitation and Recommendation for Future Research

The participants of this study were all undergraduates from a single city in China, excluding postgraduate and international students, who are also important groups in Chinese higher education. This limitation may affect the generalizability of the findings. Future research should expand the sampling scope and include participants from diverse regions. Subsequent studies could also explore whether student–instructor interaction predicts the online engagement of postgraduates and international students, and compare those results with the present study. Moreover, the data in this study were entirely based on self-reported questionnaires from undergraduates, which may be subject to social desirability bias. To enhance the authenticity and objectivity of future research, triangulation methods should be employed, integrating data collected from instructors and learning records from online platforms for comprehensive analysis.

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