Student-Content Interaction and Learning Outcomes in MOOCs: The Moderating Role of Self-Efficacy

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Abstract

This study examines how self-efficacy moderates the relationship between student-content interaction and two key outcomes in Massive Open Online Courses: perceived course quality and sustained learning interest. Using survey data from 343 participants in the *Learning How to Learn MOOC* on Coursera, we employed structural equation modeling to test main and interaction effects. Participants were predominantly adult learners with diverse educational backgrounds, balanced gender representation, and varied language backgrounds. Results indicate that student-content interaction positively predicts perceived course quality and sustained learning interest. Moderation analyses further show that the positive effects of student-content interaction are strongest for learners with lower self-efficacy and weaker for learners with higher self-efficacy, suggesting a compensatory or ceiling effect. These findings extend prior MOOC research by empirically modeling self-efficacy as a moderating condition rather than only a direct predictor. Practical implications highlight the importance of designing interactive content and self-efficacy-supportive features to promote engagement in large-scale autonomous learning environments. Limitations include reliance on self-reported data and cross-sectional design. Future research should incorporate objective learning analytics and longitudinal approaches to examine how these relationships evolve over time.

Keywords: Self-efficacy; MOOCs; student-content interaction; online engagement; learning outcomes

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Massive Open Online Courses (MOOCs) have emerged as a central platform for lifelong learning, offering broad access to learning opportunities for millions of learners worldwide (Loh et al., 2024; Zhu & Doo, 2022). By removing traditional barriers of cost, location, and prerequisite requirements, MOOCs have opened pathways to quality education regardless of learners' geographic or institutional affiliations. As learners from diverse backgrounds engage in MOOCs (Moore & Blackmon, 2022), researchers have recognized that learning experiences, such as how learners perceive the quality of the MOOCs they take and whether they sustain interest in the topics they study, are more meaningful indicators of MOOC success than traditional outcomes such as completion rates (Cho et al., 2025; Long & Liu, 2025).

These two outcomes represent complementary dimensions, one evaluative and one motivational, that reflect both the quality and sustainability of learning in open environments. Perceived course quality reflects learners' evaluations of instructional design, content value, and overall educational experience (Chen et al., 2025; Jung et al., 2019). Sustained learning interest, meanwhile, captures learners' motivation to persist with course content and maintain curiosity over time (Dai et al., 2020; Lee & Song, 2022), a particularly important outcome given that MOOC learners self-direct their participation without external pressures such as grades or tuition investment. Critically, these two outcomes serve as proximal predictors of continued lifelong learning behavior; learners who perceive high quality and maintain interest are more likely to continue taking additional MOOCs for self-directed learning (Moore & Wang, 2021). Yet, our understanding of what predicts these outcomes remains incomplete.

Among the factors that may predict these outcomes, learner interaction with course content is critical given the structural characteristics of MOOCs. Moore (1989) identified three types of interaction in online learning: student-content, student-instructor, and student-student. Of these, student-content interaction is the most consequential in MOOCs. The nature of MOOC environments severely constrains student-instructor and student-student interactions (Alemayehu & Chen, 2023); where hundreds or thousands of learners with different academic backgrounds and living on different continents participate, meaningful exchanges with instructors and peers are not realistically sustained (Loh et al., 2024; Long & Liu, 2025). Moreover, MOOC learners typically do not expect extensive interaction with peers or instructors, recognizing that they enrolled primarily for access to content rather than interpersonal interaction (Gamage et al., 2020). Student-content interaction, the process by which learners interact with and extract meaning from course materials, thus represents the core behavioral pathway through which MOOC learners may develop positive quality perceptions and sustain their interest over time.

While student-content interaction may benefit learners broadly, its effects may vary across learners. Individual differences in self-efficacy may shape how effectively learners capitalize on their interaction with course materials. Self-efficacy, defined as one's belief in their capability to succeed at specific tasks (Bandura, 1997), has been well established as a powerful predictor of learning outcomes (Cheng et al., 2023; Wang et al., 2022). Learners with high self-efficacy approach challenges with confidence, persist through difficulties, and interpret their efforts as productive. In self-directed learning environments such as MOOCs, self-efficacy becomes particularly important because learners must regulate their own interaction with the learning materials without external scaffolding (Cho & Shen, 2013; Kizilcec et al., 2017; Tsai et al., 2020). However, while prior research has established self-efficacy as a direct predictor of MOOC learning outcomes (Ghali & Amari, 2024), its role as a boundary condition, specifically, whether it amplifies or attenuates the effects of student-content interaction on learning outcomes, remains unexamined.

The present study addresses this gap by examining how student-content interaction relates to two key learning outcomes in MOOCs: (1) perceived course quality and (2) sustained learning interest. We further investigate self-efficacy as a potential moderator of these relationships, exploring whether learners with higher self-efficacy are more likely to show better learning outcomes through content interaction than those with lower self-efficacy. In doing so, this study integrates Moore's (1989) interaction framework with Bandura's (1997) social cognitive theory to offer a deeper understanding of how student-content interaction and self-efficacy jointly shape learning outcomes in a MOOC environment.

Theoretical Framework

This study is guided by two complementary theoretical frameworks. Moore's (1989) interaction framework and Bandura's (1997) social cognitive theory. Moore's framework identifies three types of interaction in online learning, student-content, student-instructor, and student-student, and provides the conceptual basis for understanding how learning occurs in online learning environments. Bandura's social cognitive theory, particularly self-efficacy, provides a cognitive and behavioral lens for understanding why the same interaction behaviors may produce different outcomes for different learners. Together, these frameworks suggest that learning outcomes in MOOCs are shaped not only by what learners do, that is, their interaction with content, but also by the beliefs they hold about their own capabilities, that is, their self-efficacy.

In MOOC environments, student-instructor and student-student interactions are limited due to the scale, asynchronous nature, and learner diversity that characterize these courses (Alemayehu & Chen, 2023; Loh et al., 2024). Student-content interaction therefore becomes the primary behavioral pathway through which learners shape their experience. Research has demonstrated that learners who actively interact with course materials report stronger perceptions of course quality and greater intentions for future learning (Cho et al., 2025; Moore & Blackmon, 2022). These findings suggest that the depth and quality of student-content interaction is a key determinant of learning outcomes and sustained learning interest in MOOCs.

