Learning and Instruction 100 (2025) 102232

Contents lists available at ScienceDirect

Learning and Instruction

journal homepage: www.elsevier.com/locate/learninstruc

Decoding the success of collaboration in computational thinking

Stella Xin Yin [a,*], Dion Hoe-Lian Goh [a], Choon Lang Quek [b]

[a] Wee Kim Wee School of Communication and Information, Nanyang Technological University, 31 Nanyang Link, 637718, Singapore
[b] National Institute of Education, Nanyang Technological University, 1 Nanyang Walk, 637616, Singapore

ARTICLE INFO

Keywords:
Collaborative learning
Computational thinking
Engagement
Motivation
Pair programming

ABSTRACT

Background: Computational Thinking (CT) is a key component of information literacy and future employment skills. While pair programming (PP) has been recognized as an effective collaborative strategy for CT education, the motivational mechanism behind remains underexplored.
Aims: We aim to examine how self-efficacy, engagement, and collaboration preference influence CT skills and learning satisfaction. Further, we compare the relationships among these motivational factors between PP and individual learning contexts.
Sample: Participants were 79 fifth-grade elementary school students. Forty of participants were randomly paired and assigned to the PP group and 39 were assigned to the individual learning group.
Methods: We implemented a four-week intervention. Students in the PP group collaborated on CT tasks, while students in the individual learning group completed the tasks individually.
Results: Experiment results demonstrated that PP significantly improved students' self-efficacy compared to individual learning. In both groups, students with high self-efficacy beliefs were more engaged in CT learning, consequently leading to better performance in CT tests and higher learning satisfaction. Notably, the positive effects of self-efficacy and collaboration preference on cognitive engagement were stronger in the PP group. Moreover, positive PP experiences reinforced students' preference for future collaborative learning.
Conclusions: These insights contribute to motivation research in CT education and provide practical implications for designing more engaging and effective PP activities in developing CT skills.

1. Introduction

Computational Thinking (CT) is recognized as an integral component of digital and information literacy, and a fundamental skill for students preparing for the workforce in the information society (Miao & Holmes, 2023). CT includes not only the basic concepts of computer science but also the cognitive and social dimensions of problem-solving skills. Given the growing importance of CT skills, researchers and educators have designed curricula and supported CT education across K-12 levels. To better facilitate CT learning, pair programming (PP) stands out as one of the popular collaborative learning activities (Yin et al., 2024). In PP, two learners alternate roles as driver and navigator to solve CT tasks together on one computer.

To evaluate the effectiveness of PP, researchers have compared CT test scores (Iskrenovic-Momcilovic, 2019) and self-efficacy (Wei et al., 2021) between students in PP conditions and those programming individually. These results revealed that students who completed tasks with a partner performed better in CT tests and perceived higher self-efficacy than students who worked individually. While empirical evidence supports the effectiveness of PP over individual learning, few studies have examined the multi-dimensional motivation that contribute to this effectiveness and how these factors affect the PP process. Since motivation is a multifaceted construct that serves as the most prominent factor in explaining, predicting, and influencing learning outcomes and processes (Pintrich, 2003), understanding this underlying motivational mechanism could provide valuable insights to help educators design more effective and engaging PP activities in CT courses.

Several gaps remain in current research. First, empirical evidence indicates that students with strong self-efficacy in their academic abilities demonstrate higher levels of classroom engagement in terms of behavior, cognition, and emotion, consequently leading to better academic performance (Linnenbrink & Pintrich, 2003). However, this relationship has not been investigated in CT education yet. While some studies examined the relationship between engagement and performance (Li et al., 2024; Liu et al., 2023), these investigations were limited to individual learning contexts. This leaves a significant gap in

* Corresponding author.
E-mail address: xin013@e.ntu.edu.sg (S.X. Yin).

https://doi.org/10.1016/j.learninstruc.2025.102232
Received 2 April 2025; Received in revised form 7 August 2025; Accepted 21 September 2025
Available online 24 September 2025

understanding how the relationships between self-efficacy, engagement, and performance might differ between PP and individual learning contexts. Second, although students' attitudes toward collaboration significantly influence their self-efficacy and learning engagement, little is known about how these collaborative preferences vary between PP and individual learning contexts, as well as the role of these preferences in relationships among students' self-efficacy, engagement, and CT performance. Third, learning satisfaction is an indicator of effective learning and instruction (Keller, 1987), and it directly reflects students' engagement and motivation throughout the learning process (Kim & Kim, 2021). However, current studies have primarily focused on comparing academic performance and attitudes, with none examining learning satisfaction in CT classes.

Therefore, in this study, we examine motivation through three factors: self-efficacy, engagement, and collaboration preference. By focusing on these interconnected motivational factors, we aim to investigate not only whether PP is effective in developing students' CT skills, but also to understand the motivational mechanisms that explain its effectiveness. To achieve these objectives, we answer three questions:

RQ1: To what extent does PP improve students' self-efficacy and CT skills?
RQ2: What are the differences in self-efficacy, collaboration preference, engagement, CT skills, and satisfaction between students in the PP and the individual learning group?
RQ3: What are the relationships among self-efficacy, collaboration preference, engagement, CT skills, and satisfaction in the PP group versus the individual learning group?

2. Literature review

2.1. Pair programming in CT education

In computer science education, PP is a collaborative activity in which two learners alternate roles as driver and navigator. The driver codes while the navigator reviews and suggests improvements. Two learners switch roles regularly to ensure shared understanding, consensus, and engagement in the programming process (Yin et al., 2024). PP has gained increasing popularity in K-12 CT education as an effective way to teach CT concepts and skills to novice learners (Lai et al., 2023; Yin et al., 2024).

The effectiveness of PP can be explained through several theoretical perspectives. First, from a social constructivist view (Vygotsky, 1978), PP creates a zone of proximal development where learners can complete challenging tasks with peer support that they could not complete independently. The interactions during PP promote knowledge construction, where partners externalize their thinking processes, challenge each other's ideas, and build shared understanding (Stahl, 2006). Second, PP aligns with cognitive load theory (Sweller, 2011). When learners work in pairs, they can distribute cognitive load across partners, with the navigator handling higher-level strategic thinking while the driver focuses on implementation details. This division allows learners to manage complex tasks more effectively than when working alone (Zhong et al., 2017). Third, according to Piaget's (1971)cognitive development theory, children aged 7–11 develop logical and organized thinking, problem-solving skills, and the ability to understand other people's thinking and feelings. During PP, both students have the opportunity to practice their individual CT skills while interacting with peers to learn from each other (Yin et al., 2025). We thus believe that PP is an ideal approach for teaching CT skills at the elementary school level, as it aligns with children's cognitive development.

Recent research on the effectiveness of PP in CT education highlights its multifaceted benefits and challenges. Studies have found that PP not only supported CT skill development but also enhanced collaboration skills and reduced learning anxiety (Hsu et al., 2022; Xu et al., 2023). Research also revealed that effectiveness can vary based on learner backgrounds and collaborative patterns (Wei et al., 2021). When integrated with cross-disciplinary classes such as language learning, PP benefits both students' CT skills, language skills, and social development (Chen & Huang, 2024). In the K-12 context, Iskrenovic-Momcilovic (2019) and Wei et al. (2021) found that elementary school students who completed tasks through PP showed significantly greater improvements in CT and self-efficacy compared to those who worked independently.

Despite this theoretical and empirical support for PP's effectiveness, the specific motivational mechanisms through which PP enhances learning outcomes remain underexplored in K-12 contexts. Understanding how PP influences motivational factors such as self-efficacy, engagement, and collaboration preference is essential for optimizing its implementation in CT education.

2.2. Self-efficacy, engagement, and learning performance

As a central component of motivation, self-efficacy refers to the level of an individual's confidence in his or her ability to complete a task (Bandura, 1977). Students with higher self-efficacy are more willing to put effort into learning tasks and have greater motivation to achieve better outcomes. In CT education, previous findings demonstrated a significant influence of self-efficacy on CT skills (Kong et al., 2018). Students with higher self-efficacy showed more confidence in performing the given tasks, and are more intend to continue on CT learning, which ultimately led to better learning outcomes. Further, students in PP contexts had greater self-efficacy and higher performance than individual learners (Kong et al., 2018; Wei et al., 2021)

Student engagement is another factor that influences academic success, and refers to the investment of both cognitive and emotional energy in learning tasks (Schunk & Mullen, 2012). It consists of three dimensions - behavioral, cognitive, and emotional - to understand students' learning and achievement in school (Fredricks et al., 2005). Throughout this paper, we use this three-dimensional conceptualization of engagement across all analyses and discussions. Behavioral engagement refers to observable behavior, such as effort, persistence, and help-seeking. Cognitive engagement refers to how deeply, critically, and creatively students think about the content they have learned. Put differently, the quality of students' effort in the task reflects cognitive engagement, while simple quantity of effort reflects behavioral engagement. Emotional engagement relates to students' interest, value, and affect when learning content or completing tasks. Prior studies showed that the three dimensions of engagement have significantly impact on students' learning performance and other positive outcomes (Bergdahl et al., 2020; Hazzam & Wilkins, 2023). Further, student engagement plays a mediating role between self-efficacy and performance (Linnenbrink & Pintrich, 2003). Students with greater self-efficacy beliefs were more actively engaged in the classroom in terms of their behavior, cognition, and emotion, consequently leading to better academic performance (Qureshi et al., 2023).

