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RESEARCH ARTICLE

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What influences computational thinking? A theoretical and empirical study based on the influence of learning engagement on computational thinking in higher education

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Abstract

As an important part of core competencies in the 21st century, computational thinking has received a lot of attention from all over the world. In the field of higher education, cultivating the ability of computational thinking has become an important goal of teaching. Previous research has shown that students' learning engagement is related to partial dimensions within computational thinking. However, there was a lack of research on the overall relationship between learning engagement and computational thinking. Therefore, this study aims at constructing an overall relationship model between learning engagement and computational thinking to examine the influence of three dimensions of learning engagement on the five dimensions of computational thinking. The participants were 341 freshmen from central China. The results show that compared with behavioral engagement, both emotional engagement and cognitive engagement had a stronger predictive power for computational thinking. In addition, the learning environment played a significant role in the relationship between learning engagement and computational thinking. On the whole, when compared with traditional multimedia classrooms, the relationship between learning engagement and computational thinking in smart classrooms was closer. A theoretical and empirical study of the relationship between learning engagement and computational thinking presents researchers and education practitioners with a method to improve students' computational thinking by building a learning environment and designing pedagogy.

KEYWORDS

computational thinking, learning engagement, relationship model, smart classrooms

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1 | INTRODUCTION

Computational thinking is a crucial skill for problem-solving in the 21st century, with applications across multiple academic disciplines and daily life [20]. Since its introduction by Wing [50], computational thinking has become an increasingly important topic in the field of information technology (IT) education. Besides reading, writing, and calculation, computational thinking is considered a fundamental skill for learners to develop themselves [14]. Previous research has shown that students' engagement in various classroom activities, such as programming, game-based learning, collaborative learning, and assessment can effectively promote computational thinking [22, 38].

Since computational thinking is developed by participation in educational activities, the study of how students' learning engagement improves computational thinking has become an interesting research domain. Students' learning engagement refers to their participation in tasks and activities within the classroom [2]. Prior studies have indicated that students' learning engagement is related to partial dimensions of computational thinking [32, 39, 54]. However, we have limited knowledge about how learning engagement promotes the development of students' computational thinking.

Thus, the relationship between students' learning engagement and their computational thinking has been underexplored. Therefore, this study seeks to explore the relationship between students' learning engagement and their computational thinking. Specifically, the main objectives of this study were to answer the following two questions:

Q1. Do relationships exist between learning engagement and computational thinking? If so, to what extent does learning engagement predict computational thinking?

Q2. Is there any different influence of learning engagement on computational thinking between smart classrooms and traditional multimedia classrooms?

2 | THEORETICAL FRAMEWORK

2.1 | Computational thinking

The term "computational thinking" was first used by Papert [36], who proposed that computers could improve thinking and alter the way knowledge was accessed. According to Wing [50], computational thinking was an ability that everyone should have. Since then, educators and educational researchers have become increasingly interested in computational thinking and have recognized it as a crucial competence [45]. The definition and framework of computational thinking were still subject to debate among researchers, but some researchers believed that it was related to problem-solving. Furthermore, computational thinking was widely regarded as a universal problem-solving approach that was not restricted by an individual's particular domain knowledge or programming ability [21].

Korkmaz et al. [25] designed an instrument for measuring college students' computational thinking, which consisted of five dimensions: (1) creativity, (2) algorithmic thinking, (3) cooperation, (4) critical thinking, and (5) problem-solving. The creativity dimension was designed to evaluate their ability to express themselves and use their imagination and cognitive skills. The algorithmic dimension was designed to assess the ability of critical thinking, comprehending, applying, evaluating, and generating algorithms. The cooperation dimension was developed to assess a learning method that aims to maximize the learning of individual and group members in small groups. The critical thinking dimension was developed to measure the possibility of using cognitive skills or strategies to increase intended behavior. The problem-solving dimension was designed to evaluate capacities to overcome the problems encountered in the process of reaching a certain purpose or intellection. Thus, for the current study, we used Korkmaz et al.'s five dimensions not only to investigate college students' computational thinking but also to examine the relationship between students' learning engagement and their computational thinking.

2.2 | Learning engagement

Since as early as the 1990s, learning engagement has attracted significant interest from a growing body of educators, and it had been defined from various perspectives. This was because learning engagement was crucial for understanding why students exhibited low academic performance, high levels of boredom, classroom alienation, and dropout rates [26, 48]. Learning engagement was a multidimensional structure that could be defined and measured in various ways across multiple dimensions.

According to existing research, students' learning engagement consisted of behavioral, emotional, and cognitive engagement. Behavioral engagement referred to positive and non-destructive behaviors exhibited by students, such as completing academic tasks, adhering to discipline, and actively participating in academic activities [47]. Emotional engagement reflected students' positive emotional involvement in academic activities,

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including expressing interest and enthusiasm, establishing connections with others, and forming positive learning attitudes and emotional experiences [13]. Cognitive engagement involved self-regulated learning, which included the use of both shallow and deep learning strategies to comprehend and master the material [47].