While student-content interaction may be related to positive learning outcomes broadly, self-efficacy theory suggests that the degree of positive learning outcomes may vary across learners. Self-efficacy (Bandura, 1997) has been well established as a direct predictor of learning outcomes in online settings (Cheng et al., 2023; Kizilcec et al., 2017; Wang et al., 2022). However, most studies have examined self-efficacy as a direct predictor rather than as a moderating variable. Differentiating self-efficacy as a direct predictor and as a moderator is critical to better understand students' online learning, as the moderating perspective reveals whether learners with higher self-efficacy benefit more from the same interaction behaviors. Drawing on Bandura's (1997) concept of triadic reciprocal determinism, in which behavior (student-content interaction in this study), personal beliefs (self-efficacy), and environment (the

MOOC context) interact dynamically, we propose that self-efficacy shapes how student-content interaction translates into learning outcomes in a MOOC environment.

Student-Content Interaction and Learning Outcomes in MOOCs

Student-content interaction has been identified as a significant predictor of various learning outcomes in online learning environments. In MOOCs, where learners independently navigate course materials, the quality and depth of their interaction with content directly shapes their learning experience. When learners actively interact with course materials by pausing videos to take notes, attempting practice problems, and revisiting difficult concepts, they are positioned to recognize the coherence and value of the instructional design. Active interaction creates opportunities for learners to appreciate how content is structured, to connect new information with prior knowledge, and to experience the satisfaction of mastering challenging material (Jung et al., 2019; Long & Liu, 2025). In contrast, passive or superficial interaction may leave learners unable to recognize the quality embedded in well-designed content, as they have not interacted deeply enough to extract its value. Chen et al. (2025) found that while content quality positively predicted learning effectiveness in MOOCs, simply providing a large volume of content did not improve learning experiences; MOOC learners' active and meaningful interaction with content determined their learning experiences. These findings indicate that student-content interaction is closely tied to how learners evaluate the overall quality of a MOOC.

Student-content interaction may also play a critical role in sustaining learning interest over time. In MOOCs, where external motivators such as grades, tuition investment, or instructor accountability are largely absent, learners need to generate and maintain their own learning interest throughout the course. Meaningful interaction with content produces cognitive stimulation, the experience of learning something new, solving problems, or gaining insight creates intrinsic rewards that fuel continued learning interest (Lee & Song, 2022). Active interaction also generates a sense of progress and competence; as learners complete modules and master concepts, they experience a sense of accomplishment that reinforces their interest in continuing to learn (Dai et al., 2020). Research on interest development supports these mechanisms. Situational interest, triggered by interacting with stimulating content, can develop into more stable individual interest through repeated positive experiences (Hidi & Renninger, 2006). In MOOCs, learners who interact consistently with course content are more likely to persist through the course and express intentions for future learning (Cho et al., 2021; Moore & Wang, 2021). Based on the theoretical and empirical evidence presented above, we propose the following hypotheses:

H1: Student-content interaction positively predicts perceived course quality in MOOCs.

H2: Student-content interaction positively predicts sustained learning interest in MOOCs.

Self-Efficacy as a Moderator of Student-Content Interaction and Learning Outcomes

Self-efficacy plays a critical role in autonomous learning environments like MOOCs. In traditional classrooms, instructors provide structure, feedback, and encouragement that can partially compensate for low learner self-efficacy. Peers offer social support that helps learners gauge their progress. These external scaffolds are largely absent in MOOCs, placing greater weight on learners' own self-efficacy beliefs to control their interaction with course materials (Cho & Shen, 2013; Tsai et al., 2020). In this context, we propose that self-efficacy moderates the relationship between student-content interaction and learning outcomes. Specifically, we expect that the positive effects of content interaction will be stronger for learners with higher self-efficacy and weaker for learners with lower self-efficacy.

Regarding perceived course quality, we expect that high-efficacy learners who interact extensively with course content will perceive higher course quality because they approach challenging material with confidence and interpret difficulty as a natural part of learning, which allows them to extract greater value from their interaction with content (Kizilcec et al., 2017; Wang et al., 2022). The same level of interaction may yield smaller gains in perceived quality for low-efficacy learners, who may approach content with anxiety or doubt, interpret challenges as evidence of poor course design or their own inadequacy, and consequently undervalue the learning experience despite having interacted with the same materials. Ghali and Amari (2024) provide initial support for this reasoning, finding that self-efficacy moderated the relationship between interaction and online learning effectiveness. In MOOCs, where learners evaluate course quality based largely on their own interaction experiences without external validation from instructors or peers, self-efficacy beliefs are likely to play an even more prominent role in shaping these quality perceptions.

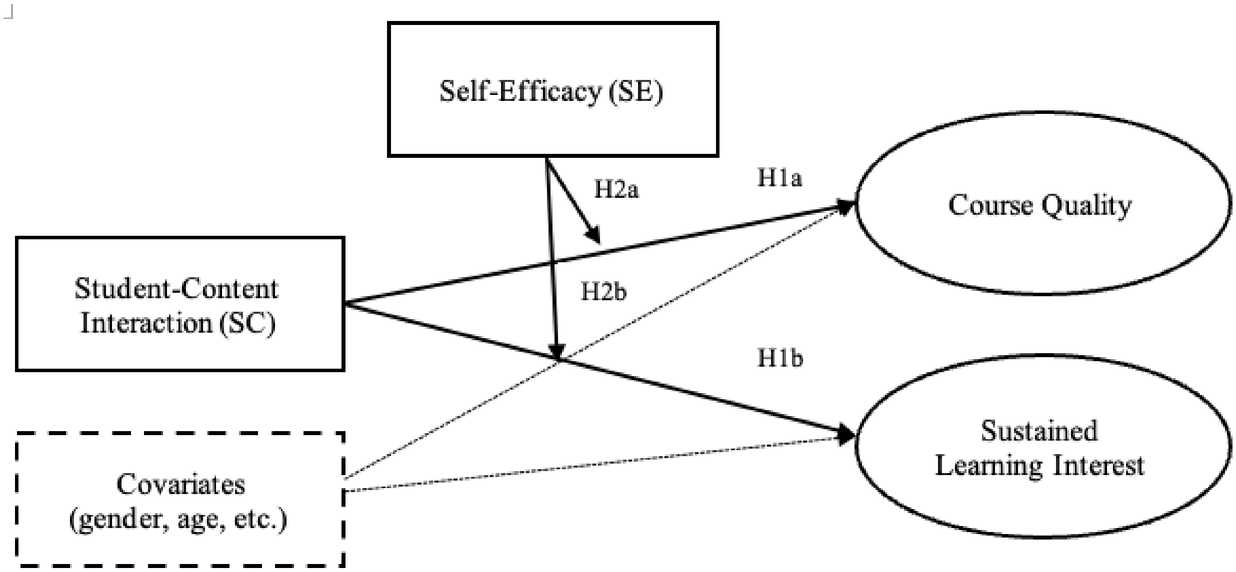
Similarly, we expect that content interaction will strongly sustain learning interest for high-efficacy learners. High-efficacy learners experience interaction with content as rewarding and interpret their progress as evidence of capability, which reinforces their interest in continuing to learn (Cheng et al., 2023; Lee & Song, 2022). When they encounter difficulty, they are more likely to persist and view challenges as opportunities for growth rather than as reasons to disengage. Low-efficacy learners, by contrast, may find that content interaction does not sustain their interest as effectively, particularly if challenges trigger doubt rather than curiosity. Over time, this pattern may widen the gap between high-efficacy and low-efficacy learners, even when both groups interact with the same content at similar levels. Based on this theoretical rationale and supporting evidence, we propose the following hypotheses:

H3: Self-efficacy moderates the relationship between student-content interaction and perceived course quality, such that the relationship is stronger for learners with higher self-efficacy.