In CT education, several studies have examined the relationship between engagement and performance (Li et al., 2024; Liu et al., 2023). The results indicate that both emotional engagement and cognitive engagement had strong predictive power for CT. However, these studies are all conducted in individual learning contexts, and it is unknown whether and to what extent the relationship between self-efficacy, engagement, and performance differs between PP and individual learning. Given that students in groups have shown more positive attitudes toward learning, greater willingness to participate in classroom activities, and better performance in tasks (Özmutlu et al., 2021), we hypothesize that:

H1a/b/c. Self-efficacy is positively related to a) behavior, b) emotional, and c) cognitive engagement. The relationship is more positive for students in the PP group.

H2a/b/c. a) behavior, b) emotional, and c) cognitive engagement are positively related to learning performance. The relationship is more positive for students in the PP group.

H3. Self-efficacy has positive impact on learning performance. The relationship is more positive for students in the PP group.

2.3. Collaboration preference

Collaboration preference refers to the degree to which individuals have strong preferences for collaboration rather than individual work (Shaw, 2000). Research indicates that individuals who prefer group work are more confident in learning and are more likely to be effective in completing tasks compared to those who favor working independently (Hendry et al., 2005). In addition, drawing on the theory of planned behavior (Ajzen, 1991), students' preferences for collaboration can predict their behavioral tendencies and intentions to engage in PP activities, as these preferences shape their attitudes toward collaborative work and perceived social norms.

Empirical studies have shown that students who prefer collaboration tend to actively participate in group-based projects and understand the necessity of engaging in supportive group processes. Consequently, this leads to higher performance and higher satisfaction with learning (Shaw, 2000). In CT education, past research revealed that when students collaborate in pairs or small groups on programming activities, they showed improved programming performance and increased confidence (Kong et al., 2018; Yin et al., 2025). Particularly, students who hold positive attitudes toward collaboration are more likely to recognize the mutual benefits and shared objectives of working with peers. These students tend to invest greater effort in group work, develop better collaborative skills, and solve difficult problems more effectively. Hence, we hypothesize that:

H4. Collaboration preference is positively related to self-efficacy. The relationship is more positive for students in the PP group.

H5a/b/c. Collaboration preference is positively related to a) behavior, b) emotional, and c) cognitive engagement. The relationship is more positive for students in the PP group.

2.4. Satisfaction as learning outcomes

Learner satisfaction relates to students' confidence in their ability to succeed and their feelings about their actual achievements, which is an indicator of effective learning and instruction (Keller, 1987). Practically, learner satisfaction is often measured through post-learning surveys in which students rate their overall satisfaction with the learning experience. To guide improvements in instructional design and educational practice, it is essential to examine multiple variables that contribute to learner satisfaction. First, self-efficacy has been reported as a consistent variable in predicting students' satisfaction in learning environments. Aldhahi et al. (2022) suggested that self-efficacy was a significant predictor of both the satisfaction of learners and their intention to take future similar courses. Second, student engagement closely relates to students' learning satisfaction (Kucuk & Richardson, 2019). Students with higher engagement levels, characterized by positive emotions and active participation in classrooms, tend to report greater satisfaction with their course (Kim & Kim, 2021). The findings revealed that self-efficacy acts as a motivational driver, encouraging students to use various learning strategies and improve their cognitive competency to tackle difficult problems. Thus, students with higher level of self-efficacy showed more engagement in learning activities and reported greater satisfaction with their learning experience.

While the above relationships have been examined in various learning contexts, they remain unexplored in CT education. CT learning differs from traditional subjects as it involves human-computer interaction, and peer collaboration is centered around digital artifacts. Understanding how different learning environments impact the relationship between these factors is essential for educators to design effective CT learning activities. Thus, the following hypothesis is proposed:

H6a/b/c: a) behavior, b) emotional, and c) cognitive engagement are positively related to learning satisfaction.

2.5. Research model

Building upon Linnenbrink and Pintrich's (2003) motivational framework, we integrate insights from social cognitive theory (Bandura, 1977), engagement theory (Fredricks et al., 2005), and the theory of planned behavior (Ajzen, 1991) to examine PP effectiveness in elementary school CT education. Our theoretical framework identifies three motivational factors - self-efficacy, engagement, and collaboration preferences - that collectively influence learning outcomes in both individual and collaboration contexts (see Fig. 1).

Self-efficacy, grounded in social cognitive theory, refers to the level of an individual's confidence in his or her ability to complete a task (Bandura, 1977). Engagement, from engagement theory, manifests motivation through behavioral, emotional, and cognitive investment in learning, which serves as the mediating role between self-efficacy and learning outcomes (Linnenbrink & Pintrich, 2003). Collaboration preference, based on the theory of planned behavior, reflects the degree to which individuals have strong preferences for collaboration rather than individual work (Shaw, 2000).

3. Method

3.1. Participants and curriculum

Following the university's Institutional Review Board approval (IRB-2024-062), we sent invitation emails to elementary schools in Singapore. After getting school principals' approval, we reached out to parents individually to introduce the research project and ask them to sign consent forms for their children's participation. The consent form clearly stated that participation was entirely voluntary, all collected information would be anonymized and kept confidential, and participants could withdraw from the study at any time without consequences. Only children whose parents agreed to participate were included in the study. We then assigned a unique number to each participating child, which was used for data collection. We recruited 79 fifth-grade students (49 male and 30 female, *Mean age* = 10.78, *SD* = 0.48) from two elementary schools to participate in a four-week CT intervention.

The course contents were adapted from Code.org, a learning platform offering educational resources and tools suitable for K-12 CT classrooms (Code.org, 2021). Since its launch, Code.org has been widely applied to teach students CT skills across K-12 levels. In our study, since participants did not attend CT classes in previous semesters, we selected Course D as an introductory module because it was particularly suitable for students aged 9–10 years old with no prior CT learning experience. Therefore, we developed a four-week course based on Course D content. The instructional goal of this course was to teach students basic CT concepts (i.e., sequencing, loops, and events) identified by Brennan & Resnick (2012). By the end of the course, students were able to apply these CT concepts to design and create interactive games.

The course consisted of four lessons, with each lesson containing 10 CT tasks. To complete each task, as shown in Fig. 2, students read the instructions to understand the goal of the task. They then created their program by dragging and dropping code blocks from the "Blocks" section on the left side and arranging them in the correct sequence in the "Workspace" section on the right side. Finally, students clicked the "Run" button to execute their program and viewed the visualized results.

The course syllabus is described in Table 1. In week 1, students learned the "sequencing" concept and practiced sequencing to solve online puzzles while learning to identify and debug errors in their programs. In week 2, students reinforced the concept of "sequencing" by programming characters to collect treasures on the map. These practices

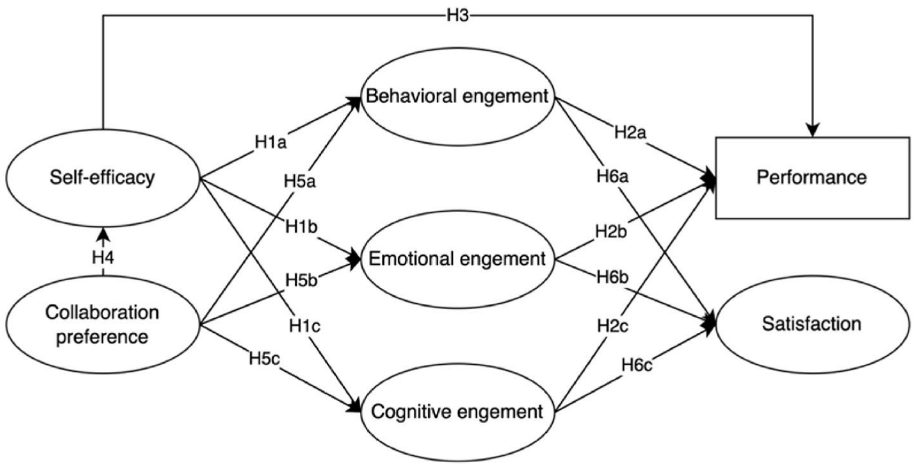

Fig. 1. Research model.

