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PAPER

How Academic Self-Efficacy Influences Online Learning Engagement: The Mediating Role of Boredom

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ABSTRACT

Academic self-efficacy and boredom were identified as key predictors of learning engagement in online learning. However, there has been little research designed to examine the mediating role of boredom in the relationship between academic self-efficacy and online learning engagement. To address this gap in knowledge, the present study utilizes social cognitive theory, control-value theory, and the self-system process model to examine the following: (1) the impact of academic self-efficacy on three sub-dimensions of learning engagement in online learning; and (2) whether four sub-dimensions of boredom mediate the relationships between academic self-efficacy and the three sub-dimensions of learning engagement in online learning. Data were collected from 528 university students (Mage = 19.77, SDage = 1.24) who voluntarily completed questionnaires assessing academic self-efficacy, boredom, and learning engagement. The results of the structural equation modeling indicated the following findings: (1) academic self-efficacy can predict online learning engagement; (2) affective boredom mediates the relationship between academic self-efficacy and behavioral and cognitive engagement; (3) cognitive boredom mediates the relationship between academic self-efficacy and cognitive engagement; (4) motivational boredom mediates the relationship between academic self-efficacy and behavioral and emotional engagement; and (5) physiological boredom mediates the relationship between academic self-efficacy and behavioral, emotional, and cognitive engagement. Finally, this study supports the notion that academic self-efficacy can influence learning engagement by addressing boredom in online learning. It also offers significant theoretical and practical implications for promoting students' release from boredom and enhancing their engagement in online education.

KEYWORDS

academic self-efficacy, boredom, learning engagement, online learning

1 INTRODUCTION

Due to its flexibility and convenience in terms of time and space, online learning is growing rapidly and becoming increasingly popular [1, 2]. Especially during

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the COVID-19 pandemic, online learning environments provide Chinese students with the opportunity to pursue courses using the most reliable and efficient alternatives [3]. Educators are becoming increasingly conscious of the importance of online learning for students who are unable to attend traditional schooling [4–6], as well as the various teaching technologies that enable more interactive experiences in higher education [7, 8]. However, researchers found that keeping students engaged and interested in the online learning environment remains a challenge for higher education institutions in China [9, 10]. These students rarely persevere and lack resilience in the face of obstacles compared to students in traditional educational settings. In such cases, further research is needed to explore effective strategies for engaging students in online learning [11, 12].

Among the antecedents of learning engagement, academic self-efficacy is believed to be one of the key factors influencing students' learning engagement [13–15]. According to the self-system model [16, 17], students' sense of competence leads to positive cognitive, behavioral, and emotional engagement in the classroom. This, in turn, leads to optimal academic achievement and a high level of academic self-efficacy, which enables students to be more involved in their learning. However, most previous research focuses on the association between academic self-efficacy and learning engagement in a traditional offline learning environment [18–26], while only a small number of studies have examined this relationship in an online learning environment [15, 27–29]. Additionally, the limited research did not identify how academic self-efficacy affects specific dimensions of engagement in online learning. Therefore, there is a need for more research to understand how academic self-efficacy is related to various types of online learning engagement.

Emotions are powerful determinants of learning and achievement [30]. The negative emotions are generally believed to impede students' desire and level of engagement by limiting their energy and enthusiasm to participate in learning activities [31, 32]. As one of the most common negative emotions in classrooms, boredom is associated with a variety of negative learning behaviors and outcomes [31, 33, 34]. According to Pekrun [30], boredom can occur when students lack value and control over learning activities. That is, boredom is influenced by how students perceive their competence in the task and how valuable they consider the task to be. Researchers have discovered that when students believe in their competence to perform activities in the learning environment, boredom is reduced. This is most likely due to intentionality, foresight, and self-regulation mechanisms [30, 35, 36]. Therefore, we contend that academic self-efficacy can be transformed into personal resources to combat boredom. This, in turn, sustains and supports learner engagement. Boredom, in other words, is likely to serve as a bridge between academic self-efficacy and learning engagement. To clarify, we propose that academic self-efficacy plays a role in regulating boredom, which ultimately leads to increased engagement in online learning.

Both academic self-efficacy and boredom play very important roles in students' learning. To the best of our knowledge, there has been little research examining the relationship between academic self-efficacy, boredom, and learning engagement in the context of online learning. Additionally, more attention needs to be given to research on how academic self-efficacy affects learning, particularly in relation to boredom. To address these research gaps, the present study aims to examine the direct effects of academic self-efficacy, boredom, and learning engagement on online learning. Additionally, it aims to explore the indirect effect of academic self-efficacy on learning engagement through boredom in online learning.