H4: Self-efficacy moderates the relationship between student-content interaction and sustained learning interest, such that the relationship is stronger for learners with higher self-efficacy.

Figure 1 presents the conceptual model guiding this study. Student-content interaction serves as the focal predictor of perceived course quality and sustained learning interest. Self-efficacy is positioned as a moderating condition shaping the strength of these relationships. In addition, demographic variables are included as covariates to control for background influences.

Figure 1
Conceptual Model of Self-Efficacy as a Moderator of Student-Content Interaction Effects



Methods

Study Context and Research Design

This study focuses on the self-paced MOOC *Learning How to Learn*, which has been available on Coursera since August 2014. The course aims to equip learners with essential learning strategies based on neuroscience and cognitive science, including chunking, metaphors, and the Pomodoro technique, to help mitigate memory constraints. Structured into four modules, the course is designed to be completed over four weeks. Each module contains ten mandatory videos and two to four optional ones, each approximately 20 minutes long. To assess comprehension, students are required to complete quizzes at the end of each module. The course is led by two instructors, allowing learners to progress at their own pace.

New students can enroll every Monday, ensuring a continuous influx of participants. The course is offered for free, with an option to purchase a Coursera certificate upon successful completion. Instructors maintain engagement through regular announcements and reminders, while also fostering an interactive learning environment by encouraging discussions and reflections on message boards. Even after completing the course, students retain access to materials for ongoing review and learning. Learning How to Learn provides a valuable setting for analyzing the relationship between student motivation, engagement, and their impact on learning outcomes.

We employed a cross-sectional survey design to examine associations among learner motivation, engagement, course quality perceptions, and sustained learning interest within a self-paced MOOC context. A cross-sectional design was selected because the study aimed to capture learners' retrospective perceptions and experiences following course completion rather than to track changes over time. This study seeks to highlight the role of these factors in shaping the learning experience within self-paced MOOCs, contributing to the growing body of research on online education effectiveness.

Data Collection and Participants

For data collection**,** we used a voluntary convenience sampling approach and invited learners who had completed the *Learning How to Learn* course between 2014 and 2023 to participate in the study, with the final survey response recorded on April 25, 2023. Participants were recruited using a voluntary convenience sampling approach. Eligibility was limited to course completers to ensure that all respondents had sufficient exposure to the course content and learning environment. To enhance participation, the course instructor, Dr. Barbara Oakley, promoted the survey in her weekly *Cheery Friday* newsletter. The survey invitation appeared in three issues, with the last reminder sent in early 2023. This recruitment strategy allowed broad outreach to a diverse learner population while preserving voluntary participation.

Participation was voluntary, and an implied consent was obtained electronically prior to survey initiation. All respondents were informed of the study purpose, their right to withdraw at any time, and the anonymous nature of their responses. No identifying information was collected. Survey data were stored securely and accessed only by the research team for analysis. To enhance data validity, we implemented several procedures, including restricting participation to course completers, removing empty submissions, and screening for incomplete responses prior to analysis. All measures were drawn from previously published instruments or adapted from established scales used in online learning research.

A total of 454 survey responses were received, but 111 submissions contained no data and were excluded. As a result, the final analysis was based on 343 responses. Among these, missing data varied between 1% and 16% across variable. Respondents ranged in age from 16 to 85 years, with an average age of 46.25 (SD = 15.17). In terms of gender distribution, 145 respondents (42.9%) identified as male, while 186 (55%) identified as female. Regarding language background, 175 participants (51.8%) reported English as their first language, while 160 (47.3%) indicated a different primary language. In terms of educational attainment, 28 participants (8%) had a high school diploma, 63 (14.3%) held a college-level degree, 151 (34.3%) had a master's degree, and 34 (7.7%) had a doctoral degree, while 7 respondents (2%) had not completed high school.

Measures

We conducted an anonymous online survey using the Qualtrics platform, which comprised two main sections: (a) demographics and (b) questionnaire. The demographics section collected information about participants' backgrounds (see Appendix A for specific demographic questions), while the questionnaire section focused on self-efficacy, student-content interaction, course quality, and sustained learning interest. In the questionnaire section, participants rated their responses on a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). Study variables were measured using validated instruments and adapted items aligned with established theoretical frameworks. For each construct, we report the reference source. Demographic variables were collected as covariates to account for potential confounding effects. Descriptive statistics and bivariate correlations (Table 1) were examined to summarize the data and provide preliminary evidence of construct reliability. The construct validity of key variables is confirmed in this study through a confirmatory factor analysis (CFA) approach within the structural equation modeling (SEM) framework, which demonstrated high factor loadings across the four scales and acceptable model fit (CFI = 0.963; SRMR = .06). See Appendix B for CFA model results.

Course quality.

Course quality was measured using two items adapted from a validated scale assessing learners' self-reported understanding and knowledge gains from the MOOC. A sample item is, *"I feel that I learned a great deal of knowledge in this course."* (Bacon, 2016). Responses were recorded on a five-point Likert scale (1 = Strongly disagree to 5 = Strongly agree), with higher scores reflecting a greater perception of course quality. The mean score for course quality was 4.73 (*SD* = 0.55), suggesting that participants generally reported strong learning outcomes. Prior studies have shown that this scale maintains reliable internal consistency, with Cronbach's alpha values exceeding 0.70. In the current study, the adapted version of the scale demonstrated a reliability coefficient of 0.73. The convergent validity is verified in the Confirmatory factor analysis (CFA) of the SEM model, showing high factor loadings (Table 3 and Appendix B).

Sustained learning interest.