3 | RESEARCH MODEL AND HYPOTHESES

This study aims to explore the relationship between learning engagement dimensions and each dimension of computational thinking. As shown in Figure 1, computational thinking dimensions were the dependent variables, with the learning engagement dimensions being independent variables.

3.1 | Creativity

Creativity has been defined as the ability to express themselves and use their imagination and cognitive skills [8]. Creative thinking plays a crucial role in social development. According to Plucker, Beghetto, and Dow [37], creativity involves discovering new connections and creating novel combinations from one or more concepts in the mind to gain a new perspective. Creativity can lead to new products, literature, and art that fulfill the needs of humanity.

Many studies have found that student engagement has a positive influence on the development of creativity. For example, Reid and Solomonides [39] investigated the relationship between students' engagement and creativity. The authors showed that students' learning engagement was a predictor of their creativity. Mastria, Agnoli, and Corazza [34] also found a positive relationship between students' emotional engagement and creativity, with those in a positive emotional state tending to have higher creativity levels. According to Zhang et al. [55] active learning engagement facilitated the asking of questions and the exploration of new ideas. Overall, these studies indicated that students' learning engagement catalyzes generating creative ideas. Specifically, active learning engagement by students stimulates their curiosity and creative thinking, thereby driving them to generate more creative ideas.

In light of this, we suggest that college students' learning engagement may be positively related to their level of creativity. Specifically, we put forth the following hypothesis:

H1 Students' behavioral engagement is positively related to their level of creativity.

H2 Students' emotional engagement is positively related to their level of creativity.

H3 Students' cognitive engagement is positively related to their level of creativity.

3.2 | Algorithmic thinking

Algorithmic thinking refers to an individual's capacity to construct new algorithms for solving a particular problem [15]. In practical terms, algorithmic thinking is a problem-solving approach in which an individual breaks down a complex problem into smaller and more specific sub-problems, and designs a series of operational steps to achieve the goal of problem-solving [9]. Algorithmic thinking has wide applications in fields, such as computer science, mathematics, engineering, and others.

Prior studies have primarily focused on the composition of algorithmic thinking and the method of improving algorithmic thinking. For example, Hsu and Wang [19] developed the Turtle Graphics Tutorial System, which helped students develop algorithmic thinking by allowing them to solve puzzles. According to Li et al. [28], game-based collaborative learning environments had the potential to improve students' algorithmic thinking. In addition, Erümit [10] proposed that the mathematical and game preparation activities were found to have positive effects on

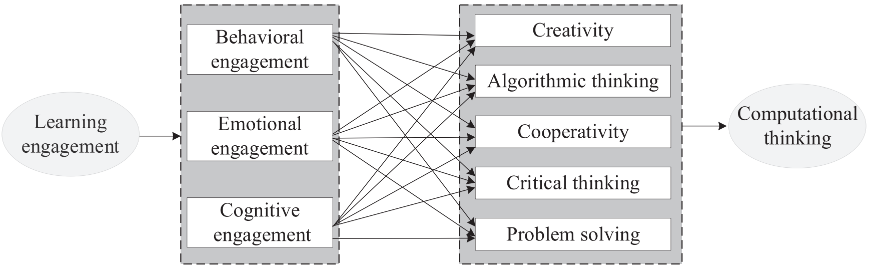

FIGURE 1 Overall relationship model between learning engagement and computational thinking.

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algorithmic thinking. These findings reveal that algorithmic thinking was developed by participation in classroom activities.

In light of this, we suggest that college students' learning engagement may be positively related to their level of algorithmic thinking. Specifically, we put forth the following hypothesis:

H4 Students' behavioral engagement is positively related to their level of algorithmic thinking.

H5 Students' emotional engagement is positively related to their level of algorithmic thinking.

H6 Students' cognitive engagement is positively related to their level of algorithmic thinking.

3.3 | Cooperativity

Cooperative learning refers to a learning method in which students work together in small groups to complete learning tasks, communicate with each other, assist each other, and ultimately achieve shared learning objectives [46]. This method holds a favorable position among learning methods due to its various contributions, including improving academic achievement, cultivating cooperative and autonomous learning ability, facilitating information sharing, and fostering social relationships among students [24, 35].

Coates [7] claimed that the students' engagement was related to students' communication and sharing, which was one of the key factors in cooperative learning. Bouta, Retalis, and Paraskeva [5] explored the impact of an online 3D virtual environment on primary mathematics education. The study found a relationship between emotional engagement and collaborative learning actions among students. Geletu [16] surveyed how teachers' competencies impact implementing cooperative learning and enhancing student engagement. The results showed that students' learning engagement was directly related to the use of cooperative learning methods.

In light of this, we suggest that college students' learning engagement may be positively related to their level of cooperativity. Specifically, we put forth the following hypothesis:

H7 Students' behavioral engagement is positively related to their level of cooperativity.

H8 Students' emotional engagement is positively related to their level of cooperativity.

H9 Students' cognitive engagement is positively related to their level of cooperativity.

3.4 | Critical thinking

Critical thinking has been defined as the use of cognitive skills or strategies that increase the possibility of the desired behaviors [18]. In simple terms, critical thinking is a cognitive ability or strategy that involves analyzing, evaluating, and reasoning to understand issues and concepts. It helps individuals identify and solve problems by thinking from different perspectives, which enables them to make wise decisions and judgments [25].