2 LITERATURE REVIEW

2.1 Academic self-efficacy and learning engagement in online learning

Studies suggest that online learning is influenced by individual factors, such as self-efficacy [29, 37, 38]. Rooted in Bandura's social cognitive theory, self-efficacy refers to an individual's personal belief in their capabilities to organize and execute courses of action required to attain designated types of performance [39]. The motivational factor behind academic self-efficacy is a crucial determinant in understanding students' behaviors in educational contexts [39–41]. Academic self-efficacy is a motivational factor that refers to one's belief in their ability to perform certain academic activities [40]. Students who have a stronger sense of academic self-efficacy are more likely to utilize more learning strategies and enhance cognitive competency [42, 43]. Additionally, they are more willing to exert effort and demonstrate perseverance when faced with learning problems [43, 44]. With the rapid expansion of the Internet and technology, numerous studies have been conducted to investigate self-efficacy in online learning contexts [15, 45, 46]. Expanding upon Bandura's notion of self-efficacy [47], academic self-efficacy within the context of online learning refers to individuals' belief and confidence in their ability to successfully complete online learning assignments and achieve desired outcomes [48]. Furthermore, students' academic self-efficacy is critical in mitigating the effects of remote learning while supporting effective and self-directed learning [49].

Self-efficacy, as a psychological factor, plays an important role in an online learning environment, and this has been supported by previous research. In terms of students' behavior, academic self-efficacy has a significant impact on their resilience and perseverance [50, 51], ability to handle challenging situations [28, 52], and focus on goals and the online learning process [28]. In terms of students' emotions, academic self-efficacy not only influences their desire to engage in and maintain interest in pursuing academic goals [13, 27], but it also has a positive connection to online learning satisfaction [49, 51, 53] and subjective well-being [54]. In terms of students' cognition, students who have higher self-efficacy are more likely to be motivated and committed to effective strategies when performing a task [55, 56]. Additionally, academic self-efficacy beliefs encourage the use of self-regulation strategies such as goal-setting, self-awareness, self-monitoring, self-reflection, and self-evaluation [57–59]. They also promote the use of metacognitive strategies like planning, reviewing, and organizing [56], as well as resource management strategies including time and learning environment management, labor management, and peer cooperation and help-seeking [56, 57, 60].

Further, learning engagement is an effective indicator of educational quality [61–63]. In an online learning context, personal agency can be seen as the driving force behind powerful, purposeful, and sustainable outcomes [64, 65]. Scholars have considered various aspects of learning engagement, including behavioral (i.e., effort and persistence), cognitive (i.e., using effective metacognitive strategies), and emotional (i.e., enthusiasm for learning and the classroom) engagement [66, 67]. According to the model of self-system processes, learning engagement can be attributed to the satisfaction of psychological needs within learning environments: autonomy, competence, and relatedness [16]. Specifically, the satisfaction of autonomy needs drives students' engagement, effort, and positive attitudes towards voluntary learning activities, while also stimulating their mental investment. Competence and satisfaction encourage learners to actively participate in behavioral and cognitive learning activities. Meanwhile, satisfaction of relatedness needs, including learners' frequent interactions with instructors and peers, will facilitate their behavioral and cognitive engagement in learning activities, which can result in more positive emotions towards the learning process. As such, students' intrinsic motivation can be engaged when they feel competent, autonomous, and connected to their environment, which motivates them to actively participate in academic tasks and achieve higher levels of performance [16, 68].

The combined insights from social cognitive theory and the model of self-system processes may explain why academic self-efficacy improves individuals' levels of engagement in online learning. We believe that students' efficacy beliefs can increase their intrinsic motivation to overcome obstacles, promote the adoption of effective self-regulation processes to meet psychological demands, and enhance engagement. In recent years, although some empirical studies have supported the direct connection between academic self-efficacy and learning engagement in online learning [15, 27–29], it remains unclear the underlying mechanism by which academic self-efficacy is associated with learning engagement.

2.2 Boredom as the mediator of the relationship between self-efficacy and learning engagement

As stated above, academic self-efficacy is considered a significant personal factor in predicting engagement in online learning [27, 29]. According to social cognitive theory [39] and control-value theory [30], positive personal resources can affect an individual's sense of control and value in their environment. This, in turn, can regulate and maintain their emotional state, ultimately assisting them in actively engaging in academic tasks. From this perspective, individual emotions can potentially have a significant influence on the relationship between academic self-efficacy and levels of engagement in the learning process.

Boredom is classified as a negative, deactivating emotion that is related to activities. It occurs when one is unable to meaningfully engage in a task, cannot sustain the necessary attention, and attributes the aversive feeling to the external environment [33, 69, 70]. Pekrun and Goetz [71] developed a comprehensive model to describe the experience of boredom. This model includes various dimensions, such as the emotional dimension (unpleasant and aversive feelings), cognitive dimension (distorted perception of time), physiological dimension (decreased arousal), expressive dimension (changes in facial expressions, vocal patterns, and body posture), and motivational dimension (desire to switch activities or exit the situation). Additionally, when considering online learning, students' boredom is connected to their level of academic self-efficacy and overall engagement with the learning process. When students experience boredom, their academic self-efficacy plays a crucial role in managing the demands of their learning environment. It also helps them utilize effective learning strategies and achieve academic success. Academic self-efficacy encourages students to pursue their goals, leverage their strengths, and remain engaged and persistent in the face of obstacles and setbacks. An abundance of empirical studies has consistently indicated a positive correlation between academic self-efficacy and students' experiences of boredom within the context of online learning [15, 72, 74]. For example, Wang and Cao [15] found that self-efficacy within an online learning environment was related to the boredom experienced by college students from various majors. In a similar vein, Raccanello and Florit [74] reported that higher levels of boredom in online multiple-text comprehension activities can be associated with reduced engagement and a lower investment of attentional resources in reading tasks. Artino and La Rochelle [72] found negative associations between boredom and self-efficacy in medical students, as well as negative effects of boredom on students' performance in online courses.