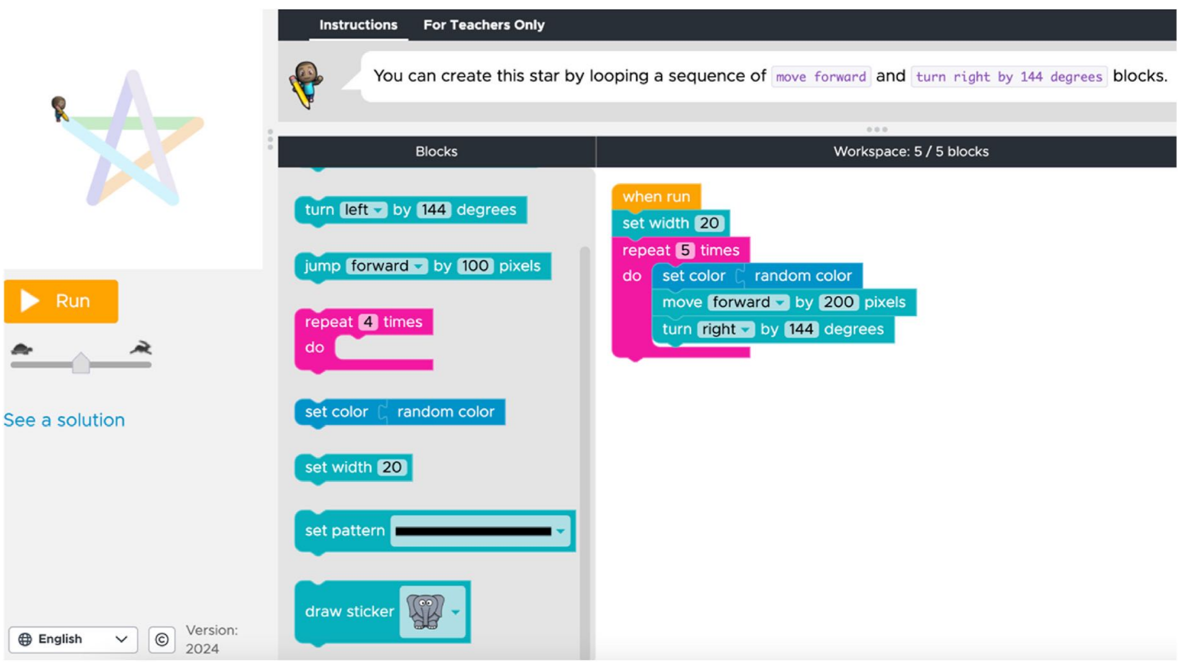

Fig. 2. Example of course contents.

Table 1
Course syllabus.

Lesson	Task description	CT concepts
Week 1: Solving Maze Puzzles	Students drag-and-drop code blocks in sequential order to solve puzzles online.	Sequencing and debugging
Week 2: Collecting Treasure	Students create program with the "collect" command to pick up all treasure on the map.	Sequencing and debugging
Week 3: Drawing Shapes with Loops	Students combine loops and sequencing to create geometric shapes on a digital canvas.	Sequencing and loops
Week 4: Building a Star Wars Game	Students create an interactive game using events, such as make their character move across the screen, make noises, and react to obstacles.	Sequencing, loops, and events

helped students learn how to solve the problem in different ways. In week 3, students used "loops" to create programs that drew shapes and designed art. Through practice, students identified the benefits of using "loop" structures instead of manual repetition. In week 4, students learned "events" through popular characters from *Star Wars and applied* their knowledge of "sequencing," "loops," and "events" to create personalized Star Wars games. This game-based learning helped students gain knowledge of CT concepts while maintaining their engagement through playing.

3.2. Experiment design

Forty of the participants were randomly assigned to the PP group, and 39 were assigned to the individual learning group. Students in the PP group were randomly paired and collaborated on CT tasks, while students in the individual learning group completed the tasks individually.

The experiment process is depicted in Fig. 3. Before the first week, participants took a pre-test to assess prior knowledge of CT and

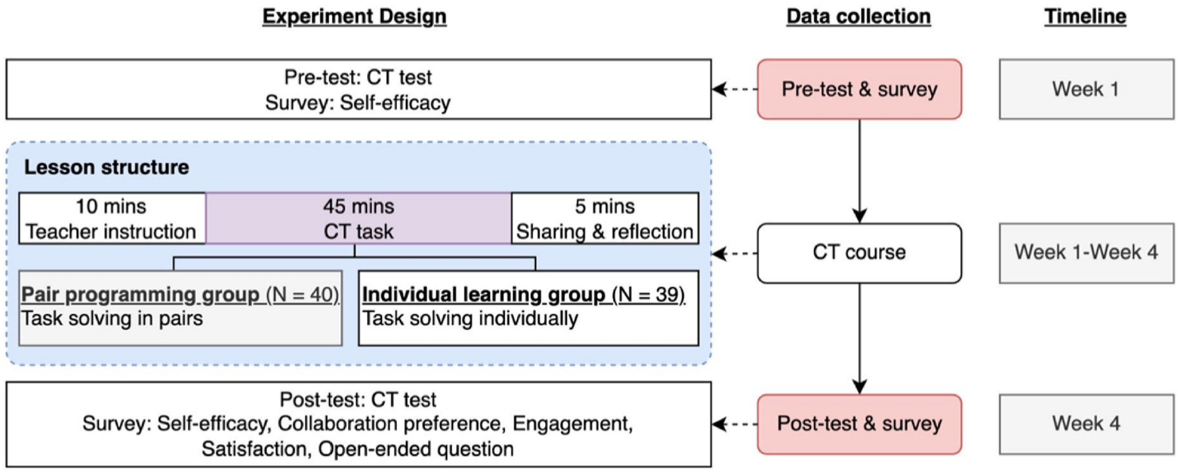

Fig. 3. Experiment design.

programming experience. Additionally, they completed a survey on self-efficacy and collaboration preference toward CT learning. From week 1 to week 4, participants attended 60-min lessons to learn basic CT concepts and practice CT tasks. Each lesson began with a 10-min introduction to CT concepts and guidelines for PP practice. Next, students had 45 min to collaboratively (or individually) complete assigned tasks. In the final 5 min, students were encouraged to share their task solutions and receive feedback from peers and teachers. In the final week, participants completed the same CT test again (with question items and options shuffled), along with a survey on collaboration preference, self-efficacy, learning engagement, and satisfaction.

During the 45-min CT practices, participants in the PP group collaborated on tasks and alternated between driver and navigator roles. When in the driver role, students controlled the keyboard and mouse, constructing and editing code. Meanwhile, students in the navigator role closely observed their partner's work, identified errors, offered structural suggestions, and sought clarification if disagreements arose. The teacher facilitated students to switch roles after a predetermined period. In contrast, students in the individual learning group were required to complete tasks on their own. They were not allowed to discuss with peers and could only seek assistance from the teacher if they had any questions.

3.3. Instruments

Students completed a survey including self-efficacy, collaboration preference, engagement, and learning satisfaction. Each survey item was rated on a 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree).

Self-efficacy was adapted from Yu et al. (2020) to assess students' perception and judgment of their abilities in accomplishing tasks. For example, "*I'm certain I can understand the ideas taught in this course.*" The items' internal consistency was α = .86.

Collaboration preference was adapted from Shaw (2000) and measured by three items. This scale measures an individual's preference for working in a group (e.g., *"If given the choice, I would prefer to work as part of a team rather than work alone.")* The scale demonstrated good reliability, with a Cronbach's alpha of .83.

Engagement was adapted from Fredricks et al. (2005). This scale measures three types of engagement: behavioral, emotional, and cognitive engagement. Behavioral engagement is assessed through three items (e.g., "*I follow the instructions of the course.*" α = .82). Emotional engagement is assessed through four items (e.g., "*I feel happy when taking this course.*" α = .90). Cognitive engagement is assessed through three items (e.g., "*I study even when I don't have a test.*" α = .79).

The *CT skill test* was adapted from Román-González et al. (2017) and designed to assess the CT skills of 5th to 10th-grade students. We selected 18 multiple-choice items from the original test, which corresponded to the four concepts covered in the course: basic directions and sequences (6 items), loop-repeat times (6 items), and event functions (6 items). The items were arranged in increasing order of difficulty. The internal consistency was reported at α = .79.

Learning satisfaction was adapted from the measure by Sher (2009). It was assessed through four items, such as "*I was very satisfied with this course.*" The scale demonstrated high internal consistency, with a reported Cronbach's alpha of 0.90.

We also included two open-ended questions (i.e., 1. *Please use 1–2 sentences to describe your learning experience in this course.* 2. *If you attend a similar course in the future, would you prefer working with a partner? Why?*) at the end of the survey to understand how do the students perceive this course and the reasons to choose (not choose) collaboration in future PP activities. These questions provided insights for improving future PP instructional design.

3.4. Data analysis

Data analysis was completed through four steps. To address RQ1, we compared the CT test results using analysis of covariance (ANCOVA). We set students' pre-test scores as a covariate to control for initial differences in CT abilities to provide a more accurate assessment of our intervention's effect. Similarly, self-efficacy results were compared using ANCOVA, with students' initial self-efficacy as a covariate. For RQ2, we examined the difference in self-efficacy, collaboration preference, engagement, CT skills, and satisfaction between the PP and the individual learning groups using one-way analysis of variance (ANOVA). To address RQ3, we applied structural equation modeling (SEM) analysis to examine the relationships among students' self-efficacy, collaboration preference, engagement, CT skills, and satisfaction, as well as the differences between PP and individual learning groups. Prior experience and gender were included as control variables.

4. Results[1]

Table 2 presents descriptive statistics of CT test scores and all survey variables between PP group and individual group. Table 3 demonstrates the correlations among variables. Both pre- and post-test, pre- and post-self-efficacy show a strong correlation ($p < .001$). Self-efficacy correlates positively with three dimensions of engagement and post-test scores ($p < .05$), while learning preference correlates only with satisfaction ($p <$

[1] The data can be accessed through https://osf.io/e4v29/.

Table 2
Descriptive statistics between PP and individual groups.