Sustained learning interest was assessed using two items adapted from Oakley, Poole, and Nestor (2016), which explored students' motivation to pursue further learning beyond their MOOC experience. This construct captured both participants' ongoing engagement with the course material (sustained engagement) and their intention to enroll in future MOOCs to deepen their knowledge or skills (future learning intent). The first item measured the former: *"My interest in this course increased over time while taking this course."* The second item assessed future learning intent: *"I am going to take a similar MOOC to extend my knowledge or expertise in the topic."* Participants rated their responses on a five-point Likert scale (1 = Strongly disagree to 5 = Strongly agree). Prior research on MOOC participation has shown consistently high sustained learning interest rates and a strong inclination toward continued learning, with reported sustained learning interest scores averaging 4.55 out of 5.0. In this study, the reliability coefficient for the adapted scale was 0.51, indicating low internal consistency, likely due to the limited number of items capturing conceptually distinct aspects of sustained interest (Streiner, 2003; Tavakol & Dennick, 2011). Accordingly, results involving this construct should be interpreted with caution, as lower reliability may attenuate observed relationships rather than inflate them (Nunnally & Bernstein, 1994). Despite this limitation, confirmatory factor analysis indicated acceptable convergent validity for the sustained learning interest items (see Appendix B).

Self-efficacy.

Self-efficacy was measured using three items adapted from Zimmerman's (2000) framework on self-regulated learning, which emphasizes learners' confidence in their ability to effectively engage with and master course content. This construct captured participants' perceived capability to understand and apply complex MOOC material. One representative item is: *"I was certain I could understand the most difficult content presented in this MOOC."* Responses were recorded on a five-point Likert scale (1 = Strongly disagree to 5 = Strongly agree), with higher scores reflecting greater self-efficacy. Prior research has established the critical role of self-efficacy in online learning success, linking higher confidence levels to improved engagement and performance in digital education environments. In this study, the mean self-efficacy score was 3.80 (SD = 0.85), suggesting moderate confidence among participants. The adapted scale demonstrated a reliability of .86, suggesting a high internal consistency.

<u>Student-content interaction.</u>

Student-content interaction was evaluated using three items derived from Moore's (1989) framework, which conceptualizes this interaction as the learner's engagement with course materials to build knowledge and track progress. This construct examined the extent to which participants actively interacted with course content and monitored their own learning. A sample item included: *"I monitored my own progress to make sure that I was on the right track in this MOOC."* Responses were measured on a five-point Likert scale (1 = Strongly disagree to 5 = Strongly agree). Previous studies have reported a reliability coefficient of approximately 0.80 for student-content interaction scales, indicating strong internal consistency. In this study, the adapted scale demonstrated a reliability of 0.69, suggesting moderate internal consistency. Because objective learning outcomes such as assessment performance or course completion were not measured in this study, findings related to student–content interaction should be interpreted as reflecting perceived engagement rather than direct learning performance.

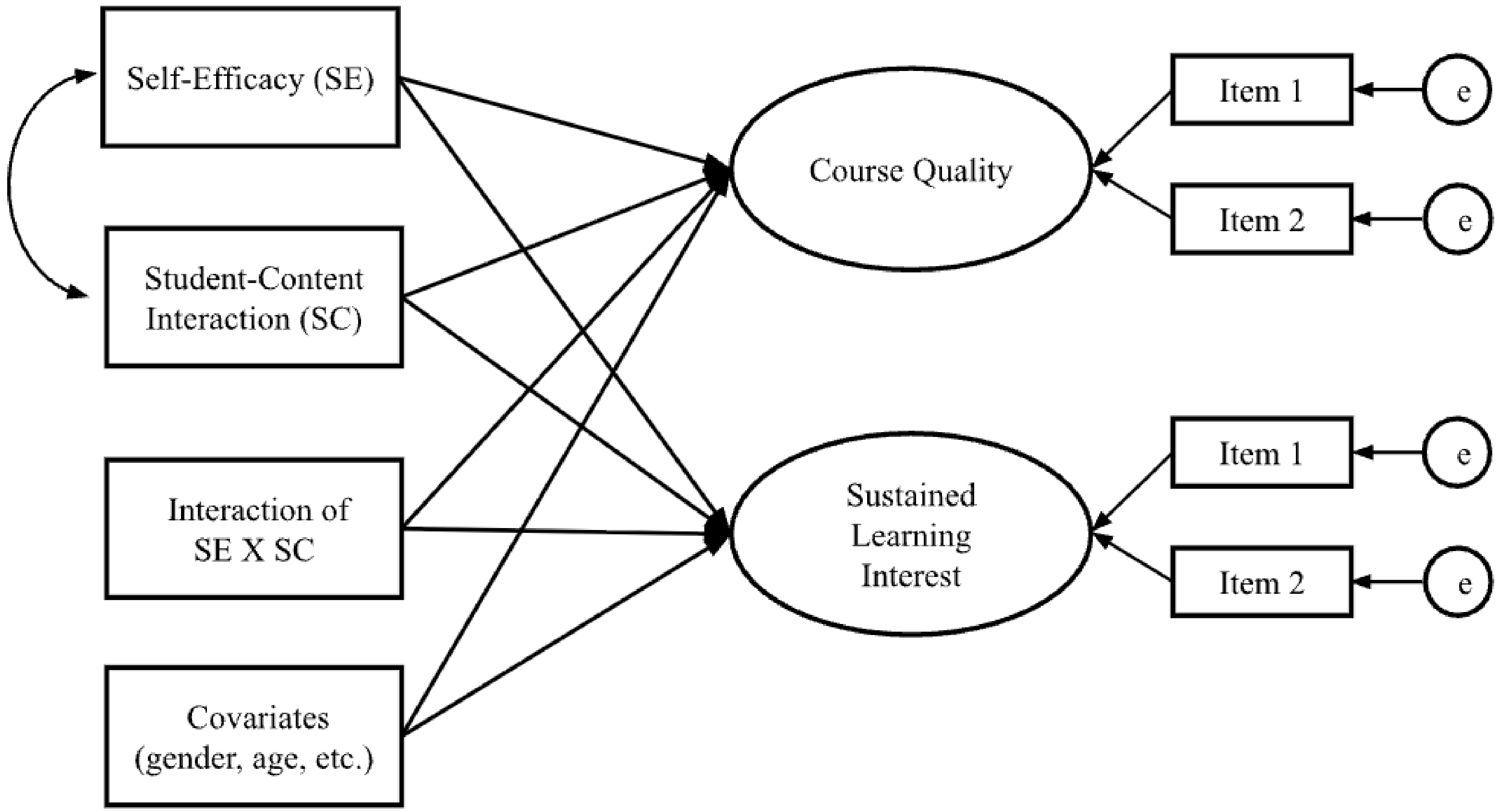
<u>Demographic variables.</u>

Demographic data were collected as covariates to account for potential confounding influences on the study variables. Variables included age (*M* = 46.25, *SD* = 15.18), degree (*M* = 5.09, SD = 1.55, representing varying levels of education), income-education index (*M* = 15.69, *SD* = 19.01), gender, ethnicity, socioeconomic status, first-generation college status, and certificate completion. These variables were not examined as focal predictors or moderators because the study was not theoretically grounded to expect demographic differences in the tested moderation effects; instead, they were included as covariates to adjust model estimates for background characteristics.