Boredom may, in turn, predict engagement in online learning. In accordance with control value theory [30], boredom is a common emotional state that is believed to negatively impact an individual's learning engagement and performance. Empirical studies have indicated that learners who experience boredom are less inclined to persist in learning and may have reduced engagement in online learning [15, 75–77]. For instance, Dubovi and Adler [75] found that undergraduates experiencing boredom would decrease their emotional and behavioral engagement in computer-based simulations during distance learning. In a study about online learning, Parker and Perry [76] documented that feelings of boredom, combined with a lack of control, hindered students' engagement and learning in their courses. Further, Sabourin and Lester [77] suggested that boredom and other negative emotions may be linked to disengagement in technology-based learning environments. Based on prior theory and research, academic self-efficacy has a negative impact on students' boredom, which, in turn, predicts their level of engagement in online education. Therefore, it is reasonable to suggest that boredom may mediate the relationship between academic self-efficacy and learning engagement in online education. This process, known as mediation, involves variable B (boredom) as the mediator that links variable A (academic self-efficacy) to variable C (learning engagement) [78].

3 RESEARCH HYPOTHESIS

Drawing upon the aforementioned theories and empirical research, the present study formulates the following set of two hypotheses:

1. There are significant direct effects of academic self-efficacy on three sub-dimensions of learning engagement in online learning among undergraduate students.
2. There are significant mediation effects between academic self-efficacy and three sub-dimensions of learning engagement through four sub-dimensions of boredom in online learning among undergraduate students.
   - There are significant direct effects of academic self-efficacy on three sub-dimensions of learning engagement in online learning among undergraduate students.
   - There are significant indirect effects of academic self-efficacy and four sub-dimensions of boredom in online learning among undergraduate students.
   - There are significant indirect effects of four sub-dimensions of boredom on three sub-dimensions of learning engagement in online learning among undergraduate students.

4 METHOD

4.1 Participants

In the spring semester of 2023, an online survey was conducted at a university in central China. 569 university students were randomly selected as participants.

Data collected from participants who either did not complete the questionnaire in its entirety or provided invalid responses were excluded from the study. Ultimately, there are a total of 528 samples, with 276 (46.71%) being male and 252 (52.96%) being female. The average age of the participants was 19.77 years (SD = 1.24), ranging from 18 to 24 years old. Among them, 118 (22.3%) were freshmen, 132 (25%) were sophomores, 169 (32%) were juniors, and 109 (20.6%) were seniors.

The study obtained approval from the principals of the participating universities. Before filling out the questionnaire, students were provided with information regarding the purpose of the study and given the choice to participate voluntarily. The participants then proceeded to answer a series of questionnaires, which included items on demographic information, academic self-efficacy, boredom, and engagement in online courses. It's worth noting that all participants had prior experience with online courses and had completed at least 1–2 courses. The questionnaires were provided in Chinese.

4.2 Measures

Academic self-efficacy. Greene and Miller [79] compiled the academic self-efficacy questionnaire. The scale consisted of seven items. Several examples of the questionnaire were: "I am confident in my ability to complete the assignments in this class," "I am certain that I can comprehend the material presented in this class," and "I am confident in my ability to understand the concepts and skills taught in this course." Two experts with extensive research expertise in applied linguistics and educational psychology were invited to translate the questionnaire. To ensure suitability for online learning environments, certain modifications were made to the phrasing of "this class or this course" in the items. This was done to make them more applicable to this study (e.g., I am confident in my ability to complete assignments in an online class; I am confident in my ability to comprehend the concepts and skills taught in an online course, etc.). Each item was rated on a 5-point Likert scale, ranging from 1 (completely disagree) to 5 (completely agree). The higher the scores, the more academic self-efficacy they perceive in online courses. The internal reliability of the total scale was adequate ($\alpha = 0.915$). The fit of confirmatory factor analysis was accepted ($\chi^2/df = 1.099$, root means square error of approximation (RMSEA) = 0.029, GFI = 0.969, incremental fit index (IFI) = 0.997, Tucker-Lewis fit index (TLI) = 0.996).

Boredom. The boredom questionnaire was adapted from the achievement emotions questionnaire-class-related boredom scale, which was compiled by Pekrun and Goetz [80]. This questionnaire consisted of 11 items designed to assess the level of boredom experienced by students in their classes. It included four dimensions: affective boredom, cognitive boredom, motivational boredom, and physiological boredom. The Achievement Emotions Questionnaire was originally developed in the field of general educational psychology, making it applicable to any specific domain. Two experts with extensive research expertise in applied linguistics and educational psychology were invited to translate the questionnaire. 11 items were revised in relation to the specific domain of online courses in the present study. An example of the questions was: "I get bored in online classes," "The lecture bores me in online classes," "Because the time drags, I frequently look at my watch in online classes," and "I get so bored I have problems staying alert in online classes." Each item was rated on a 5-point Likert scale, ranging from 1 (completely disagree) to 5 (completely agree). The higher the scores, the greater the degree of boredom. The internal reliability of the total scale was adequate, with $\alpha = 0.804$, cognitive boredom: α = 0.840, motivational boredom: α = 0.871, physiological boredom: α = 0.972). The fit of the confirmatory factor (χ^2/df = 1.394, RMSEA = 0.058, GFI = 0.920, IFI = 0.988, TLI = 0.983) of the total scale was adequate.