Prior studies consistently reported that students' engagement was positively related to their critical thinking. For example, Yuan et al. [54] investigated the development of critical thinking among undergraduate students. The study found that the students' critical thinking skills were improved through various forms of research engagement. Álvarez-Huerta, Muela, and Larrea [1] conducted an experimental study with college students to examine the relationship between critical thinking and engagement. The findings showed a positive and direct relationship between students' engagement and their critical thinking. Lv et al. [32] found that students' engagement was positively related to their level of critical thinking.

In light of this, we suggest that college students' learning engagement may be positively related to their level of critical thinking. Specifically, we put forth the following hypothesis:

H10 Students' behavioral engagement is positively related to their level of critical thinking.

H11 Students' emotional engagement is positively related to their level of critical thinking.

H12 Students' cognitive engagement is positively related to their level of critical thinking.

3.5 | Problem-solving

Problem-solving is a crucial higher-order thinking ability for human beings [42]. It refers to an individual's capacity to find effective methods and strategies to solve problems through processes, such as thinking, analyzing, judging, and innovating when faced with difficulties, challenges, or unknown situations. This can be seen in various problem-solving tasks, such as mathematical, analogical, complex, and situated problem-solving. A

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person's problem-solving ability can be enhanced through learning and practice [49].

According to Coates [7], the level of a student's engagement was linked to their active participation in discussions aimed at resolving mathematical problems. Zhao et al. [56] claimed that students' engagement played a moderating role in the relationship between learning contextual factors and the development of problem-solving skills. Xing [51] used learning analytics to study the impact of learning engagement on problem-solving. The study found that students' behavioral and cognitive engagement significantly promote problem-solving performance.

In light of this, we suggest that college students' learning engagement may be positively related to their level of problem-solving. Specifically, we put forth the following hypothesis:

H13 Students' behavioral engagement is positively related to their level of problem-solving.

H14 Students' emotional engagement is positively related to their level of problem-solving.

H15 Students' cognitive engagement is positively related to their level of problem-solving.

4 | METHOD

4.1 | Participants

To answer these research questions, this study selected 376 freshmen from eight classes at a university located in central China as the survey subjects. 355 questionnaires were collected, with a questionnaire recovery rate of 97%. Among them, 341 were valid, with a valid questionnaire rate of 96%. Therefore, the response data of 341 participants were included in the analysis. Eight classes were randomly split into two learning environments: smart classroom ($n = 176$) and traditional multimedia classroom ($n = 165$), with each learning environment consisting of four classes. All participants of this study were aged 17–19 years old with similar academic backgrounds. Among the included participants, there were 242 female students and 99 male students. A description of the sample was given in Table 1.

Higher mathematics was taken as the learning subject. This study involved two instructors. One instructor taught in a smart classroom, while the other taught in a traditional multimedia classroom. It should be noted that although two instructors participated in this study, the two instructors are male, of the same age, with similar teaching experience and teaching age, so they can be considered to have the same level of teaching ability. The instructor in the smart classroom, after receiving training, was capable of proficiently using smart classroom technology, possessing substantial teaching experience and corresponding teaching methods, and was able to effectively teach within this environment. Moreover, 341 participants had the same age, learning experience, and professional background, so they can be considered to have the same level of learning ability.

4.2 | Learning environment

The smart classroom in this study was a multiscreen learning environment that included four 86-inch Seewo teaching integrated machines (STIM) also called Seewo teaching interactive smart tablets. STIM is a multimedia teaching demonstration and operation platform that integrates the functions of traditional projectors, televisions, computers, electronic whiteboards, speakers, and other products [29]. These STIM are capable of displaying learning content synchronously or as tools for displaying group discussion results during classroom teaching. There were 54 movable desks and chairs in the classroom that could be flexibly arranged according to different learning activities to meet various forms of group collaboration learning needs. The smart classroom was equipped with speakers, daylight lamps, and a wireless network to ensure the normal conduct of classroom teaching. In addition, the smart classroom was also equipped with relevant smart teaching systems,

TABLE 1 Demographic composition of the sample.

Learning environment	Major	Number of students	Instructional approach
Smart classroom	Artificial intelligence Educational technology	176	Flipped classroom
Traditional multimedia classroom	Artificial intelligence Educational technology	165	Lecture-based teaching

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such as the Chaoxing learning platform, intelligent recording and broadcasting system, and others. The Chaoxing learning platform is a multifunctional personalized learning app developed by Chaoxing Group in 2016. This application (app) not only contains abundant digital education resources accumulated by Chaoxing, but also integrates complete network teaching functions and course interaction plug-ins, which can realize mobile teaching, live classrooms, and multiscreen interactions [31].

In comparison, the traditional multimedia classroom in this study was a relatively simple learning environment, consisting mainly of one blackboard, one computer, one projector, and 70 fixed desks and chairs.