	Pre-test		Post-test		SE-pre		SE-post	
	PP	IN	PP	IN	PP	IN	PP	IN
Mean	13.13	12.13	15.68	15.72	3.65	3.69	4.31	4.13
SD	3.15	2.58	2.02	2.10	0.69	0.90	0.52	0.60

	LP		BE		EE		CE		SA	
	PP	IN	PP	IN	PP	IN	PP	IN	PP	IN
Mean	3.94	3.89	4.58	4.27	4.48	4.26	4.01	3.68	4.48	4.15
SD	1.42	0.86	0.43	0.48	0.59	0.82	0.60	1.00	0.58	0.79

Notes. PP = Pair-programming group, IN = Individual learning group, LP = Learning preference, SE = Self-efficacy, BE = Behavioral engagement, EE = Emotional engagement, CE = Cognitive engagement, SA = Satisfaction.

Table 3
Descriptive statistics, correlations, and reliabilities among variables.

Variable	Pre-test	Post-test	LP	SE-pre	SE-post	BE	EE	CE	SA
1. Pre-test	–								
2. Post-test	0.6***	–							
3. LP	−0.17	−0.12	–						
5. SE-pre	0.13	0.23*	0.04	–					
6. SE-post	0.13	0.24*	0.11	0.48***	–				
7. BE	0.08	0.18	0.07	0.06	0.44***	–			
8. EE	0.20	0.33**	0.10	0.30**	0.43***	0.27*	–		
9. CE	0.08	0.15	0.01	0.4***	0.43***	0.27*	0.47***	–	
10. SA	−0.05	0.12	0.28*	−0.12	−0.03	−0.02	0.00	0.01	–
Mean	12.63	15.70	3.92	3.67	4.22	4.43	4.37	3.85	4.31
SD	2.91	2.05	1.17	0.80	0.56	0.47	0.72	0.84	0.71

Notes. N = 79. $^*p < .05$; $^{**}p < .01$; $^{***}p < .001$.
LP = Learning preference, SE = Self-efficacy, BE = Behavioral engagement, EE = Emotional engagement, CE = Cognitive engagement, SA = Satisfaction.

.05).

4.1. The effectiveness of PP on CT skills development (RQ1)

To evaluate the effectiveness of PP in this four-week course, we conducted ANCOVA to examine the improvement in CT test scores and self-efficacy for both groups. Pre-test score and self-efficacy were set as covariates to control for initial differences in students' abilities. Levene's test was not violated (F = 3.400, $p > .05$), suggesting that a common regression coefficient was appropriate for the one-way ANCOVA. As shown in Fig. 4 and Table 4, there was no significant improvement in CT skills in both groups (F (1, 76) = 1.645, $p = .204$). However, we found that self-efficacy levels improved significantly in the PP group than the individual learning group (F (1, 76) = 5.211, $p < .05$).

Table 4
ANCOVA results of CT skills and self-efficacy between PP and individual learning group.

Group	N	*Mean*	*SD*	*F*	*p*	η^2
a *One-way ANCOVA of students' CT skills*						
PP group	40	15.675	2.018	1.645	0.204	0.014
Individual learning group	39	15.718	2.102			
b *One-way ANCOVA of students' self-efficacy levels*						
PP group	40	4.308	0.521	5.211*	0.025	0.054
Individual learning group	39	4.131	0.596			

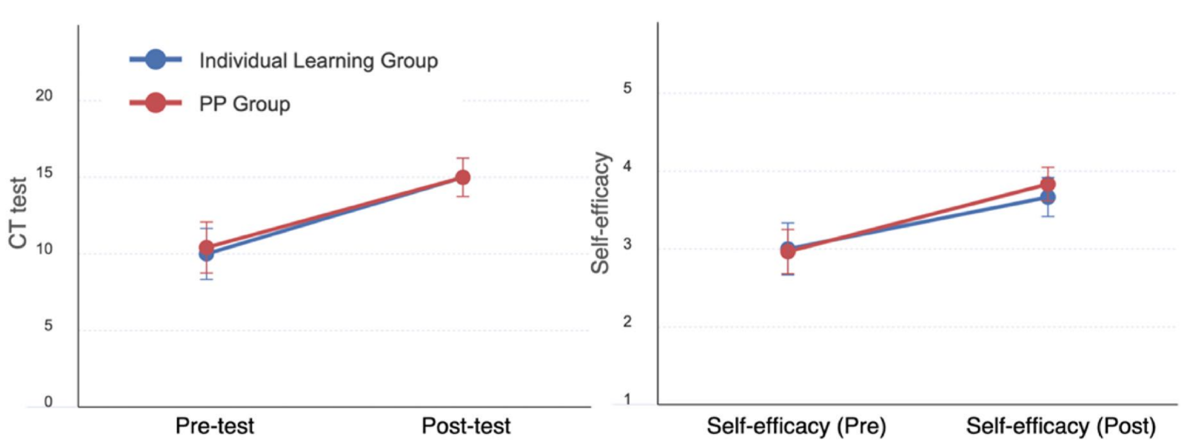

Fig. 4. Improvements in test scores and self-efficacy between PP and individual learning group.

4.2. *Differences in student collaboration, engagement, and satisfaction (RQ2)*

Fig. 5 compares the survey results between PP and individual groups. Both groups showed high scores (above 3 out of 5) across all measured variables, although the PP group had slightly higher mean scores. To determine if there were significant differences, we conducted ANOVA tests. The one-way ANOVA tests revealed certain significant differences between the groups. As shown in Table 5, students in the PP group reported significantly higher levels of behavioral engagement ($F = 7.207$, $p < .01$) and satisfaction ($F = 4.326$, $p < .05$) compared to students working individually. According to Cohen's (1988) guidelines, η^2 values of 0.01, 0.06, and 0.14 represent small, medium, and large effects, respectively. In our study, behavioral engagement showed a medium effect size ($\eta^2 = 0.108$), and satisfaction showed a small to medium effect ($\eta^2 = 0.053$). These findings suggest that while the overall learning experience was positive for both groups, PP enhanced students' behavioral engagement and satisfaction with the learning process. Additionally, cognitive engagement showed higher scores in the PP group, although the difference did not reach statistical significance ($p = .072$). This outcome suggests that students in PP settings may experience deeper cognitive processing through activities such as explaining their reasoning to partners, evaluating alternative solutions, and reflecting on their problem-solving strategies.

To obtain an in-depth understanding of students' perceptions of their learning experience and satisfaction, we analyzed their responses to the open-ended questions. Fig. 6 illustrates students' preferences for future learning formats according to their current learning experiences in either individual or PP settings. Notably, students from both groups showed interest in learning in pairs, while PP group students demonstrated a stronger tendency toward future collaborative learning (28 students) compared to those in individual learning settings (23 students). This suggests that positive PP experiences may have reinforced students' preference for collaborative learning. Regarding learning experiences, students in both groups expressed positive attitudes toward this CT course and identified several benefits they gained, including "improved programming skills", "better understanding of CT concepts", and "enhanced debugging abilities". For example, Student 9 (Male, 11 years) said, "*I can understand my program and how to spot errors more quickly.*" Another student (Female, 11 years) commented, "*I like that I was able to learn more things about CT, and the lessons were very fun and*

Table 5
ANOVA results of collaboration preference, engagement, and satisfaction between the PP group and the individual learning group.

Variables	Sum of Squares	*df*	*F*	95 % *CI*	*p*	η^2
Collaboration preference	1.125	77	0.639	[-0.356, 0.833]	0.426	0.008
Behavioral engagement	1.897	77	9.307**	[0.108, 0.512]	0.003	0.108
Emotional engagement	0.945	77	1.854	[-0.101, 0.539]	0.177	0.024
Cognitive engagement	2.257	77	3.322	[-0.031, 0.707]	0.072	0.041
Satisfaction	2.099	77	4.326*	[0.014, 0.638]	0.041	0.053