Learning engagement. Learning engagement was assessed using the learning engagement scale, which was developed by Fredricks and Blumenfeld [67] and revised by Sun and Rueda [81]. This scale was specifically designed to measure the level of engagement among graduate and undergraduate students in a distance education setting. The scale included 19 items, comprising behavioral engagement (five items), emotional engagement (six items), and cognitive engagement (eight items). Each item was rated on a 5-point Likert scale, ranging from 1 (completely disagree) to 5 (completely agree). Sample items included statements such as "I adhere to the rules of the online class," "I enjoy participating in the online class," and "I actively seek out additional materials to enhance my understanding of the topics covered in the online class." Two experts with extensive research expertise in applied linguistics and educational psychology were invited to translate the questionnaire. The learning engagement scale demonstrated good internal reliability (behavioral engagement: α = 0.971, emotional engagement: α = 0.923, cognitive engagement: α = 0.968) and satisfactory structural validity (χ^2/df = 1.249, RMSEA = 0.046, GFI = 0.871, IFI = 0.987, TLI = 0.985).

To ensure the quality of the research, a translation and back-translation process was implemented during the data collection phase in China. Initially, three linguistics professors were consulted to assess the significance and readability of each item in a questionnaire. With their assistance, the English questionnaire was translated into Chinese. Subsequently, two Ph.D. candidates, who were not involved in the study, translated the Chinese questionnaire back into English. A thorough comparison was then conducted between the translated items and the original English items to ensure consistency. Any inconsistencies were rectified, and the translation was refined accordingly.

Data analysis. Based on our theoretical framework, we have developed a comprehensive model that incorporates dependent, mediating, and independent variables. This model is informed by relevant theories and supported by empirical evidence. Given the complexity of the relationships among these variables, structural equation modeling (SEM) is an appropriate analytical approach for testing this model [82]. In this study, we used SPSS 26.0 to calculate the means, standard deviations, and correlations among all variables. To perform the structural equation modeling, we utilized AMOS 24. This software enables the simultaneous examination of variable relationships within the model and provides valuable insights into the overall model fit. To assess the goodness-of-fit of our model, we considered several indices. These include the ratio of chi-square value to degrees of freedom (χ^2/df), the RMSEA, the IFI, the TLI, and the comparative fit index (CFI). Consistent with prior research [83], acceptable fit indices are typically indicated by $\chi^2/df \leq 5$, RMSEA < 0.08, IFI approaching 0.9, and CFI and TLI approaching 0.9. Furthermore, we employed bias-corrected bootstrapping with 95% confidence intervals (CIs) to examine the significance of indirect mediating effects [84]. This approach provides a comprehensive assessment of the mediation effects within our model.

5 RESULT

To examine the relationships between the constructs, we first conducted a correlation analysis and assessed the skewness and kurtosis of the variables to ensure that they were distributed appropriately. Subsequently, confirmatory factor analysis was employed to validate the measurement instruments used in the study. A measurement model, aligned with our research hypotheses, was constructed and tested to confirm the hypothesized relationships. To ensure a clear and concise presentation of the results, we have organized our findings in Table 3 and illustrated the key outcomes in Figure 2. This visual representation enhances the understanding and interpretation of the results.

5.1 Measurement validation

In Table 1, we present the means, standard deviations, skewness, kurtosis, and correlations for the measurements in the study. To examine the relationships between the different constructs, we computed composite scores by taking the average of the item scores. Pearson correlation coefficients were then computed to assess the associations among the constructs. The analysis revealed a correlation between academic self-efficacy and boredom. Academic self-efficacy was found to have a significantly weak and negative correlation with affective boredom ($r = –0.09$, $p < 0.05$), cognitive boredom, and motivational boredom ($r = –0.13, –0.18$, respectively, $p < .01$). However, it did not show a significant correlation with physiological boredom ($r = –0.07$, $p > .05$). The correlation between boredom and learning engagement was found to be significant. All four sub-constructs of boredom were found to be significantly weak or moderately and negatively correlated with behavioral, emotional, and cognitive engagement ($r = –0.38, –0.42, –0.44, –0.44, –0.20, –0.29, –0.32, –0.30, –0.30, –0.32, –0.30, –0.29$, respectively, $p < .01$). To evaluate the validity and reliability of the instrument, we employed composite reliability (CR) to assess the reliability of the constructs and average variance extracted (AVE) to evaluate the convergent and discriminant validity criteria using confirmatory factor analysis [82]. As shown in Table 2, the CR for each construct ranged from 0.663 to 0.934, all of which are higher than the recommended threshold of 0.60 [85]. The AVE of each construct is higher than the shared variance (the square of the Pearson correlation), indicating appropriate discriminant validity [86]. The results indicate satisfactory convergent and discriminant validity.