Data Analysis

We first performed data screening for skewness and kurtosis and computed descriptive statistics (means, standard deviations, correlations) of all variables. To examine whether self-regulation in interaction between student and content moderates the effect of self-efficacy on course outcomes, we estimated in Mplus version 8.0 (Muthén & Muthén) a structural equation model for this study (Figure 2).

Figure 2
Measurement Model of the Key Constructs



Following data screening, we specified and evaluated a measurement model prior to estimating the structural paths. In this model, we specified outcome variables as latent constructs, which included course quality (indicated by two raw items) and student sustained learning interest (indicated by two raw items). Specifying outcome variables (endogenous variables) as latent constructs is important to create unbiased estimators by estimating measurement error and removing it from estimates of variable relations, which can lead to less biased estimates for the outcomes (Spirtes et al., 2001). Although it is ideal to also estimate exogenous variables (the predictors and the interaction variable) as latent constructs (e.g., through a framework of latent moderated structural equations), the current study sample size and thus statistical power is not large enough to support the estimation of a full latent structure model (i.e., the model will be non-identified). Thus, we used observed variables for the predictors (i.e., self-efficacy and student-content interaction) and interaction but kept latent constructs for the endogenous variables (the outcomes). This modeling decision reflects a trade-off between model complexity and statistical power, allowing for more stable estimation of the focal outcomes while avoiding model non-identification. This approach allowed us to maintain statistical power to produce model results while maximizing unbiased estimation for the outcomes.

The model fit was evaluated according to Hu and Bentler's (1998) criteria which included the chi-square statistics, comparative fit index (CFI), the root means square residual error of approximation (RMSEA), and the Standardized Root Mean Square (SRMR). A CFI value of ≥ 0.95, RMSEA value of ≤ 0.06, and SRMR value of ≤ 0.08 would indicate a good fit (Hu & Bentler, 1998). Hu and Bentler recommended that researchers should combine SRMR with another fit index (e.g., CFI or RMSEA) for indication of model fit. We then added structural paths to the measurement model to test if self-efficacy and student-content interaction predicted course quality and student sustained learning interest. Gender, age, ethnicity, education degree, socioeconomic status, first language used, first-generation college student status, and whether receiving a certificate or not were included as covariates to adjust for potential demographic confounding effects.

Missing data is handled by full maximum information likelihood in the model estimation. In addition to estimating the main effects of self-efficacy and student-content interaction on course quality and sustained learning interest, we also examined the moderating effects of student-content interaction by estimating the interaction term between student-content interaction and self-efficacy. Significant interaction terms were interpreted by plotting simple slopes at three levels of the moderator: one standard deviation below the mean (low), at the mean (moderate), and one standard deviation above the mean (high), following established procedures for probing interaction effects (Aiken & West, 1991). Given the number of parameters estimated, we applied Bonferroni adjustment to avoid inflation of type one error rate, such that only p-value significant at $p < .0125$ will be reported as significant.

Results

Preliminary Analysis

Table 1 presents descriptive statistics and bivariate correlations for all variables. Table 2 presents descriptive statistics for the categorical variables. Student-content interaction was positively correlated with self-efficacy ($r = .18$, $p < .01$), and both learning outcomes, including course quality ($r = .24$, $p < .01$) and sustained learning interest ($r = .26$, $p < .01$). Self-efficacy was also positively correlated with course quality ($r = .23$, $p < .01$) and sustained learning interest ($r = .15$, $p < .01$), and the strongest correlation was observed between course quality and sustained learning interest ($r = .58$, $p < .01$). The demographic variables such as age, degree (level of education), and socioeconomic status did not correlate significantly with any learning outcomes nor with self-efficacy and self-regulation in interaction between student and content.

Table 1
Descriptive Statistics and Bivariate Correlations for All Variable

	Key Variables	Descriptive Statistics				Bivariate Correlations						
		M	SD	N	% Missing	1	2	3	4	5	6	7
1	Age	46.25	15.176	306	9.5	1	.317**	-.265**	0.037	0.035	-0.064	-0.046
2	Degree	5.09	1.554	334	1.2		1	-0.06	0.019	0.105	0.013	-0.098
3	Income-Education	15.693	19.009	322	4.7			1	0.002	0.066	-0.023	0.005
4	Student-Content Interaction	3.8011	0.8514	305	9.8				1	.179**	.242**	.260**
5	Self-Efficacy									1	.232**	.153**
6	Course Quality	4.7333	0.5507	300	11.2						1	.585**
7	Sustained Learning Interest	4.1959	0.7933	296	12.4							1

Note. * Correlation is significant at the 0.05 level (2-tailed).
** Correlation is significant at the 0.01 level (2-tailed).

Table 2
Descriptive Statistics for Categorical Variables

Demographics	Final Sample (*N* = 338)	
	N	%
Gender		
Male	145	42.9
Female	186	55
Other	7	2.1
Ethnicity		
White	220	65.1
Hispanic or Latino	32	9.5
Black or African American	17	5
Native American or American Indian	1	0.3
Asian/Pacific Islander	33	9.8
Other	32	9.5
Missing	3	0.9
English as First Language		
Yes	175	51.8
No	160	47.3
Missing	3	0.9
First-Generation College Student		
Yes	114	33.7
No	214	63.3
Missing	10	3
Receive Certificate		
Yes	131	38.8
No	205	60.7
Missing	2	0.6

Structural Model

We estimated the structural equation model as the baseline model, in which only main effects were estimated, and no demographic variables were included yet. This baseline model fits the data well, $\chi^2(7) = 2266$, $p = .94$, CFI = .980, RMSEA = .00 [90% CI = .00 to .013], SRMR = .014. In the measurement part of the model, all factor loadings were significant at the $p < .001$ level. We then estimated the conditional model in which demographic variables are included as covariates. These include gender, ethnicity, age, degree, language, status of first-generation students, socioeconomic status, and certificate status; the interaction between self-efficacy and student-content interaction was also estimated to test the moderating effect. The conditional model fit the data well, $\chi^2(29) = 38.16$, $p = .118$, CFI = .976, RMSEA = .038 [90% CI = .00 to .068], SRMR = .032.