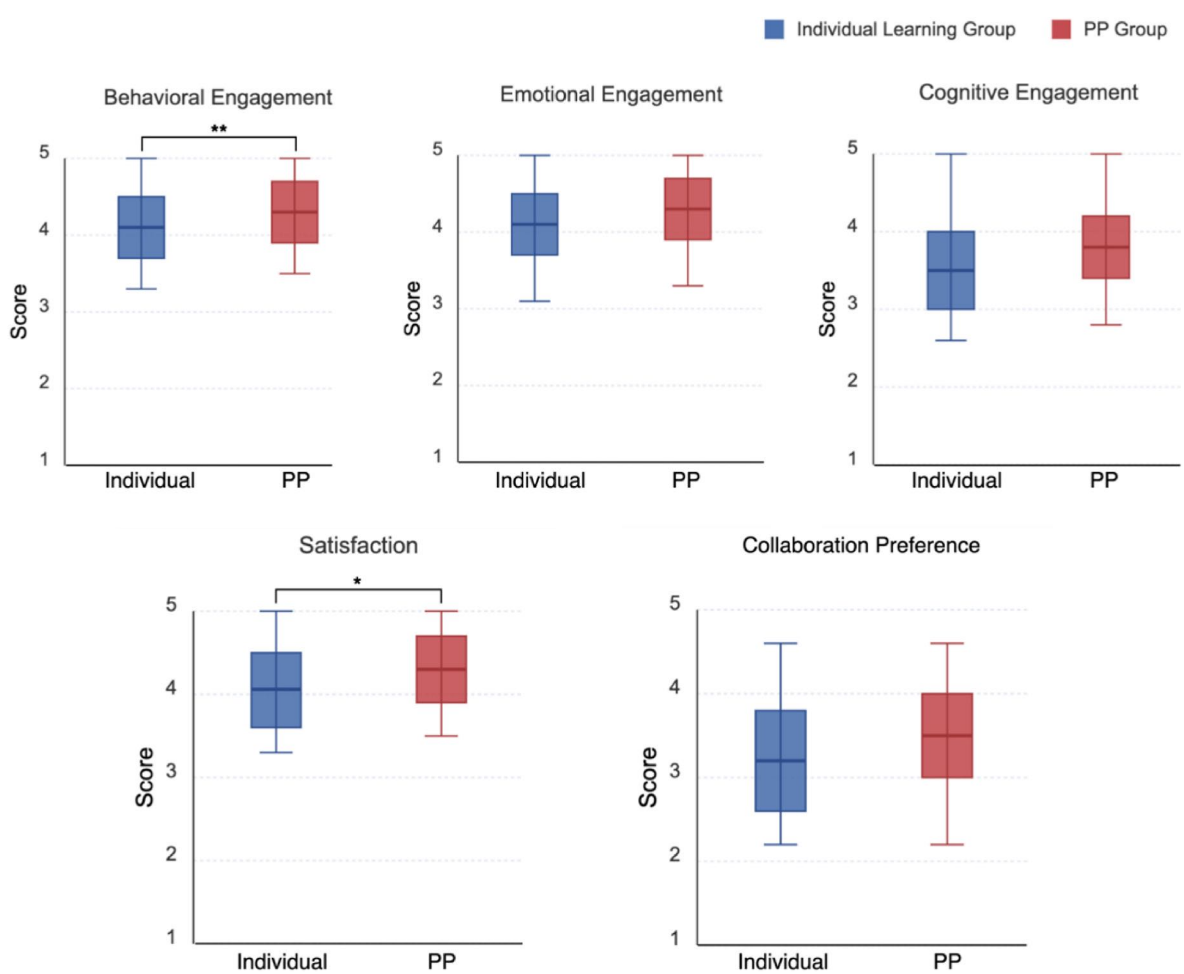

Fig. 5. Survey results on collaboration preference, engagement, and satisfaction between PP and individual group.

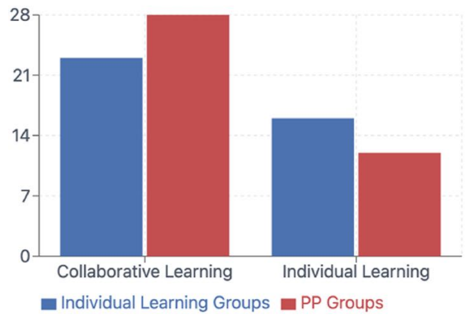

Fig. 6. The distribution of collaboration preference in future classes.

interesting."

Students identified several advantages of PP learning, including "enhanced engagement," "knowledge sharing," and "the development of peer support and friendship" during the learning process. For example, Student 15 (Female, 11 years) said, "*Working with my partner made the lessons more exciting because we could help each other solve problems together.*" Student 22 (Male, 10 years) noted, "*I learned new ways to think about coding from my partner, and we became good friends too.*". However, students also expressed concerns about participating in PP learning. One student thought, "*Individual learning could allow me to be more focused with less distraction and noise* (Student 37, Male, 10 years)." Similarly, Student 1 (Male, 11 years) mentioned, "*Sometimes my partner talks too much when I am working on the coding tasks.*" Others said they would choose individual learning in the future because they did not know how to manage interpersonal conflicts and disagreements. For example, Student 30 (Male, 11 years) said, "*If I work with a partner, I think that there will be arguments, but what if my groupmate does not listen to me?*"

4.3. The relationships among motivational factors, CT skills, and satisfaction (RQ3)

4.3.1. Structural Equation Modeling (SEM)

Confirmatory Factor Analysis (CFA) revealed a good model fit with the following indices: $\chi 2 = 186.92$, $p < .001$, CFI = 0.96, TLI = 0.94, RMSEA = 0.06 (95 % CI = [0.04, 0.06]), and SRMR = 0.07. All standardized factor loadings were statistically significant ($p < .001$) and exceeded the recommended threshold of 0.5 (Keith, 2019), demonstrating good convergent validity of the measurement scales. Furthermore, the average variance extracted (AVE) exceeded 0.50, indicating good discriminant validity across all constructs. Table 6 presents the details of measurement model results.

Table 6
Measurement model results.

Construct	Items	Factor Loadings	Cronbach's α	CR	AVE
Self-efficacy	SE_1	0.831***	0.86	0.78	0.65
	SE_2	0.775***			
Collaboration Preference	CP_1	0.949***	0.83	0.92	0.80
	CP_2	0.872***			
	CP_3	0.860***			
Behavioral Engagement	BE_1	0.854***	0.82	0.83	0.71
	BE_2	0.825***			
Emotional Engagement	EE_1	0.954***	0.90	0.92	0.70
	EE_2	0.800***			
	EE_3	0.906***			
	EE_4	0.872***			
Cognitive Engagement	CE_1	0.624***	0.79	0.81	0.58
	CE_2	0.831***			
	CE_3	0.819***			
Satisfaction	SA_1	0.762***	0.90	0.83	0.54
	SA_2	0.762***			
	SA_3	0.794***			
	SA_4	0.616***			

As shown in Fig. 7 and Table 7, H1a/b/c are supported. Self-efficacy significantly influenced behavioral engagement ($\beta = 0.842$, $p < .001$), emotional engagement ($\beta = 0.693$, $p < .001$), and cognitive engagement ($\beta = 0.502$, $p < .001$). In addition, H3 is supported as self-efficacy directly predicted learning performance ($\beta = 0.854$, $p < .001$). Although self-efficacy did not directly predict satisfaction, its influence on satisfaction was mediated through the engagement dimensions. Emotional engagement positively predicted both learning performance ($\beta = 0.454$, $p < .01$), which supported H2b, and satisfaction ($\beta = 0.720$, $p < .001$), which supported H6b. Cognitive engagement contributed significantly to students' satisfaction ($\beta = 0.534$, $p < .001$), which confirmed H6c hypothesis.

However, Behavioral engagement showed no significant relationship with either CT performance ($\beta = -0.125$, $p > .05$) or learning satisfaction ($\beta = -0.038$, $p > .05$), indicating that H2a and H6a were not supported. On the other hand, collaboration preference had no direct influence on performance and satisfaction, only influencing emotional engagement ($\beta = 0.324$, $p < .01$), which provides support for H5b while H4, H5a, and H5c were not supported.

The mediation results revealed several significant indirect pathways through which self-efficacy and collaboration preference influenced student outcomes. The relationship between self-efficacy and satisfaction was significantly mediated by both emotional engagement ($\beta = 0.459$, 95 % CI [0.32, 1.07], $p < .001$) and cognitive engagement ($\beta = 0.246$, 95 % CI [0.10, 0.65], $p < .01$). The analysis also indicated that emotional engagement was the most significant mediator in our proposed model. It significantly mediated both the relationship between collaboration preference and satisfaction ($\beta = 0.218$, 95 % CI [0.03, 1.07], $p < .01$) and the path from collaboration preference to performance ($\beta = 0.147$, 95 % CI [0.02, 0.21], $p < .05$).

Next, we constructed a structural model. The model demonstrated an acceptable fit with CFI = 0.94, TLI = 0.92, RMSEA = 0.07 (95 % CI = [0.05, 0.09]), and SRMR = 0.07. The model's squared multiple correlations (R^2) explained 74 % of the variance in student learning performance and 90.8 % of the variance in learning satisfaction. Fig. 7 illustrates the path coefficients and their significance levels, showing the relationships among self-efficacy, collaboration preference, engagement, computational thinking skills, and satisfaction.

4.3.2. Multigroup SEM

To examine differences between the two groups, we tested a metric-invariant model in which structural paths were constrained to be equal across groups. The results revealed that the learning context (PP versus individual learning) moderated these relationships. Specifically, the relationship between self-efficacy and cognitive engagement was more positive in the PP context ($\beta = 0.481$) than the individual learning context ($\beta = -0.006$), $\Delta\beta = 0.487$, $p < .05$. Similarly, the influence of collaboration preference on cognitive engagement was more positive in PP groups ($\beta = 0.295$) than individual learning groups ($\beta = -0.141$), $\Delta\beta = 0.436$, $p < .05$. These observations indicate that students with high self-efficacy become more cognitively engaged when working in pairs. Moreover, students who preferred collaboration showed increased cognitive engagement when completing projects in PP settings.