Table 1. Means, standard deviation and correlations for measured variables

	1	2	3	4	5	6	7	8
1. SE	1							
2. AB	–0.09*	1						
3. CB	–0.13**	0.59**	1					
4. MB	–0.18**	0.59**	0.75**	1				
5. PB	–0.07	0.55**	0.64**	0.59**	1			
6. BE	0.12**	–0.38**	–0.42**	–0.44**	–0.44**	1		
7. EE	0.38**	–0.20**	–0.29**	–0.32**	–0.30**	0.55**	1	
8. CE	0.32**	–0.30**	–0.32**	–0.30**	–0.29**	0.46**	0.42**	1
M	3.09	2.33	3.22	2.85	2.51	3.08	3.06	3.28
SD	0.80	0.85	0.95	0.96	0.88	0.40	0.58	0.72
Skewness	–0.501	0.282	–0.086	–0.130	0.298	–0.510	–0.426	–0.718
Kurtosis	–0.853	–0.889	–0.568	–0.914	–0.683	–0.184	–0.228	–0.062

Notes: SE = academic self-efficacy; AB = affective boredom; CB = cognitive boredom; MB = motivational boredom; PB = physiological boredom; BL = behavioral engagement; EL = emotional engagement; CL = cognitive engagement. *p < .05, **p < .01; M = Means; SD = Standard deviations.

Table 2. Instrument reliability and validity

Variable	Dimension	Factor Loadings	Cronbach's α	Composite Reliability (CR)	Average Variance Extracted (AVE)
Academic self-efficacy			0.915	0.663	0.932
Boredom	Affective	0.756	0.804	0.788	0.650
		0.854			
	Cognitive	0.601	0.840	0.664	0.502
		0.802			
	Motivational	0.727	0.871	0.765	0.522
		0.663			
		0.773			
	Physiological	0.896	0.972	0.934	0.778
		0.832			
		0.895			
		0.904			
Learning engagement	Behavioral	0.758	0.971	0.834	0.502
		0.728			
		0.685			
		0.681			
		0.688			
	Emotional	0.760	0.923	0.827	0.446
		0.697			
		0.688			
		0.586			
		0.681			
		0.557			
	Cognitive	0.764	0.968	0.901	0.532
		0.708			
		0.752			
		0.798			
		0.739			
		0.698			
		0.670			
		0.696			

5.2 Test of the structural equation model

To comprehensively explore the relationship between academic self-efficacy, boredom, and learning engagement in online courses, we utilized AMOS 24 to evaluate the overall fit and explanatory power of the SEM using the maximum likelihood estimate (MLE). Before examining the mediation model, we initially established a total effect model (as depicted in Figure 1) to confirm the direct impact of academic self-efficacy on learning engagement in online courses. As depicted in Figure 1, academic self-efficacy has a significantly positive impact on behavioral engagement ($\beta = 0.5$, $p < .001$), emotional engagement ($\beta = 0.7$, $p < .001$), and cognitive engagement ($\beta = 0.6$, $p < .001$). This served as the foundation for our subsequent comparison of the mediating models.

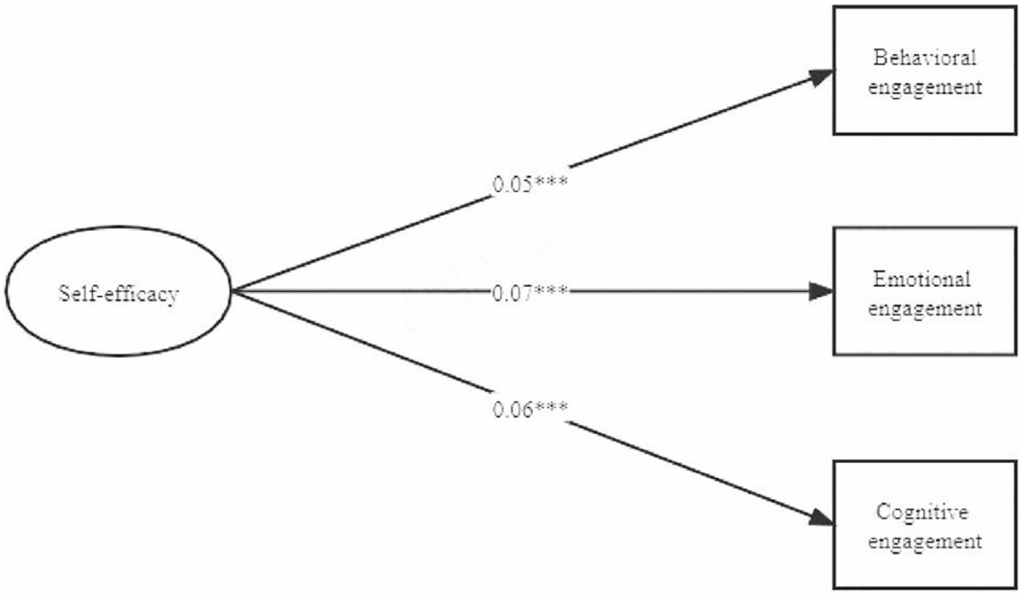

Fig. 1. The direct effects model

Note: ***p < .001.