Smart classrooms used the three-stage (i.e., pre-class, in-class, and after-class) flipped classroom instructional approach, while traditional multimedia classrooms used the lecture-based instructional approach. According to the definition provided by several researchers, the flipped classroom is an instructional approach in which learning content is learned by students before in-class meetings, then in-class time can be used for interactive group learning tasks and active learning [6, 12]. The flipped classroom instructional approach in smart classrooms emphasized student-centered learning and focused on cultivating students' conceptual understanding and problem-solving abilities. In contrast, the lecture-based instructional approach in traditional multimedia classrooms was centered around the teacher and focused on delivering content [41]. Table 2 illustrated the comparison of the two instructional approaches.

4.3 | Instrumentation

To examine the relationship between learning engagement and computational thinking, this study employed two scales: Learning Engagement Scale (LES) and Computational Thinking Scale (CTS).

LES from Kuo, Tsai, and Wang [27] was adopted to measure college students' level of learning engagement. The LES consisted of three dimensions and a total of 14 items. Participants were asked to rate each item on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). An example item from the behavioral engagement dimension is "I complete exercises on time." The three dimensions and their corresponding Cronbach's α coefficient were as follows:

TABLE 2 Comparison of the two instructional approaches.

	Flipped classroom instructional approach	Lecture-based instructional approach
Pre-class	T: Uploaded the learning resources to the Chaoxing learning platform and set up pass tasks.	
	S: Logged in to the Chaoxing learning platform to read learning resources and complete the pass tasks.	
In-class	T: Established an interactive relationship with the students using the STIM, Chaoxing learning platform, and smartphones. Meanwhile, they used resources from the STIM and Chaoxing learning platforms to achieve functions, such as classroom control, content display, resource management, and response feedback.	T: Mainly used a projector to show multimedia teaching resources to students, and used the blackboard to write down teaching content.
	S: Completed learning tasks, such as asking questions, independent exploration, collaborative research, sharing results, feedback and evaluation through STIM, Chaoxing learning platform, and mobile terminals.	S: Listened to the lecture passively, answered the questions passively, and completed drill and practice.
After-class	T: Could achieve resource sharing, task distribution, and online assistance through the Chaoxing learning platform.	T: Reviewed homework.
	S: Used mobile terminals to browse learning resources and obtain learning assistance on the Chaoxing learning platform.	S: Completed homework and submitted it.
Teaching activities	Group teaching.	Lecture-based teaching.
Resource tools	STIM, Chaoxing learning platform, mobile terminals.	Blackboard, projector, QQ.

Abbreviation: STIM, Seewo teaching integrated machine.

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behavioral engagement ($\alpha = .80$), emotional engagement ($\alpha = .90$), and cognitive engagement ($\alpha = .92$).

CTS from Korkmaz, Çakir, and Özden [25] was adopted to measure college students' level of computational thinking. The CTS consisted of five dimensions and a total of 29 items. Participants were asked to rate each item on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). An example item from the algorithmic thinking dimension is "I can mathematically express the solution ways of the problems I face in daily life." The five dimensions and their corresponding Cronbach's α coefficient were as follows: creativity ($\alpha = .89$), algorithmic thinking ($\alpha = .90$), cooperativity ($\alpha = .91$), critical thinking ($\alpha = .87$), and problem-solving ($\alpha = .84$).

4.4 | Data collection and analysis procedure

With the assistance of instructors, data was collected at the end of the autumn semester of 2022. During the survey implementation, instructors invited students to complete online surveys through instant messaging tools, such as Tencent QQ and WeChat. The survey was open for 2 weeks.

To examine the relationship between college students' learning engagement and computational thinking, a quantitative method was utilized in this study. Data was filtered and then analyzed in SPSS 27.0 and AMOS 22.0. Descriptive statistics were mainly used to demonstrate the overall level of students' learning engagement and their computational thinking, and illustrate whether there are differences between learning engagement and computational thinking in different environments by using the independent sample t-test. Then, we conducted Spearman's correlation tests and structural equation model (SEM) to explore the relationships between college students' learning engagement and their computational thinking. In the follow-up stage of the study, to explore the different influences of learning engagement on computational thinking in the different learning environments. The standardized path coefficients from two SEMs were conducted to compare the differences.

5 | RESULTS

5.1 | Descriptive statistics

Skewness and kurtosis are two commonly used concepts when describing data distribution, which are used to describe the deviation degree between data distribution and normal distribution [33, 44]. Therefore, this study uses skewness and kurtosis for the normality test. The normal distribution of descriptive statistics about students' learning engagement and computational thinking were shown in Table 3. According to the suggestion of Ghasemi and Zahediasl [17], the absolute values of Z_{skewness} and Z_{kurtosis} are less than 1.96, which can be considered that the sample data conforms to normal distribution. It can be seen from Table 3 that the absolute values of Z_{skewness} and Z_{kurtosis} are less than 1.96, indicating that the sample data in this study conform to normal distribution. Then, the results also show that the average value of college students' overall computational thinking was 3.86. Creativity obtained the highest mean scores ($M = 4.15$). Meanwhile, cooperativity,

TABLE 3 Normal distribution descriptive statistics of learning engagement and computational thinking.