5. Discussion

Our study provides new evidence regarding the positive impact of PP on students' CT learning experience, which is aligned with previous work (Wei et al., 2021). Moreover, this study extends prior work and contributes to motivation research in CT education by uncovering the motivational mechanism underlying PP's effectiveness. Specifically, we examined the relationships between students' CT skills, collaboration preferences, self-efficacy, engagement, and satisfaction in both collaboration and individual learning contexts. Several noteworthy findings

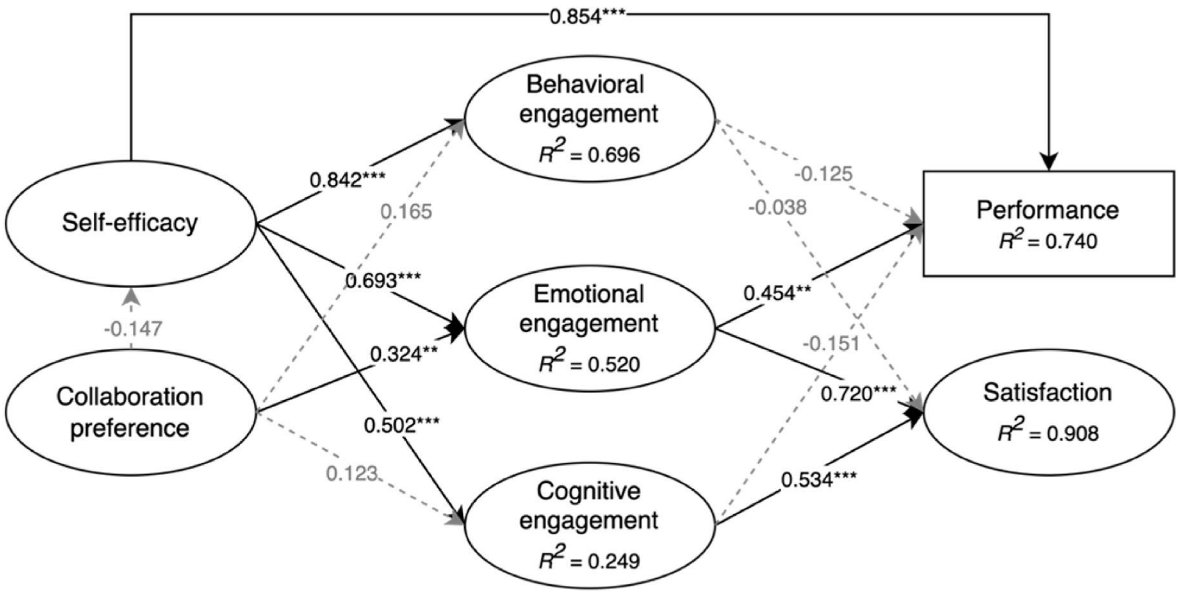

Fig. 7. Path coefficients, level of significance, and R^2 value results of SEM.

Table 7
Hypothesis testing results based on SEM analysis.

Hypothesis		Path Coefficient	Supported
H1a:	Self-efficacy → Behavioral engagement	0.842***	Yes
H1b:	Self-efficacy → Emotional engagement	0.693***	Yes
H1c:	Self-efficacy → Cognitive engagement	0.502***	Yes
H2a:	Behavioral engagement → Performance	−0.125	No
H2b:	Emotional engagement → Performance	0.454**	Yes
H2c:	Cognitive engagement → Performance	−0.151	No
H3:	Self-efficacy → Performance	0.854***	Yes
H4:	Collaboration preference → Self-efficacy	−0.147	No
H5a:	Collaboration preference → Behavioral engagement	0.165	No
H5b:	Collaboration preference → Emotional engagement	0.324**	Yes
H5c:	Collaboration preference → Cognitive engagement	0.123	No
H6a:	Behavioral engagement → Satisfaction	−0.038	No
H6b:	Emotional engagement → Satisfaction	0.720***	Yes
H6c:	Cognitive engagement → Satisfaction	0.534***	Yes

emerged in our analysis.

5.1. The positive impact of PP on CT skills and self-efficacy

Aligning with previous findings (Kong et al., 2018; Wei et al., 2021), our experiment demonstrated that students in the PP group showed significantly greater improvement in self-efficacy compared to those working individually. However, we did not observe significant differences between PP and individual groups in CT test score improvements. Several factors may explain this unexpected result. One, the four-week intervention was probably too short for students to adapt to PP and benefit from PP. Two, ability grouping may have impact on students' learning experiences and outcomes. According to a previous study, groups consisting of high-ability and low-ability students reported higher learning performance than groups of students with similar ability levels (An & Zhang, 2024; Lei et al., 2025). Additionally, when both students in a pair have low ability levels, they tend to struggle with task completion and result in lower performance (Murphy et al., 2017).

The positive impact of self-efficacy on cognitive engagement is amplified by collaborative learning settings. According to social learning theory (Bandura, 1977), learning is a social process that occurs through observation, imitation, and modeling and is influenced by factors such as attention, motivation, attitudes, and emotions. In the PP group, students with higher self-efficacy tend to be more attentive to their partners' problem-solving approaches and observe their thinking processes through drag-and-drop blocks. For example, Student 31 (Female, 10 years) said, "*Sometimes, I found that my partner's code is shorter than mine. It is interesting to see other people's creativity and codes.*" This process helps students reflect, use of learning strategies, and enhance their cognitive engagement (She et al., 2021).

In addition, the interaction between self-efficacy, cognitive engagement, and collaborative nature in PP creates a positive feedback loop, where students in pairs contribute to shared knowledge and group cognition, which in turn reinforce individual engagement and learning (Stahl, 2005). This is reflected in students' perspectives. For example, Student 36 (Female, 11 years) showed a positive attitude toward collaboration because "*[they] can share ideas and complete tasks together*" and Student 20 (Male, 11 years) preferred collaborative problem-solving because he believed that "*Two heads are better than one. We can hear others' suggestions and create something bigger together.*"

5.2. Three dimensions of engagement in PP and individual learning contexts

The ANOVA results demonstrated that students in the PP group showed significantly higher behavioral engagement in CT learning. Behavioral engagement concerns involvement in learning tasks and includes behaviors such as effort, persistence, concentration, attention, discussion and asking questions (Fredricks et al., 2005). The interactive nature of PP promotes more frequent and meaningful interactions and discussions between learners, such as explaining concepts, questioning solutions, and arguing or negotiating algorithm steps with partners. In our study, students working in pairs shared positive learning experiences related to behavioral engagement. For example, Student 7 (Male, 11 years) said, "*When I do not understand a concept, I can always ask my partner*", while Student 10 (Female, 11 years) shared that "*we can help out one another whenever we don't understand a certain question and we can also create a stronger bond together.*" On the other hand, students who worked on their own felt they lacked peer support and feedback. For example, "*I hope there would be someone checking my mistakes, and I can check my partner's, and we could discuss the solutions* (Student 64, Male, 11 years)." These findings suggest that PP promotes peer interaction, which is positively associated with students' behavioral engagement (Lai, 2021).

However, it should be noted that the higher behavioral engagement did not translate into significant improvement in CT test scores in the PP group. This can be explained by two reasons. First, behavioral engagement, such as time effort and class participation, may require a long time to consolidate into measurable CT skill improvements. The four-week intervention may have been insufficient for these engagement behaviors to yield enhanced performance. Second, the interactive nature of PP likely increased students' self-reported participation and peer discussion, but these subjective measures of engagement may not directly correspond to objective learning outcomes.

While we observed higher behavioral engagement in the PP group, emotional engagement showed no significant difference between PP and individual learning groups. Although peer interaction can improve engagement, potential conflicts between partners may affect their emotional engagement and active learning (Molinillo et al., 2018). Conflicts often emerge during the problem-solving process when individuals bring different ideas and opinions to group tasks. These differences can produce negative emotions arising from perceived threats to individual or group goals, ultimately becoming a crucial factor in performance (Jordan & Troth, 2021). For example, Student 29 (Female, 10 years) complained about her partner, "*Most of the time we discussed off-topic things that distracted me from my work. My partner also did not participate in task solving, which means I have to handle the heavy workload all by myself. Sometimes, he was bossy and told me what to do while just sitting there doing nothing.*" Similarly, Student 21 (Male, 11 years) shared his concern, "*I don't want to get into trouble because my partner did not agree with me on everything.*" These negative emotions may explain the adverse impact of PP on emotional engagement.

5.3. The mediating role of engagement in learning

Our study demonstrated that emotional engagement was the most significant mediator in learning, which is consistent with other studies that students with higher self-efficacy showed more interest in learning and a sense of pride and achievement after completing tasks (Panigrahi et al., 2021; Wang & Fredricks, 2014). Such emotional engagement positively influenced their learning performance and overall satisfaction. Student 13 (Female, 11 years), who showed significant improvement between pre- and post-tests, shared that "*I'm really proud of being able to create my own Star Wars games and share my work with others. I would like to recommend this to others. Very amazing and interesting course!*" In contrast, students with lower self-efficacy, reported negative emotional experience, such as anxiety and losing interest in CT learning, which led to reduced participation and poorer learning outcomes (Wang & Fredricks, 2014). For example, Student 4 (Female, 10 years) expressed her struggles: "*I am not sure I can complete the challenging tasks, especially those that require using 'loops.' Sometimes, it makes me feel anxious, and I lose track of time and thus makes me to not finish all the tasks in the allocated time.*"

Although prior studies showed that the three dimensions of engagement were significantly related to students' learning performance and other positive outcomes (Bergdahl et al., 2020; Hazzam & Wilkins, 2023), our study did not find significant relationships between behavioral engagement and performance, nor between cognitive engagement and performance. Similar results were presented in a meta-analysis by Lei et al. (2018), which found weak or non-significant relationships between these two types of engagement and performance (Liu et al., 2023). There are two possible explanations for these findings. First, behavioral engagement may not accurately reflect students' ability, as high-ability students may spend less time and effort on CT tasks because they master CT concepts and skills quickly. Conversely, low-ability students may struggle to understand CT concepts and complete tasks on time. Even with increased effort, their performance may not meet expectations. For example, we observed that low-ability students asked more questions related to "loops" concept and spent more time on challenging tasks (e.g., "*The character is moving too fast and goes off the screen - how do I make it bounce back?*" and "*Oh no, I can't make.*" (Student 28, Female, 11 years)). However, this increased behavioral engagement does not directly translate into improved test scores.