Building upon the total effect model, we proceeded to examine a multiple mediating effect model (Figure 2). In this model, we explored the association between academic self-efficacy and learning engagement (behavioral engagement, emotional engagement, and cognitive engagement) by considering boredom (affective boredom, cognitive boredom, motivational boredom, and physiological boredom) as mediators. Based on the criteria of Hu and Bentler [83], our model demonstrates a satisfactory fit. The χ^2/df ratio ($\chi^2 = 1943.48$; df = 605) statistic is 3.21 ($p < .001$). Additionally, the CFI is 0.90, the RMSEA is 0.065, the IFI is 0.90, and the TLI is 0.89.

Additionally, Figure 2 displays the standardized path coefficients for both direct and indirect effects. The results showed that academic self-efficacy was able to predict affective boredom ($\beta = -0.13$, $p < .05$), which in turn predicted behavioral engagement ($\beta = -0.11$, $p < .05$) and cognitive engagement ($\beta = -0.15$, $p < .05$). Similarly, academic self-efficacy was able to predict motivational boredom ($\beta = -0.22$, $p < .001$), which in turn predicted behavioral engagement ($\beta = -0.19$, p < .001) and emotional engagement (β = –0.13, p < .05). However, academic self-efficacy could not predict cognitive boredom (β = –0.16, p < .001), which in turn only predicted cognitive engagement (β = –0.14, p < .05). As expected, academic self-efficacy can predict physiological boredom (β = –0.09, p < .05), which in turn predicts behavioral engagement (β = –0.36, p < .001), emotional engagement (β = –0.18, p < .001), and cognitive engagement (β = –0.14, p < .05).

Based on the bias-corrected bootstrapping test results (Table 3), the indirect effects of academic self-efficacy on behavioral engagement (indirect effect = 0.02, 95% CI = [0.001, 0.05]) and cognitive engagement (indirect effect = 0.02, 95% CI = [0.002, 0.04]) through affective boredom were found to be significant. The results indicated that affective boredom played a mediating role in the associations between academic self-efficacy and behavioral engagement, as well as academic self-efficacy and cognitive engagement. The study found significant indirect effects of academic self-efficacy on behavioral engagement (indirect effect = 0.05, 95% CI = [0.01, 0.10]) and emotional engagement (indirect effect = 0.03, 95% CI = [0.001, 0.06]) through motivational boredom. This suggests that motivational boredom plays a mediating role in the relationships between academic self-efficacy and both behavioral engagement and emotional engagement. Furthermore, the study found significant indirect effects of academic self-efficacy on emotional engagement (indirect effect = 0.01, 95% CI = [0.001, 0.03]) and cognitive engagement (indirect effect = 0.01, 95% CI = [0.001, 0.03]) through physiological boredom. This result shows that motivational boredom acts as a mediator in the relationships between academic self-efficacy and behavioral engagement, as well as academic self-efficacy and emotional engagement.

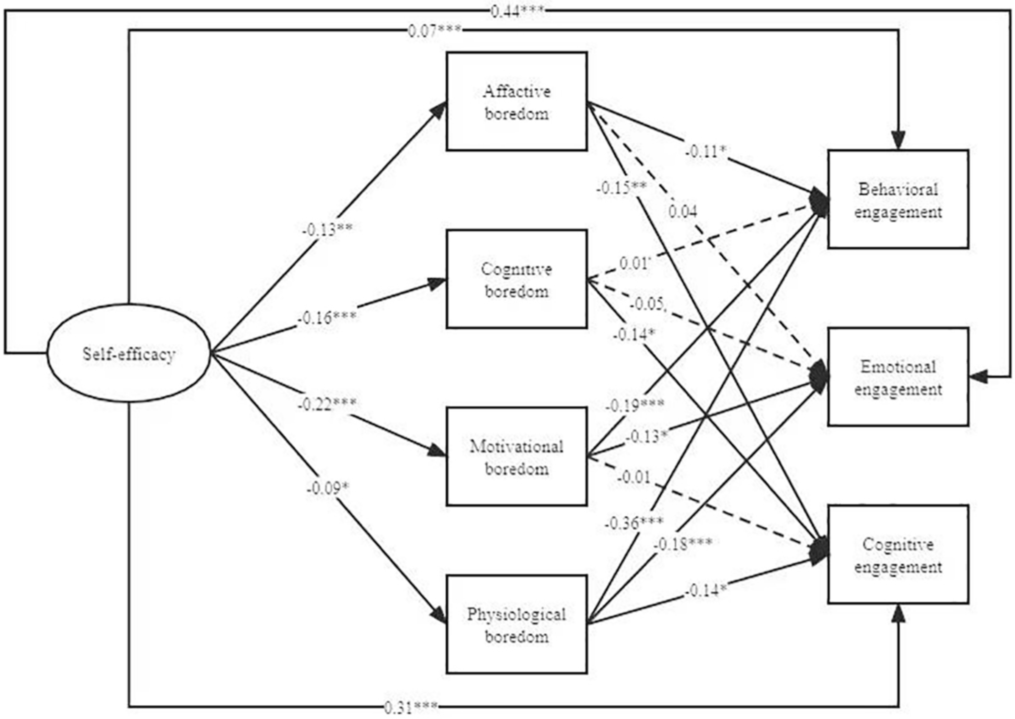

Fig. 2. The multiple indirect effects model

Notes: *p < .05, **p < .01, ***p < .001.