The findings of structural paths showed that the latent construct of course quality was significantly predicted by self-efficacy ($b = .18$, $SE = .05$, $p = .001$) and student-content interaction ($b = .14$, $SE = .04$, $p < .001$), meaning that the more student-content interaction and perceived self-efficacy, the higher the perceived course quality outcome. None of the demographic variables predicted course quality. Course quality was also predicted by the interaction between self-efficacy and student-content interaction ($b = -.22$, $SE = .04$, $p < .001$), indicating that the effect of self-efficacy on course quality may be dependent on the level of student-content interaction, and vice versa.

For the latent construct of sustained learning interest, it was not predicted by self-efficacy ($b = .08$, $SE = .08$, $p = .28$), but it was significantly predicted by student-content interaction ($b = .27$, $SE = .06$, $p < .001$), indicating that the higher level of student-content interaction, the higher reported sustained learning interest. Moreover, sustained learning interest was significantly predicted by the interaction between self-efficacy and student-content interaction ($b = -.22$, $SE = .06$, $p < .001$), indicating that the effect of student-content interaction on sustained learning interest may be dependent on the level of self-efficacy. Most demographic variables did not predict student sustained learning interest, except for gender ($b = .23$, $SE = .09$, $p = .019$) and ethnicity, ($b = .52$, $SE = .22$, $p = .021$). Female students reported higher sustained learning interest than male students; Black students reported higher sustained learning interest than White students. Note that these differences are at the marginal level, and they are deemed non-significant after the Bonferroni adjustment.

Together, the model explained 36% of the total variance in course quality, and 34% of the total variance in student sustained learning interest. Unstandardized path coefficients and total R^2s for each model are presented in Table 3.

Table 3
Unstandardized Model Results

Factor Loadings	Estimate	S.E.	P-Value	R-Square
Course Quality				
PL1	1	0	999	0.63
PL2	0.844	0.071	<.001	0.78
Sustained Learning Interest				
SAT1	1	0	999	0.65
SAT2	0.792	0.13	<.001	0.24

Regression Path	Estimate	S.E.	P-Value	R-Square
Course Quality				0.356
Self-Efficacy	0.179	0.053	0.001	
Student-Content Int (SC)	0.142	0.039	<.001	
Self-Efficacy*SC	-0.221	0.041	<.001	
Gender (M = 1;F = 2)	0.014	0.065	0.832	
Latinx	-0.247	0.12	0.04	
Black	0.023	0.149	0.875	
Asian	-0.088	0.111	0.429	
Other	0.098	0.122	0.424	
Age	0	0.002	0.935	
Degree	0.016	0.023	0.485	
Language	0.138	0.074	0.062	
First Generation	-0.073	0.068	0.289	
Socioeconomic	-0.001	0.002	0.695	
Certificate	0.045	0.066	0.5	
Sustained Learning Interest predicted by				0.336
Self-Efficacy	0.084	0.078	0.28	
Student-Content Int (SC)	0.272	0.058	<.001	
Self-Efficacy*SC	-0.221	0.061	<.001	
Gender (M=1;F=2)	0.231	0.099	0.019	
Latinx	-0.075	0.181	0.678	
Black	0.518	0.224	0.021	
Asian	0.181	0.168	0.282	
Other	-0.077	0.184	0.676	
Age	0.001	0.004	0.865	
Degree	-0.037	0.035	0.287	
Language	0.117	0.108	0.28	
First Generation	-0.031	0.102	0.763	
Socioeconomic	-0.002	0.003	0.358	

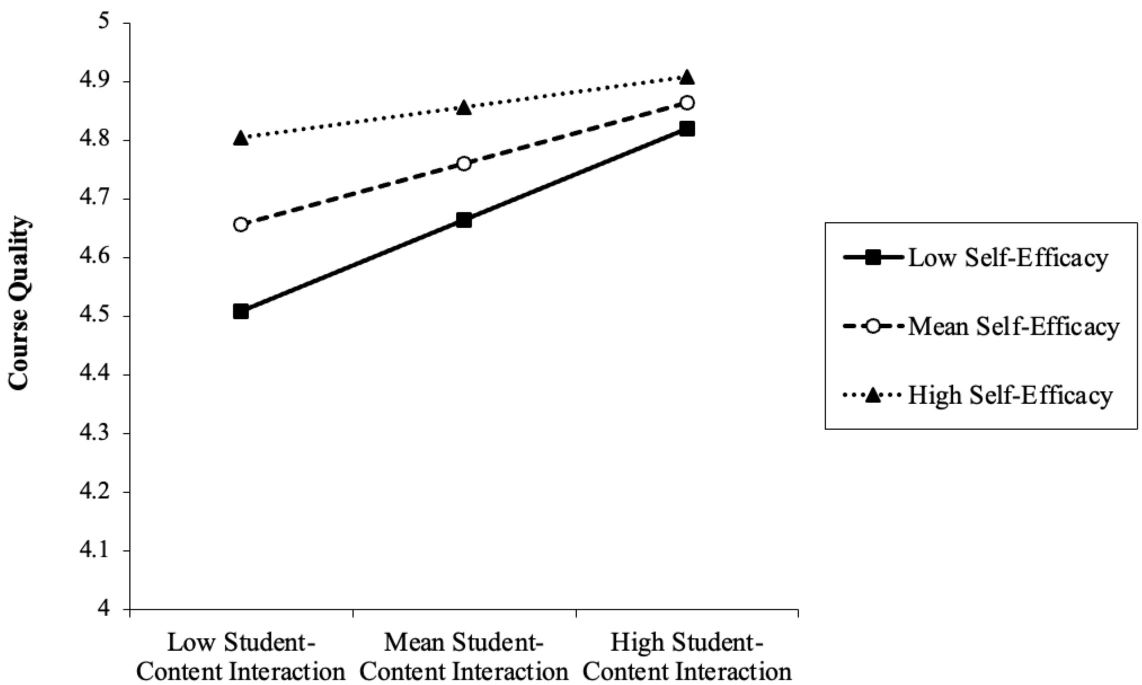
Certificate	0.057	0.099	0.568

Moderation Effect

Given that results showed a significant interaction between self-efficacy and student-content interaction on both course quality and student sustained learning interest, we applied simple slope analyses to chart out the interaction effect. As depicted in Figure 3, simple slopes revealed that the positive effects of student-content interaction on course quality were the strongest for students with a low level of self-efficacy (b = .36, SE = .05, p < .001), followed by a weaker association for students with a moderate level of self-efficacy (b = .14, SE = .03, p < .001). The positive effects of student-content interaction on course quality were deemed non-significant for students with a high level of self-efficacy (b =-.08, SE = .05, p = .168).