			Skewness			Kurtosis		
	Mean	SD	Statistic	SE	Z	Statistic	SE	Z
Learning engagement	3.96	0.61	−0.102	0.132	0.77	0.512	0.263	1.95
Behavioral engagement	4.18	0.71	−0.237		1.80	−0.415		−1.58
Emotional engagement	4.00	0.67	0.107		0.81	−0.432		−1.64
Cognitive engagement	3.72	0.70	0.241		1.83	−0.338		−1.29
Computational thinking	3.86	0.52	−0.246		−1.86	−0.443		−1.68
Creativity	4.15	0.63	−0.223		−1.69	−0.432		−1.64
Algorithmic thinking	3.55	0.62	0.253		1.92	−0.031		−0.12
Cooperativity	4.01	0.78	−0.259		−1.96	−0.398		−1.51
Critical thinking	3.84	0.63	−0.248		−1.88	0.513		1.95
Problem-solving	3.76	0.63	0.15		1.14	−0.516		−1.96

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critical thinking, and problem-solving obtained 4.01, 3.84, and 3.76. For their part, algorithmic thinking obtained the lowest scores ($M = 3.55$). The results also showed that college students displayed moderate levels of learning engagement ($M = 3.96$). Behavioral engagement ($M = 4.18$) was identified as the dimension with the highest score, while cognitive engagement ($M = 3.72$) obtained the lowest score.

To examine the differences between learning engagement and computational thinking in the two types of learning environments, an independent sample *t*-test was conducted to evaluate the significance of the difference between students in smart classrooms and traditional multimedia classrooms. The results of the independent sample *t*-test were presented in Table 4.

On the basis of the information provided in Table 4, there were significant differences between smart classroom and traditional multimedia classroom in the mean scores of behavioral engagement ($t = 6.97$, $p < .001$), emotional engagement ($t = 10.26$, $p < .001$), cognitive engagement ($t = 10.89$, $p < .001$), creativity ($t = 6.63$, $p < .001$), algorithmic thinking ($t = 19.07$, $p < .001$), cooperativity ($t = 11.83$, $p < .001$), critical thinking ($t = 7.67$, $p < .001$), and problem-solving ($t = 14.57$, $p < .001$).

5.2 | Relationship between learning engagement and computational thinking

To answer Q1, the study employed correlation analyses to examine the relationships between college students' learning engagement and computational thinking. As shown in Table 5, all three dimensions of learning engagement were observed as significantly correlated with each dimension of computational thinking.

After confirming the relationship between learning engagement and computational thinking, an SEM was developed using AMOS 22.0 software to identify whether the three dimensions of learning engagement acted as a predictor of each dimension of computational thinking. SEM, a commonly used method in social sciences, is employed to analyze the interrelationships among variables [4]. The measurement model fit the data ($\chi2/\text{df} = 2.71 > 3$, $p < .001$, $\text{AGFI} = 0.853 > 0.8$, $\text{GFI} = 0.891 \approx 0.9$, $\text{CFI} = 0.912 > 0.9$, $\text{RMSEA} = 0.068 < 0.08$). All fit indexes were deemed acceptable based on the suggested cutoff values by Arpaci and Baloğlu [3]. To enhance the model's simplicity and interpretability, insignificant lines, namely, H4 and H13, were removed. Upon reanalyzing the model's fit, it was found that the results remained largely unchanged. The summary statistics of the measurement model were presented in Table 6.

Fifteen hypotheses were proposed, except for H4 and H13, all hypotheses were supported as shown in Table 6. Further analysis showed that behavioral engagement was the factor that contribute the most to creativity with values of 0.63. Emotional engagement was the factor that contribute the most to the cooperativity with values of 0.40. Cognitive engagement was the factor that contribute the most to the algorithmic thinking with values of 0.54. Besides that, behavioral engagement had a relatively lower influence on algorithmic thinking and problem-solving (0.05 and 0.07, respectively). Emotional engagement and cognitive engagement had a relatively

TABLE 4 Results of the *t* test for students' learning engagement and computational thinking scores.

		Group					
		Smart classroom ($n = 176$)		Traditional multimedia classroom ($n = 165$)			
Scale	Factor	Mean	SD	Mean	SD	t	p
LE	Behavioral engagement	4.42	0.55	3.92	0.76	6.97	0.000***
	Emotional engagement	4.31	0.58	3.66	0.59	10.26	0.000***
	Cognitive engagement	4.06	0.66	3.35	0.53	10.89	0.000***
CT	Creativity	4.35	0.53	3.93	0.66	6.63	0.000***
	Algorithmic thinking	3.98	0.50	3.10	0.35	19.07	0.000***
	Cooperativity	4.42	0.52	3.57	0.78	11.83	0.000***
	Critical thinking	4.07	0.38	3.59	0.74	7.67	0.000***
	Problem-solving	4.14	0.50	3.36	0.49	14.57	0.000***

Abbreviations: CT, computational thinking; LE, learning engagement.

***$p < .001$.

TABLE 5 Correlational analysis of learning engagement and computational thinking.

	Creativity	Algorithmic thinking	Cooperativity	Critical thinking	Problem-solving
Behavioral engagement	0.696***	0.495***	0.593***	0.575***	0.434***
Emotional engagement	0.648***	0.637***	0.678***	0.579***	0.570***
Cognitive engagement	0.656***	0.638***	0.661***	0.546***	0.545***

***$p < .001$.

TABLE 6 Results of the structural model.