Table 3. Bias-corrected bootstrap test on the mediating effects of boredom in online courses

Model Pathways	Effect	95% CI	
		Lower	Upper
Academic self-efficacy-affective boredom-behavioral engagement	0.02	0.001	0.05
Academic self-efficacy-affective boredom-emotional engagement	–0.004	–0.02	0.01
Academic self-efficacy-affective boredom-cognitive engagement	0.02	0.002	0.04
Academic self-efficacy-cognitive boredom-behavioral engagement	–0.002	–0.03	0.04
Academic self-efficacy-cognitive boredom-emotional engagement	0.01	–0.01	0.03
Academic self-efficacy-cognitive boredom-cognitive engagement	0.02	–0.001	0.05
Academic self-efficacy-motivational boredom-behavioral engagement	0.05	0.01	0.10
Academic self-efficacy-motivational boredom-emotional engagement	0.03	0.001	0.06
Academic self-efficacy-motivational boredom-cognitive engagement	0.002	–0.03	0.03
Academic self-efficacy-physiological boredom-behavioral engagement	0.04	–0.002	0.09
Academic self-efficacy-physiological boredom-emotional engagement	0.01	0.001	0.03
Academic self-efficacy-physiological boredom-cognitive engagement	0.01	0.001	0.03

6 DISCUSSION

Drawing inspiration from previous theories and empirical studies, this study aimed to investigate the mediating role of boredom. Specifically, the study focuses on examining the connection between academic self-efficacy and learning engagement in the context of online learning. Overall, the results highlighted the importance of boredom in understanding the connection between academic self-efficacy and learning engagement. Furthermore, significant differences were observed in terms of the predictive impact of the four sub-dimensions of boredom on the three sub-dimensions of learning engagement. These findings not only support existing theories but also provide valuable empirical insights for improving online educational practices.

6.1 Direct effect of academic self-efficacy on learning engagement

First, in line with the findings in the literature [15, 27–29], this study discovered that academic self-efficacy can predict students' engagement in online learning. The results fully support Hypothesis 1, which states that there are significant direct effects of academic self-efficacy on three sub-dimensions of learning engagement in online learning among undergraduates. Social cognitive theory [47] emphasizes the importance of self-efficacy in learning and suggests that self-efficacy can influence attitudes and self-regulation in online education. As a result, students with high self-efficacy have greater confidence and more positive attitudes. This, in turn, encourages them to actively utilize self-regulation strategies to fulfill their psychological needs, motivates them to achieve their learning goals, and invest more mental energy and effort into the learning process. Specifically, in an online learning environment, academic self-efficacy can influence students' learning behavior choices.

Individuals with high academic self-efficacy believe in their abilities and have a more positive self-evaluation [39, 43]. In the face of challenges and setbacks, individuals can engage in effective self-regulation processes, including self-observation, self-evaluation, and self-adjustment. These processes allow individuals to align their behavior with their aspirations and leverage their strengths, thereby providing direction and purpose to their actions [43, 56, 60]. Academic self-efficacy can influence students' emotional state in online learning. Affective engagement is closely related to the satisfaction of relatedness needs [16, 17]. Academic self-efficacy promotes students' engagement and interaction with their peers and instructors, facilitating the exchange of ideas and the ability to ask questions. This, in turn, helps students perceive greater emotional support and experience fewer negative emotions [15, 18, 65]. Lastly, academic self-efficacy can affect students' cognitive effort. Students' perceptions of autonomy support in online learning allow them more latitude in deciding on learning goals, learning resources, and learning strategies. This may encourage them to invest more enthusiasm and thoughtfulness in mastering difficult skills, comprehending complicated concepts, and employing deep learning strategies [13, 29, 60, 65]. Taken together, these results consolidate the argument that academic self-efficacy significantly influences behavioral, emotional, and cognitive engagement in online learning. However, it is noted that the standardized path coefficients of academic self-efficacy on learning engagement are weak, which is inconsistent with previous studies. We can also explain that academic self-efficacy has an indirect and significant effect on learning engagement through various other factors. Further, according to social cognitive theory [47] and control value theory [30], we can infer that a lack of positive environmental or emotional factors in online contexts might hinder learning engagement, even among self-efficacious students.