Figure 3

Interaction Between Self-Efficacy and Student-Content Interaction on Perceived Course Quality



Similarly, as depicted in Figure 4, simple slopes revealed that the positive effects of student-content interaction on student sustained learning interest were the strongest for students with a low level of self-efficacy (b = .31, SE = .08, p < .001). The positive effects of student-content interaction on student sustained learning interest were non-significant for students with a moderate level of self-efficacy (b = .08, SE = .03, p = .28), and not significant for students with a high level of self-efficacy (b =-.14, SE = .11, p = .225).

Figure 4
Interaction Between Self-Efficacy and Student-Content Interaction on Sustained Learning Interest

Discussion

The present study examined the relationships among student-content interaction, self-efficacy, and two learning outcomes in MOOCs. The findings supported the main effect hypotheses that student-content interaction predicts perceived course quality and sustained learning interest. However, the moderation hypotheses were not supported in the expected direction. Instead of amplifying the benefits of interaction, self-efficacy showed a compensatory pattern in which interaction effects were strongest for learners with lower self-efficacy, indicating support for H1 and H2 but not for H3 and H4.

Self-Efficacy as a Predictor of Learning and Sustained Learning Interest

The findings indicate that self-efficacy significantly predicts perceived course quality among MOOC participants but does not directly predict sustained learning interest once student-content interaction is considered. This pattern is consistent with Bandura's (1997) social cognitive theory, which suggests that efficacy beliefs shape how individuals interpret performance and evaluate their learning experience, rather than determining persistence across contexts. Learners with higher self-efficacy reported greater perceived course quality, highlighting the role of confidence as an interpretive lens for judging instructional value; however, sustained learning interest appears to depend more strongly on continued engagement with course materials. This interpretation aligns with Zimmerman's (2000) emphasis on the motivational and self-regulatory functions of self-efficacy, while also suggesting that in autonomous learning environments, behavioral engagement may be a more proximal driver of ongoing motivation.

While prior research has investigated self-efficacy broadly to online learning outcomes (Rabin et al., 2020; Rodríguez & Armellini, 2017; Wang & Newlin, 2002), its influence may vary across MOOC contexts and outcomes. The *Learning How to Learn* course, which focuses on learning strategies, may attract learners who already feel capable or may foster early mastery experiences that shape quality judgments more than persistence. Future research should examine diverse MOOC subjects and designs to determine when self-efficacy functions primarily as a direct predictor and when it operates instead as a boundary condition influencing how engagement translates into sustained interest.

Student-Content Interaction

The study found that student-content interaction significantly predicted both perceived course quality and sustained learning interest. This result is consistent with interaction theory in online learning, which positions engagement with learning materials as the primary mechanism through which learners construct meaning in large scale asynchronous environments (Moore, 1989). In MOOCs, where instructor and peer interaction are limited, interaction with content functions as the central behavioral pathway shaping learning experience. Learners who more actively engaged with course materials reported higher perceived course quality and stronger sustained learning interest, supporting prior research emphasizing the importance of meaningful engagement for motivation and perceived value (Jung et al., 2019; Moore & Wang, 2021).

Moderating Role of Self-Efficacy

A key contribution of this study is modeling self-efficacy as a moderator of the relationship between student-content interaction and two learning outcomes, perceived course quality and sustained learning interest. The moderation analyses indicate a compensatory pattern. Specifically, the positive effects of student-content interaction were strongest for learners with lower self-efficacy, weaker for learners with moderate self-efficacy, and non-significant for learners with high self-efficacy. This pattern is consistent with the observed negative interaction coefficients and the plotted simple slopes, and it suggests diminishing returns for learners who already hold strong efficacy beliefs.

It is worthwhile to note that these findings diverge from the proposed moderation hypotheses, which assumed that self-efficacy would amplify the benefits of student-content interaction. Instead, learners with higher self-efficacy reported more favorable outcomes overall, yet additional increases in student-content interaction yielded smaller marginal gains for them. For learners with lower self-efficacy, increases in interaction may provide structure and mastery cues that help them translate effort into more positive quality judgments and sustained interest. From a social cognitive perspective, this may reflect differences in how learners interpret difficulty and progress; interactive opportunities can function as confidence-building experiences for low-efficacy learners, whereas high-efficacy learners may sustain engagement even when interaction opportunities are less robust (Bandura, 1997; Zimmerman, 2000).

Implications for MOOC Design

The findings suggest several practical implications for MOOC design and delivery. First, student-content interaction should be treated as a central design lever for supporting perceived course quality and sustained learning interest, particularly for learners with lower self-efficacy. Because the positive effects of interaction were strongest for low self-efficacy learners, designers should prioritize frequent opportunities for active processing that are simple to initiate and easy to sustain across the course. This implication is consistent with interaction theory in distance learning and with evidence that engagement with content is a primary pathway shaping learner experience in MOOCs (Moore, 1989; Jung et al., 2019; Moore & Wang, 2021).

Second, course features that support self-efficacy should be designed as scalable structures rather than individualized services. Although personalized feedback is often limited in MOOCs, designers can still support efficacy through clear weekly goals, progress indicators, low-stakes practice activities with immediate feedback, and prompts that help learners plan and monitor their learning. These features align with social cognitive theory and self-regulated learning perspectives, which emphasize that efficacy beliefs influence effort and persistence, especially in self-directed environments (Bandura, 1997; Zimmerman, 2000; Cho & Shen, 2013; Kizilcec et al., 2017).

Third, the results imply that one design goal is to reduce the early drop-off risk for learners who enter with weaker self-efficacy by lowering the threshold for meaningful interaction. In large-scale autonomous courses, interest is more likely to be sustained when learners repeatedly experience progress through engagement with the material. Therefore, interaction opportunities should be distributed throughout the course and designed to create repeated mastery cues, such as short retrieval practice, worked examples, and brief application tasks that increase in challenge gradually (Bandura, 1997; Dai et al., 2020; Lee & Song, 2022). Based on the present findings, MOOC developers can implement several concrete steps. Early low-stakes quizzes with immediate feedback can create mastery experiences that help low self-efficacy learners interpret effort as productive. Interactive checkpoints embedded in videos can prompt active engagement rather than passive viewing. Short optional practice tasks before higher-stakes assessments can reduce uncertainty and support persistence. Onboarding modules that teach simple planning, monitoring, and reflection routines can strengthen self-regulation and help learners sustain engagement with course materials over time (Cho & Shen, 2013; Kizilcec et al., 2017; Zimmerman, 2000).