Hypothesis	Estimate	SE	CR	Std. R.W	Results
H1. BE -> Creativity	0.42***	0.05	7.82	0.63	Supported
H2. EE -> Creativity	0.16*	0.07	2.38	0.17	Supported
H3. CE -> Creativity	0.35***	0.07	5.23	0.40	Supported
H4. BE -> Algorithmic thinking	0.03	0.04	0.75	0.05	Rejected
H5. EE -> Algorithmic thinking	0.29***	0.07	4.36	0.35	Supported
H6. CE -> Algorithmic thinking	0.41***	0.07	5.96	0.54	Supported
H7. BE -> Cooperativity	0.33***	0.06	5.38	0.38	Supported
H8. EE -> Cooperativity	0.50***	0.10	4.95	0.40	Supported
H9. CE -> Cooperativity	0.49***	0.09	5.27	0.42	Supported
H10. BE -> Critical thinking	0.34***	0.06	5.53	0.42	Supported
H11. EE -> Critical thinking	0.32***	0.09	3.48	0.28	Supported
H12. CE -> Critical thinking	0.27***	0.09	3.21	0.25	Supported
H13. BE -> Problem-solving	0.04	0.04	1.01	0.07	Rejected
H14. EE -> Problem-solving	0.29***	0.07	4.05	0.35	Supported
H15. CE -> Problem-solving	0.33***	0.07	4.65	0.42	Supported

Abbreviations: BE, behavioral engagement; CE, cognitive engagement; EE, emotional engagement; Std. R.W, standardized regression weight.

*$p < .01$; ***$p < .001$.

lower influence on creativity (0.17) and critical thinking (0.25), respectively.

5.3 | Different influences of learning engagement on computational thinking in different learning environments

Q2 aimed to investigate the different influences of learning engagement on computational thinking in different learning environments. The initial SEM results provided an overview of the learning engagement influencing computational thinking. However, because the *t*-test results showed that participants were not one homogeneous group concerning learning engagement, we also sought to investigate whether students in different learning environment types had different learning engagement profiles, which influenced their computational thinking. Therefore, two additional SEM models based on participants of smart classrooms and traditional multimedia classrooms were created. The standardized path coefficients for each group were presented in Figures 2 and 3, respectively.

As shown in Figure 2, behavioral engagement was found to be a positive predictor of two out of three computational thinking dimensions in the smart classroom: creativity and cooperativity. Further analysis showed that behavioral engagement was the factor that contribute the most to creativity with values of 0.60, and had a relatively lower influence on cooperativity (0.48). However, behavioral engagement was not a predictor of college students' critical thinking.

Emotional engagement was found to be a positive predictor of all dimensions of computational thinking in the smart classroom: creativity, algorithmic thinking, cooperativity, critical thinking, and problem-solving. Further analysis showed that emotional engagement was the factor that contribute the most to problem-solving with

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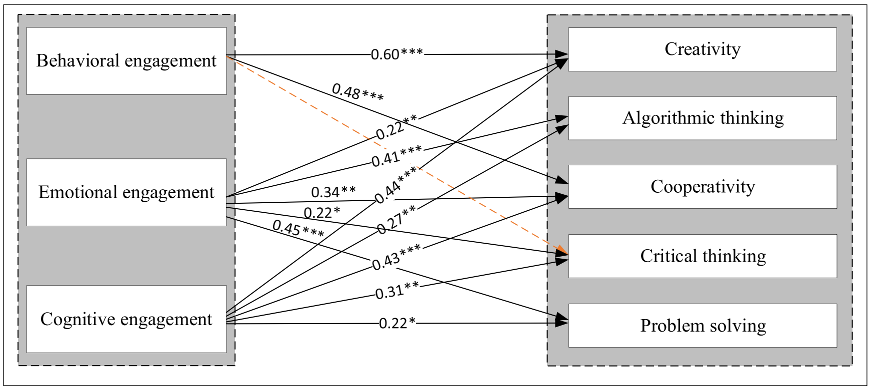

FIGURE 2 Structural model within the smart classroom. *$p < .05$, **$p < .01$, and ***$p < .001$; dashed lines indicate nonsignificant paths.