Second, gender may moderate the relationship between student engagement and academic achievement. Previous research indicated that the relationships between behavioral and/or cognitive engagement and academic performance were stronger in samples with more female students, but weaker in samples with more male students (Lei et al., 2018). This was explained by gender differences in self-esteem, with boys often reporting higher levels than girls (Hu et al., 2023). Higher self-esteem leads boys to disengage from academic tasks because they seek to protect their self-image from potential failure or ridicule (Arshad et al., 2015). In our study, the larger proportion of male participants (49 males out of 79 participants) may therefore help explain the weak relationships between cognitive engagement and performance.

5.4. Implications

Theoretically, we contribute to CT education research by uncovering the motivational mechanisms that explain the effectiveness of PP in CT skill development. First, we extend the applicability of Linnenbrink and Pintrich's (2003) motivational framework to the CT education context. Our findings demonstrate its robustness in understanding the relationship between self-efficacy, engagement, and performance in CT learning. Second, we augment the model by including two additional factors: collaboration preference and learning satisfaction. This extended framework provides a more comprehensive understanding of student learning processes in both collaborative and individual contexts, which can be applied to other computer-supported collaboration learning contexts. Further, our study emphasizes the mediating role of three dimensions of engagement in the above relationships and reveals the different influences of this mediator in PP and individual learning contexts. These insights could inform the development of targeted interventions to effectively engage students in the learning process.

Our study also provides practical implications for CT education. First, task difficulty levels may influence students' cognitive and behavioral engagement. CT tasks should be designed with different difficulty levels to keep both high and low-ability students engaged. CT practice could progress from basic-level tasks to intermediate-level tasks, with additional challenging tasks as extra practice. This helps high-ability students remain engaged through challenging tasks while preventing low-ability students from being overwhelmed. Second, ability grouping may impact students' learning experiences and outcomes. Therefore, to promote productive collaboration, instructors should consider mixed-ability pairing, as groups with high- and low-ability students reported higher learning performance than groups of students with similar ability levels.

Third, conflict and disagreement are often accompanied by unfavorable socio-emotional tension (e.g., irritation and anxiety) that may threaten collaborative participation (Chen, 2020). Instructors should teach specific collaboration skills, particularly strategies for managing disagreements during collaboration. For example, it would be helpful to create guidelines for productive peer interactions, such as using "I" statements, active listening techniques, and encouraging positive social-emotional expressions (Isohätälä et al., 2018). Finally, given that some students, like Student 37, perceived benefits from collaboration while valuing independent focus time, we recommend implementing a hybrid PP model that includes collaborative and independent work phases in each lesson. For example, students could begin by working independently on basic tasks to develop individual understanding (15–20 min), then collaborate on more challenging problems through peer discussion (20–25 min). This approach accommodates different learning preferences while maintaining the benefits of collaboration.

6. Conclusion

6.1. Summary of main findings

First, our study demonstrated that students learning in pairs showed significantly greater improvement in self-efficacy compared to those working individually. In addition, these students reported significantly higher levels of behavioral engagement and satisfaction compared to students working individually. Second, the SEM analysis revealed that students in both groups with high self-efficacy beliefs were more engaged in CT learning in terms of their behavior, cognition, and motivation, consequently leading to better CT skill test and satisfaction scores toward learning. However, the positive effects of self-efficacy and collaboration preference on cognitive engagement were stronger in the PP group. Lastly, positive PP experiences may have reinforced students' preference for future collaborative learning. Students identified peer support and knowledge sharing as primary motivations to work collaboratively. However, we also noticed that disagreement resolution may impede students who work in groups.

6.2. Limitations and future research directions

Several limitations should be noted. First, the four-week intervention may not fully reflect the development of students' CT skills. Future studies should consider longitudinal designs that span a full semester or academic year to capture the progressive development and CT knowledge acquisition. Nevertheless, our findings provide informative and useful insights that can guide future research and educational practices. Second, participants were recruited from local elementary schools, which limits the generalizability of the findings. In Singapore, CT classes are implemented as enrichment classes rather than compulsory subjects. Since CT is not included in official examinations, this may influence students' engagement levels and motivation. Hence, future research should examine the implementation of CT education across different educational contexts to better understand how institutional policies and curriculum design affect learning outcomes. Third, we randomly paired students for PP. As discussed earlier, the ability levels of students in pairs may influence their learning experience and engagement level. We recommend future research to also group students based on ability levels to examine whether same-ability or mixed-ability groups influence CT performance differently. Fourth, our analysis relies on self-reported survey data, which are post-reflections rather than "in the moment" data. This makes it difficult to gain an in-depth understanding of how PP influences CT skills development during the collaboration process. Future research should employ mixed-method approaches, such as classroom observations and interaction analysis, to triangulate our findings and investigate the learning process.

CRediT authorship contribution statement

Stella Xin Yin: Writing – original draft, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Dion Hoe-Lian Goh:** Writing – review & editing, Supervision. **Choon Lang Quek:** Supervision, Project administration.

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

References

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179–211.

Aldhahi, M. I., Alqahtani, A. S., Baattaiah, B. A., & Al-Mohammed, H. I. (2022). Exploring the relationship between students' learning satisfaction and self-efficacy during the emergency transition to remote learning amid the coronavirus pandemic: A cross-sectional study. *Education and Information Technologies, 27*(1), 1323–1340. https://doi.org/10.1007/s10639-021-10644-7

An, S., & Zhang, S. (2024). Effects of ability grouping on students' collaborative problem solving patterns: Evidence from lag sequence analysis and epistemic network analysis. *Thinking Skills and Creativity, 51*, Article 101453. https://doi.org/10.1016/j.tsc.2023.101453

Arshad, M., Muhammad, S., & Mahmood, K. (2015). Self-esteem **and** academic performance among university students. *Journal of Education and Practice, 6*(1), 156–162.

Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review, 84*(2), 191–215. https://doi.org/10.1007/978-3-319-75361-4

Bergdahl, N., Nouri, J., Fors, U., & Knutsson, O. (2020). Engagement, disengagement and performance when learning with technologies in upper secondary school. *Computers & Education, 149*, Article 103783. https://doi.org/10.1016/j.compedu.2019.103783

Brennan, K., & Resnick, M. (2012). *New frameworks for studying and assessing the development of computational thinking, 1*, 25.

Chen, C. M., & Huang, M. Y. (2024). Enhancing programming learning performance through a Jigsaw collaborative learning method in a metaverse virtual space. *International Journal of STEM Education, 11*(1), 36.

Chen, W. (2020). Disagreement in peer interaction: Its effect on learner task performance. *System, 88*, Article 102179. https://doi.org/10.1016/j.system.2019.102179

Fredricks, J. A., Blumenfeld, P., Friedel, J., & Paris, A. (2005). School engagement. In K. A. Moore, & L. H. Lippman (Eds.), *What do children need to flourish?* (pp. 305–321). Springer US. https://doi.org/10.1007/0-387-23823-9_19.

Hazzam, J., & Wilkins, S. (2023). The influences of lecturer charismatic leadership and technology use on student online engagement, learning performance, and satisfaction. *Computers & Education, 200*, Article 104809. https://doi.org/10.1016/j.compedu.2023.104809

Hendry, G. D., Heinrich, P., Lyon, P. M., Barratt, A. L., Simpson, J. M., Hyde, S. J., Gonsalkorale, S., Hyde, M., & Mgaieth, S. (2005). Helping students understand their learning styles: Effects on study self-efficacy, preference for group work, and group climate. *Educational Psychology, 25*(4), 395–407. https://doi.org/10.1080/01443410500041706

Hsu, T. C., Wu, L. K., & Looi, C. K. (2022). Effects of a pair programming educational robot-based approach on students' interdisciplinary learning of computational thinking and language learning. *Frontiers in psychology, 13*, 888215.

Hu, Y., Cai, Y., Wang, R., Gan, Y., & He, N. (2023). The relationship between self-esteem and aggressive behavior among Chinese adolescents: A moderated chain mediation medel. *Frontiers in Psychology, 14*, 1191134.

Iskrenovic-Momcilovic, O. (2019). Pair programming with **Scratch**. *Education and Information Technologies, 24*(5), 2943–2952. https://doi.org/10.1007/s10639-019-09905-3

Isohätälä, J., Näykki, P., Järvelä, S., & Baker, M. J. (2018). Striking a balance: Socio-emotional processes during argumentation in collaborative learning interaction. *Learning, Culture and Social Interaction, 16*, 1–19. https://doi.org/10.1016/j.lcsi.2017.09.003

Jordan, P. J., & Troth, A. C. (2021). Managing emotions during team problem solving: Emotional intelligence and conflict resolution. In *Emotion and performance* (pp. 195–218). CRC Press.