Limitations

This study has several limitations. Firstly, the reliance on self-reported data introduces potential biases, as participants' perceptions may not accurately reflect actual learning outcomes (Podsakoff et al., 2003). Additionally, the cross-sectional design limits the ability to infer causality, suggesting the need for longitudinal studies to better understand the evolving impacts of self-efficacy and student-content interaction (Maxwell & Cole, 2007). The study's sample, drawn from a single MOOC, "Learning How to Learn," may affect the generalizability of the findings, given the unique focus and continuous enrollment model of this course (Günther & Witte, 2007). Furthermore, while established scales were used to measure key constructs, they may not fully capture the complexities of self-efficacy and interaction in a MOOC context (Schunk & Pajares, 2009). Addressing these limitations in future research could enhance the understanding of these dynamics across diverse online learning environments.

Several constructs in this study were measured using a small number of items. Course quality and sustained learning interest were each assessed with two-item scales, which may limit construct coverage and the ability to fully represent the multidimensional nature of these outcomes. Although these items were adapted from prior MOOC research and demonstrated acceptable reliability for exploratory modeling, restricted item sets may attenuate observed associations and reduce precision in estimating structural relationships. Therefore, findings related to these constructs should be interpreted with appropriate caution. Future studies should employ broader multi-item scales to more comprehensively represent course quality and sustained learning interest in MOOC contexts.

Because self-efficacy, student-content interaction, and learning outcomes were all assessed using self-report instruments, the study is subject to potential common-method variance. Learners who report higher self-efficacy may also be more likely to report higher engagement and stronger learning outcomes due to shared perceptual tendencies rather than purely behavioral differences. This may partially inflate observed associations among the study variables. Future research should incorporate objective indicators such as learning analytics, assessment performance, or behavioral trace data from MOOC platforms to complement self-report measures and provide a more comprehensive understanding of these relationships.

Conclusion

This study contributes to ongoing discussions about persistence equity and learner motivation in large scale online learning environments. The findings indicate that student content interaction plays a critical role in shaping perceived course quality and sustained learning interest particularly for learners with lower self-efficacy. This pattern highlights the potential of well-designed interactive content to reduce motivational disparities and support learners who may be more vulnerable to disengagement in autonomous learning settings. By identifying self-efficacy as a moderating condition rather than only a direct predictor the study provides a more nuanced understanding of for whom MOOC design features are most effective. This contribution is particularly relevant for online education practice because it indicates that interactive content design can serve as an equity mechanism by disproportionately supporting learners with lower motivational confidence.

Structural equation modeling showed that student content interaction significantly predicted perceived course quality with $b = 0.14$ $p < .001$ and sustained learning interest with $b = 0.27$ $p < .001$. Self-efficacy significantly predicted course quality with $b = 0.18$ $p = .001$. Interaction effects were significant for both outcomes with $b = -0.22$ $p < .001$ indicating stronger content interaction effects among learners with lower self-efficacy. The model explained 36% of variance in course quality and 34% of variance in sustained learning interest. These insights inform future efforts to design inclusive supportive and motivating online learning experiences that promote persistence and meaningful engagement across diverse global learner populations.

Ethics Approval
This study was reviewed by the Institutional Review Board of the Boise State University (Protocol No. IRB24-102-01) and determined to be exempt from IRB oversight.

Conflict of Interest
The authors declare no conflicts of interest.

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AI Disclosure
ChatGPT (version 5.0, OpenAI) was used solely for proofreading and grammar refinement. No content generation or data analysis was performed using AI tools.

Data Availability
The data that support the findings of this study are available from the corresponding author upon reasonable request.

Disclaimer
The opinions and assertions expressed herein are those of the author(s) and do not necessarily reflect the official policy or position of the Uniformed Services University or the Department of War.

Appendix A

Survey Instrument

Demographics	
Question	**Response Type**
What is your age?	Open-Ended
What is your gender?	Male Female Prefer not to answer Not listed ( )
In what year did you take this "Learning How to Learn" MOOC?	Open-Ended
What is your ethnicity?	White Hispanic or Latino Black or African American Native American or American Indian Asian / Pacific Islander Other ( )
What is your highest degree?	Less than high school High school graduate 2 or 3 year degree 4 year degree Professional degree/Master's degree Doctorate
How many MOOCs have you taken, including this course?	Open-Ended
Is English your first language?	Yes No
Are you a first-generation college student?	Yes No
By the end of the course, did you receive the certificate or are you expecting to receive the certificate?	Yes No
Self-efficacy	
I was certain I could understand the most difficult content presented in this MOOC I was confident I could learn the basic concepts taught in this MOOC I was certain I could master the knowledge taught in this MOOC	Strongly disagree Somewhat disagree Neither agree nor disagree Somewhat agree Strongly agree
Three types of Interactions: Student-Content	
Before starting an assignment, I planned out my work I monitored my own progress to make sure that I was on the right track in this MOOC I regularly reflected upon what I learned in this MOOC	Strongly disagree Somewhat disagree Neither agree nor disagree Somewhat agree Strongly agree
Three types of Interactions: Student-Student	
I planned my participation in online interaction with other students in advance	Strongly disagree Somewhat disagree

I regularly interacted with other students in this MOOC I regularly checked other students' messages on the discussion board	Neither agree nor disagree Somewhat agree Strongly agree
Three types of Interactions: Student-Teacher	
I asked the teaching staff (e.g., instructor, teaching assistant, technical assistant) questions if needed I sought assistance from the teaching staff if needed I asked my questions as clearly as possible for effective communication with the teaching staff	Strongly disagree Somewhat disagree Neither agree nor disagree Somewhat agree Strongly agree
Course Quality	
I feel that I learned a great deal of knowledge in this course I was satisfied with this MOOC	Strongly disagree Somewhat disagree Neither agree nor disagree Somewhat agree Strongly agree
Sustained Learning Interest	
My interest in this course increased over time while taking this course I am going to take a similar MOOC to extend my knowledge or expertise in the topic.	Strongly disagree Somewhat disagree Neither agree nor disagree Somewhat agree Strongly agree

Appendix B

Confirmatory Factor Analysis (CFA) of the Scales

Scale Construct	Factor Loading	S.E.	P-Value	R-Square
Self-Efficacy				
Item 1	0.886	0.024	<.001	0.784
Item 2	0.742	0.032	<.001	0.551
Item 3	0.827	0.027	<.001	0.683
Student-Content Interaction				
Item 1	0.605	0.048	<.001	0.366
Item 2	0.857	0.053	<.001	0.734
Item 3	0.534	0.057	<.001	0.285
Course Quality				
Item 1	0.777	0.037	<.001	0.603
Item 2	0.759	0.037	<.001	0.576
Sustained Learning Interest				
Item 1	0.848	0.055	<.001	0.719
Item 2	0.427	0.055	<.001	0.182

Note. Standardized results are presented here. The model fit indices of this CFA is acceptable, with $\chi^2(29) = 65.55$, $p < .001$, CFI = .963, RMSEA = .064 [90% CI = .043 to .085], SRMR = .062.

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