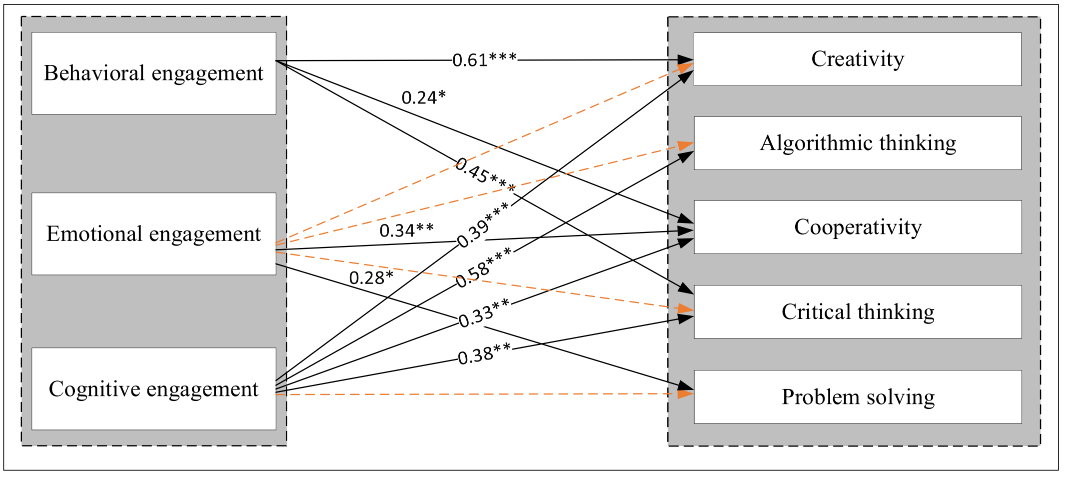

FIGURE 3 Structural model within the traditional multimedia classroom. *$p < .05$, **$p < .01$, and ***$p < .001$; dashed lines indicate nonsignificant paths.

values of 0.45, and had a relatively lower influence on creativity (0.22) and critical thinking (0.22).

Cognitive engagement significantly was found to be a positive predictor of all dimensions of computational thinking in smart classrooms: creativity, algorithmic thinking, cooperativity, critical thinking, and problem-solving. Further analysis showed that cognitive engagement was the factor that contributes the most to creativity with values of 0.44, and had a relatively lower influence on problem-solving (0.22).

As shown in Figure 3, behavioral engagement significantly predicted three dimensions of computational thinking in the traditional multimedia classroom: creativity, cooperativity, and critical thinking. Behavioral engagement was the factor that contribute the most to creativity with values of 0.61 and had a relatively lower influence on cooperativity (0.24).

Emotional engagement significantly predicted two out of five computational thinking dimensions in traditional multimedia classrooms: cooperativity and problem-solving. Emotional engagement was the factor that contribute the most to the problem-solving with values of 0.34. However, emotional engagement was not a predictor of college students' creativity, algorithmic thinking, and critical thinking.

Cognitive engagement significantly predicted four out of five computational thinking dimensions in traditional multimedia classrooms: creativity, algorithmic thinking, cooperativity, and critical thinking. cognitive engagement was the factor that contribute the most to the algorithmic thinking with values of 0.58 and had a relatively lower influence on the cooperativity (0.33). However, cognitive engagement was not a predictor of college students' problem-solving.

6 | DISCUSSION AND IMPLICATIONS

6.1 | Discussion

In this study, college students' computational thinking covered five dimensions (i.e., creativity, algorithmic thinking, cooperativity, critical thinking, and problem-solving).

Participants were seen to possess only intermediate levels (Mean = 3.86) of these aspects. From a societal perspective, college students were generally considered a well-educated demographic, but it was surprising to see that their levels of computational thinking were mediocre. However, considering the development status of instructional techniques and strategies related to computational thinking [11, 52], these findings may be expected. Regardless, the findings highlighted the importance of enhancing computational thinking through education.

The main objective of this study was to examine the relationship between college students' learning engagement and computational thinking. The analysis of the SEM indicated that all proposed hypotheses, except for H4 and H13, were supported. In other words, learning engagement had a significant influence on computational thinking, which was consistent with the partial findings of Álvarez-Huerta, Muela, and Larrea [1], and Zhang et al. [55]. The researchers found that students who exhibited high levels of learning engagement demonstrated more creativity and were highly committed to reflective learning, which were all supportive factors for improving computational thinking.

The findings also indicated that both emotional and cognitive engagement positively predicted all dimensions of computational thinking. That is, individuals' emotional engagement (i.e., learning interest, motivation, and attitude) and cognitive engagement (i.e., thinking, understanding, memory, and reasoning) [13, 47] were critical factors for predicting all dimensions of computational thinking. However, behavioral engagement was not seen to be a predictor of algorithmic thinking and problem-solving. This is because algorithmic thinking and problem-solving are advanced cognitive abilities that involve abstract thinking, logical reasoning, problem analysis, and problem-solving skills [9], requiring students to have a certain level of cognitive engagement. In contrast, behavioral engagement often involves surface-level behaviors of students, such as completing assignments on time, participating in classroom discussions [43, 53], and so on, which may not fully reflect students' algorithmic thinking and problem-solving.

This study also found differences in the relationship structure between learning engagement and computational thinking across different environments. Specifically, emotional engagement had a significant positive influence on creativity, algorithmic thinking, and critical thinking for students in smart classrooms, whereas this relationship was obscured in traditional multimedia classrooms. This finding was in agreement with the results of other related studies, which showed that learning activities in traditional multimedia classrooms were difficult to efficiently promote students' computational thinking, especially critical thinking [23]. In this study, the instructor in traditional multimedia classrooms mainly imparted knowledge, and motivated students to participate in drills and practices. However, the instructor seldom provided opportunities for students to pursue independent exploration or collaborate in groups. Therefore, the students' lack of interaction with both their peers and teachers may have caused them to feel less emotional engagement. Thus, one can understand why students' emotional engagement did not contribute to the improvement of their creativity, algorithmic thinking, and critical thinking.