6.2 Indirect effect of boredom between academic self-efficacy and learning engagement

Secondly, according to Hypothesis 2, all four sub-dimensions of boredom in online learning will mediate the relationship between academic self-efficacy and the three sub-dimensions of learning engagement. The results of this study are partially consistent with it, especially in terms of physiological boredom. These findings support the control value theory, suggesting that boredom plays a significant role as a mediator in this association. Control value theory [30] posits that appraisals of situations may affect subjective emotions, which in turn affect behaviors. On the one hand, academic self-efficacy during online learning was negatively associated with boredom (affective, cognitive, motivational, and physiological boredom). This finding is similar to prior studies [15, 72–74]. When self-efficacious students perceive boredom in online learning, they are prone to using self-regulation strategies such as goal-setting and self-monitoring, metacognitive strategies such as reviewing and organizing, and resource management strategies such as time and learning environment management, as well as peer cooperation and help-seeking strategies. These strategies provide a valuable means to reappraise or change the controllability of the current situation, which can regulate or diminish the experience of boredom and, thus, improve their learning engagement. On the other hand, there are differences in predicting boredom and its impact on learning engagement in online learning. Firstly, affective boredom significantly negatively impacts behavioral and cognitive engagement while not affecting emotional engagement. This may be due to the deactivation and transitory nature of boredom characters [30, 87]. Some students have difficulties perceiving their level of boredom in online learning, which may result in their inaccurate response in self-reporting. Besides, boredom often occurs along with a failure to sustain attention [87, 88]. As a result, students have difficulties maintaining the cognitive hardiness required to persist in online learning tasks. Secondly, we found that cognitive boredom significantly negatively impacts cognitive engagement but not behavioral or emotional engagement. According to the internal clock model [89], when individuals are engaged in a tedious task, they tend to allocate a greater portion of their attentional resources to perceiving the passage of time. Consequently, individuals may experience a distorted perception of time, resulting in a decrease in the cognitive resources available for cognitive engagement. Moreover, motivational boredom significantly impacts behavioral and emotional engagement but does not impact cognitive engagement. In detail, boredom serves as a functional emotion, propelling individuals to seek out new goals when their current pursuits no longer provide satisfaction, attraction, or significance [90]. Consequently, students who feel bored are prone to engaging in other interesting activities, which hinders their ability to concentrate and persevere when faced with difficulties. Lastly, physiological boredom significantly negatively impacts behavioral, emotional, and cognitive engagement in online learning, which is consistent with prior studies [91, 92]. When learners experience mental fatigue (indicated by a low heart rate or changes in brain waves), it becomes challenging to sustain attention on a monotonous task. As a result, they often resort to mind-wandering as a cognitive-avoidance strategy [87, 88].

7 IMPLICATION

This study investigates the relationship between academic self-efficacy, learning engagement, and boredom in online settings using structural equation modeling. Several contributions resulted from the current work. Theoretically, several contributions result from the current work. Theoretically, this research proposes and confirms that academic self-efficacy and boredom are significant antecedents of learning engagement in online learning. This discovery raises another potential, yet mostly unexplored, discussion in the online learning environment. Then, we discovered a specific pathway from academic self-efficacy to the sub-dimensions of learning engagement by way of the sub-dimensions of boredom in online learning. This finding not only complements previous studies on online education but also provides insight into the mediating roles of different types of boredom in the relationship between academic self-efficacy and specific sub-dimensions of engagement in online learning. This is a departure from earlier research conducted in an online learning environment. Understanding the mediation mechanism between academic self-efficacy and learning engagement through boredom in online learning can practically assist educators in implementing interventions to alleviate boredom and enhance students' engagement in online learning. In particular, educators and instructors in educational institutions may find it more advantageous to prioritize enhancing students' academic self-efficacy to reduce boredom and promote learning engagement in an online environment rather than investing in the development of expensive web-based education programs.

8 LIMITATION AND SUGGESTION

Drawing from social cognitive theory, control value theory, and the self-system process model, our study explains how academic self-efficacy influences learning engagement through boredom in online learning. Nevertheless, although the sample size for our study sufficiently validates our proposed model, it is important to acknowledge that our findings may not encompass all aspects of online learning phenomena. This suggests the possibility of employing alternative models, derived from different theoretical perspectives, to explore the issue of learning engagement in online education. Furthermore, based on the findings, this study offers suggestions for future research directions.

First, considering the significant impact of physiological boredom on three aspects of learning engagement in the current study, future research should investigate the role of boredom in online learning from a neuropsychological perspective. Second, considering academic boredom as a domain-specific construct, it would be interesting to explore the cross-level effect, i.e., whether boredom leads to online engagement across various online courses. Third, the current study investigates the role of boredom as a mediator between academic self-efficacy and learning engagement in online learning. In the future, further studies could investigate the interaction between various sub-dimensions of boredom in online learning. Lastly, regarding learning engagement, future work can focus on developing a more comprehensive measure. This can be achieved by either utilizing the established four constructs (behavioral, emotional, cognitive, and agentic engagement) or by developing new measures grounded in contextual or theoretical foundations. The aim is to accurately capture the variance in online learning.

9 CONCLUSION

The present research comprehensively explores the associations among academic self-efficacy, boredom, and learning engagement in online learning. The findings showed that academic self-efficacy significantly and positively predicts three sub-dimensions of online learning engagement unequally. This study further reveals the different mediating paths of academic efficacy on learning engagement, emphasizing the critical role of boredom in online learning. Specifically, the mediating path suggests that academic self-efficacy can predict behavioral engagement by regulating, affective motivational, and physiological boredom. Academic self-efficacy can predict emotional engagement by alleviating motivational and physiological boredom. Additionally, academic self-efficacy can predict cognitive engagement by reducing affective, cognitive, and physiological boredom.

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