Keller, J. M. (1987). Development and use of the **ARCS** model of motivational design. *Journal of Instructional Development, 10*, 2–10.

Kim, S., & Kim, D.-J. (2021). Structural relationship of key factors for student satisfaction and achievement in asynchronous online learning. *Sustainability, 13*(12), 6734. https://doi.org/10.3390/su13126734

Kong, S.-C., Chiu, M. M., & Lai, M. (2018). A study of primary school students' interest, collaboration attitude, and programming empowerment in computational thinking education. *Computers & Education, 127*, 178–189. https://doi.org/10.1016/j.compedu.2018.08.026

Kucuk, S., & Richardson, J. C. (2019). A structural equation model of predictors of online learners' engagement and satisfaction. *Online Learning Journal, 23*(2), 196–216. https://doi.org/10.24059/olj.v23i2.1455

Lai, H. M. (2021). Understanding what determines university students' behavioral engagement in a group-based flipped learning context. *Computers and Education, 173*, Article 104290. https://doi.org/10.1016/j.compedu.2021.104290

Lai, X., Ye, J., & Wong, G. K. W. (2023). Effectiveness of collaboration in developing computational thinking skills: A systematic review of social cognitive factors. *Journal of Computer Assisted Learning, 39*(5), 1418–1435. https://doi.org/10.1111/jcal.12845

Lei, H., Cui, Y., & Zhou, W. (2018). Relationships between student engagement and academic achievement: A meta-analysis. *Social Behavior and Personality, 46*(3), 517–528. https://doi.org/10.2224/sbp.7054

Lei, Y., Fu, X., Zhao, J., & Yi, B. (2025). The effect of ability grouping on students' computational thinking in shared regulation-supported collaborative programming. *Education and Information Technologies, 30*(2), 1417–1443.

Li, Q., Jiang, Q., Liang, J. C., Xiong, W., & Zhao, W. (2024). Engagement predicts computational thinking skills in unplugged activity: Analysis of gender differences. *Thinking Skills and Creativity, 52*, 1–16. https://doi.org/10.1016/j.tsc.2024.101537

Linnenbrink, E. A., & Pintrich, P. R. (2003). The role of self-efficacy beliefs in student engagement and learning in the classroom. *Reading & Writing Quarterly, 19*(2), 119–137. https://doi.org/10.1080/10573560308223

Liu, K., Yao, J., Tao, D., & Yang, T. (2023). Influence of individual-technology-task-environment fit on university student online learning performance: The mediating role of behavioral, emotional, and cognitive engagement. *Education and Information Technologies, 28*(12), 15949–15968. https://doi.org/10.1007/s10639-023-11833-2

Miao, F., & Holmes, W. (2023). *Guidance for generative AI in education and research*. UNESCO. https://doi.org/10.54675/EWZM9535

Molinillo, S., Aguilar-Illescas, R., Anaya-Sánchez, R., & Vallespín-Arán, M. (2018). Exploring the impacts of interactions, social presence and emotional engagement on active collaborative learning in a social web-based environment. *Computers and Education, 123*, 41–52. https://doi.org/10.1016/j.compedu.2018.04.012

Murphy, P. K., Greene, J. A., Firetto, C. M., Li, M., Lobczowski, N. G., Duke, R. F., Wei, L., & Croninger, R. M. V. (2017). Exploring the influence of homogeneous versus heterogeneous grouping on students' text-based discussions and comprehension. *Contemporary Educational Psychology, 51*, 336–355. https://doi.org/10.1016/j.cedpsych.2017.09.003

Özmutlu, M., Atay, D., & Erdoğan, B. (2021). Collaboration and engagement based coding training to enhance children's computational thinking self-efficacy. *Thinking Skills and Creativity, 40*, Article 100833. https://doi.org/10.1016/j.tsc.2021.100833

Panigrahi, R., Srivastava, P. R., & Panigrahi, P. K. (2021). Effectiveness of e-learning: The mediating role of student engagement on perceived learning effectiveness. *Information Technology & People, 34*(7), 1840–1862. https://doi.org/10.1108/ITP-07-2019-0380

Piaget. (1971). The theory of stages in cognitive development. *Measurement and Piaget*. McGraw-Hill.

Pintrich, P. R. (2003). A motivational science perspective on the role of student motivation in learning and teaching contexts. *Journal of Educational Psychology, 95* (4), 667–686. https://doi.org/10.1037/0022-0663.95.4.667

Qureshi, M. A., Khaskheli, A., Qureshi, J. A., Raza, S. A., & Yousufi, S. Q. (2023). Factors affecting students' learning performance through collaborative learning and engagement. *Interactive Learning Environments, 31*(4), 2371–2391. https://doi.org/10.1080/10494820.2021.1884886

Román-González, M., Pérez-González, J.-C., & Jiménez-Fernández, C. (2017). Which cognitive abilities underlie computational thinking? Criterion validity of the **Computational thinking Test**. *Computers in Human Behavior, 72*, 678–691. https://doi.org/10.1016/j.chb.2016.08.047

Schunk, D. H., & Mullen, C. A. (2012). Self-efficacy as an engaged learner. In S. L. Christenson, A. L. Reschly, & C. Wylie (Eds.), *Handbook of research on student engagement* (pp. 219–235). Springer US. https://doi.org/10.1007/978-1-4614-2018-7_10.

Shaw, J. (2000). Interdependence and preference for group work: Main and congruence effects on the satisfaction and performance of group members. *Journal of Management, 26*(2), 259–279. https://doi.org/10.1016/s0149-2063(99)00045-8

She, L., Ma, L., Jan, A., Sharif Nia, H., & Rahmatpour, P. (2021). Online learning satisfaction during **COVID-19** pandemic among Chinese university students: The serial mediation model. *Frontiers in Psychology, 12*. https://doi.org/10.3389/fpsyg.2021.743936

Sher, A. (2009). Assessing the relationship of student-instructor and student-student interaction to student learning and satisfaction in web-based online learning environment. *The Journal of Interactive Online Learning, 8*(2), 102–120.

Stahl, G. (2005). Group cognition in computer-assisted collaborative learning. *Journal of Computer Assisted Learning, 21*(2), 79–90. https://doi.org/10.1111/j.1365-2729.2005.00115.x

Stahl, G. (2006). *Group cognition: Computer support for building collaborative knowledge*. The MIT Press.

Sweller, J. (2011). Cognitive load theory. In *, 55. psychology of learning and motivation* (pp. 37–76). Academic Press.

Vygotsky, L. S. (1978). *Mind in Society: Development of Higher Psychological Processes*. Harvard University Press. https://doi.org/10.2307/j.ctvjf9vz4.

Wang, M. T., & Fredricks, J. A. (2014). The reciprocal links between school engagement, youth problem behaviors, and school dropout during adolescence. *Child Development, 85*(2), 722–737. https://doi.org/10.1111/cdev.12138

Wei, X., Lin, L., Meng, N., Tan, W., Kong, S.-C., & Kinshuk. (2021). The effectiveness of partial pair programming on elementary school students' **computational thinking** skills and self-efficacy. *Computers & Education, 160*, Article 104023. https://doi.org/10.1016/j.compedu.2020.104023

Xu, W., Wu, Y., & Ouyang, F. (2023). Multimodal learning analytics of collaborative patterns during pair programming in higher education. *International Journal of Educational Technology in Higher Education, 20*(1), 8.

Yin, S. X., Goh, D. H.-L., Quek, C. L., & Liu, Z. (2025). Mapping the public understanding of computational thinking education: Insights from social Q&A platform discussions. *Educational Technology & Society, 28*(2), 15–34.

Yin, S. X., Hoe-Lian Goh, D., & Quek, C. L. (2024). Collaborative learning in **K-12** computational thinking education: A systematic review. *Journal of Educational Computing Research, 62*(6), 1440–1474. https://doi.org/10.1177/07356331241249956

Yin, S. X., Liu, Z., Goh, D. H.-L., Quek, C. L., & Chen, C. F. (2025). Scaling up collaborative dialogue analysis: an AI-driven approach to understanding dialogue patterns in computational thinking education. In *Proceedings of the 15th International Learning Analytics and Knowledge Conference* (pp. 47–57).

Yu, J., Bai, C., & Roque, R. (2020). Considering parents in coding kit design. *Proceedings of the 2020 CHI conference on human factors in computing systems*. https://doi.org/10.1145/3313831.3376130

Zhong, B., Wang, Q., Chen, J., & Li, Y. (2017). Investigating the period of switching roles in pair programming in a primary school. *Journal of Educational Technology & Society, 20*(3), 220–233.

Stella Xin Yin is a Ph.D. candidate at Nanyang Technological University. Her research interests are learning analytics, computational thinking education and collaborative learning.

Dion Hoe-Lian Goh is Professor with Nanyang Technological University. He has extensive experience in game-based techniques for shaping user perceptions and motivating behavior, online information sharing and seeking.

Choon Lang Quek is Associate Professor with Nanyang Technological University. Her research interests are psycho-social learning environment, teaching and designs in K-12 and higher education.