Furthermore, cognitive engagement had a significant positive influence on problem-solving for students in smart classrooms, whereas this relationship was also obscured in traditional multimedia classrooms. As previously discussed, the lecture-based instructional approach resulted in a decrease in students' independent exploration and problem-solving during classroom activities, which further resulted in the cognitive engagement of some students having less influence on their problem-solving.

In addition, the results revealed that behavioral engagement had no significant influence on critical thinking for students in smart classrooms but had a significant positive influence on critical thinking for students in traditional multimedia classrooms. There were several guesses about the inconsistent result. The behavioral engagement in smart classrooms might have relied more on technological tools, and improper use of these tools might have led to poor concentration and disengagement, thereby affecting the development of critical thinking [43]. Besides, the conclusions drawn might have biases due to the insufficient sample size and might not truly reflect the influence of behavior engagement on students' critical thinking.

6.2 | Implications

The results of this study have significant implications for education, both in terms of theory and practice. Theoretically, the findings of this research provided a new whole relationship model for understanding and interpreting students' computational thinking. That is, the results suggested that students' learning engagement was a critical factor that might control the display of students' computational thinking. From a practitioner's perspective, these findings strongly suggested that the learning engagement and differences in the learning environment should be fully taken into account when

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designing pedagogy for improving students' computational thinking.

(1) Behavioral, emotional, and cognitive engagement had a significant positive influence on creativity. This result coincided with other research findings [34, 39]. However, the influence of the three types of learning engagement on creativity varied in different environments. Specifically, emotional engagement positively and significantly influenced students' problem-solving in smart classrooms, whereas this relationship was obscured in traditional multimedia classrooms. Theoretically speaking, there was no special need to consider emotional engagement in instruction for students' creativity in traditional multimedia classrooms.
(2) Only emotional and cognitive engagement had a significant positive influence on algorithmic thinking. The results suggested that behavioral engagement needed not to be considered when improving students' algorithmic thinking. Thus, instructors focused on providing various programming tasks, guidance [30], and emotional support [40] during classroom activities to improve students' emotional and cognitive engagement. However, the influence of emotional and cognitive engagement on creativity varied in different environments. Emotional engagement also did not significantly influence students' algorithmic thinking in traditional multimedia classrooms. Theoretically speaking, there was no particular need to consider emotional engagement in instruction for students' algorithmic thinking in traditional multimedia classrooms.
(3) Behavioral, emotional, and cognitive engagement had a significant positive influence on cooperativity whether as a whole or in different environments, which was consistent with the results [5, 7]. The implication here was that behavioral, emotional, and cognitive engagement should have been fully taken into account when building a learning environment and designing pedagogy to improve students' cooperativity.
(4) Behavioral, emotional, and cognitive engagement had a significant positive influence on critical thinking. Prior research had provided consistent findings [32, 54]. However, the influence of behavioral, emotional, and cognitive engagement on critical thinking varied in different environments. Specifically, students' critical thinking was not significantly influenced by behavioral and emotional engagement in the smart classroom and traditional multimedia classroom, respectively. Theoretically speaking, neither behavioral engagement in smart classrooms nor emotional engagement alone in traditional multimedia classrooms needed to be considered for instructing students in algorithmic thinking.
(5) Only emotional and cognitive engagement had a significant positive influence on problem-solving. This finding was inconsistent with previous studies on the relationship between learning engagement and problem-solving [51]. The previous results showed that students' problem-solving was significantly influenced by behavioral engagement. However, the influence of emotional and cognitive engagement on problem-solving varied in different environments. Specifically, cognitive engagement did not significantly influence students' problem-solving in traditional multimedia classrooms. Theoretically speaking, there was no special need to consider cognitive engagement in instruction for students' algorithmic thinking in traditional multimedia classrooms.

7 | CONCLUSION

To conclude, Q1 identified the relationship and constructed an overall relationship model between learning engagement and computational thinking. The SEM analysis confirmed that learning engagement had a significant and positive influence on computational thinking. Subsequently, Q2 addressed a gap in the existing literature by demonstrating that the different influences of learning engagement on computational thinking in different learning environments. Especially, the results showed that behavioral engagement did not have a significant influence on critical thinking for students in the smart classroom, but it had a significantly positive influence on critical thinking in traditional multimedia classrooms. Theoretically speaking, there was no special need to consider behavioral engagement in instruction for students' critical thinking in smart classrooms. These findings provided implications for differentiated instruction.

As one of the three major scientific thinking methods, computational thinking plays an important role in social development and progress, and will continue to attract the attention of researchers. On the basis of this, future research will attempt to involve more factors (e.g., learning motivation, classroom interaction, and teacher support) to make stronger inferences. Then, Future studies could collect data on students' learning engagement in various subject areas to further explore the relationship between computational thinking and learning engagement. Besides, the validity of self-perceptions

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has been criticized due to potential biases and inaccuracies. Future research attempts to use relevant equipment and technology to automatically collect and analyze student data.

DATA AVAILABILITY STATEMENT

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

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