Original Research Article

Embodied Learning for Computational Thinking in a Mixed-Reality Context

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Abstract

This study examined the effects of embodied learning experiences on students' understanding of computational thinking (CT) concepts and their ability to solve CT problems. In a mixed-reality learning environment, students mapped CT concepts, such as sequencing and loops, onto their bodily movements. These movements were later applied to robot programming tasks, where students used the same CT concepts in a different modality. By explicitly connecting embodied actions with programming tasks, the intervention aimed to enhance students' comprehension and transfer of CT skills. Forty-four first- and second-grade students participated in the study. The results showed significant improvements in students' CT competency and positive attitudes toward CT. Additionally, an analysis of robot programming performance identified common errors and revealed how students employed embodied strategies to overcome challenges. The effects of embodied learning and the impact of embodied learning strategies were discussed.

Keywords

computational thinking, embodied learning, mixed-reality, CT education, robot programming, K-5 education

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Introduction

Computational thinking (CT) has gained recognition as a fundamental skill that students should acquire (Wing, 2006). As Shute et al. (2017) defined, CT is the essential conceptual foundation for an efficient and effective solution to a problem that can be applicable to other problems in diverse contexts. Regarding the timing of learning, it has been acknowledged that early exposure to CT can benefit students' future learning and career paths, making it an area of increased attention in early education (Angeli & Valanides, 2020; Ottenbreit-Leftwich et al., 2021). However, the pedagogy for CT education in early childhood has not yet been fully developed. Therefore, it is necessary to carefully investigate age-appropriate learning strategies, considering the cognitive developmental status of young learners and the characteristics of learning tasks (Bers et al., 2014; Siegler, 1976).

CT encompasses a range of cognitive processes, including logical thinking, algorithmic thinking, pattern recognition, abstraction, evaluation of solutions, and automation of processes, all of which possess a high level of abstraction (Grover & Pea, 2018; Wing, 2008). However, young children in the concrete operational or preoperational stage of cognitive development may face challenges in comprehending these abstract concepts as they heavily rely on sensory inputs to process information. For example, students in early elementary grades may struggle with understanding conditional reasoning, such as if-then conditionals, and abstract representation of data, including variables (Müller et al., 2001; Seiter & Foreman, 2013).

Regarding these challenges, embodied cognition provides valuable insights for designing learning activities in CT education. Research on embodied cognition suggests that children utilize their perceptual, motor, and emotional systems to engage in cognitive processes, such as reasoning, language acquisition, and scientific thinking (Glenberg, 2008). For instance, when children program a robot to execute actions like "forward" or "turn right," they must employ a programming language (code) that involves transforming physical movements into symbolic representations of movement. In this regard, when children are encouraged to link sensory information (bodily movement) with symbolic representation (code) using body-based metaphors, they can enhance their programming comprehension and performance (Weisberg & Newcombe, 2017). As such, students can ground abstract mathematical proofs in concrete sensory representations, which bolsters their mathematical reasoning abilities (Nathan & Walkington, 2017).

The rapid advancement of technology has brought about remarkable innovations in education, particularly by facilitating the development of interactive learning environments. From the perspective of embodied learning, advanced technologies now offer learners simulated and immersive experiences within virtual or augmented reality (VR or AR) settings, a possibility that was previously unimaginable within traditional classroom settings. For example, motion-sensing input devices like Microsoft Kinect can capture learners' gestures and location, so that learners can interact with virtual objects (i.e., Gautam et al., 2018). Wearable devices can provide haptic feedback in response to learners' actions, which enhances the multimodal nature of learning by offering an additional channel of information (Magana & Balachandran, 2017). Moreover, AR creates immersive learning environments where learners can seamlessly interact with virtual objects overlaid on the real world as demonstrated in the current study. These environments empower children to engage their senses and utilize sensory information to enhance their conceptual understanding (Xu et al., 2022).

While embodied learning environments hold promise in providing meaningful learning experiences that foster deep understanding, there are still many questions that remain unanswered. For instance, it is unclear under which conditions embodied learning activities effectively facilitate learning, how these activities translate into conceptual understanding, and how instructors can assess the transformation of learning while observing students' learning progress.

To address these gaps, the current study focuses on a classroom learning context where a mixed-reality learning system was implemented as an embodied learning environment. The embodied learning experiences were enhanced by robot programming activities, which were intentionally designed to transfer CT concepts learned through bodily engagements to CT practices. To examine the effects of embodied learning activities within the mixed-reality system and during robot programming activities, the study analyzed students' learning performances and perceptions of learning activities. Through these efforts, the research aims to advance our understanding of how embodied learning activities support students' CT learning, particularly for those in the concrete operational developmental stage. The specific research questions addressed in this study are as follows:

1. Do students show improvement in CT learning while participating in embodied learning activities?
2. What are students' levels of self-efficacy, attitudes, and confidence toward CT after engaging in embodied learning activities?
3. To what extent does students' performance in a robot programming task demonstrate the transfer of skills acquired through embodied learning activities?

Computational Thinking for Kids

CT has been acknowledged as a fundamental skill for every student. Wing (2006) suggests that the ultimate goal of CT education is to cultivate students who think as computer scientists do. Although this argument suggests a proper direction for CT education, more specific guides are necessary to identify instructional goals, develop assessment tools, design learning activities, and create learning materials. In this endeavor, many scholars identify core CT concepts to learn and suggest CT practices to perform (e.g., Barr et al., 2011; Grover & Pea, 2013; Lee et al., 2011).

In our everyday lives, we are consistently engaged in problem-solving, whether employing CT or not. Problem-solving within the context of CT differs from general problem-solving in that it requires a "computing" process that is executed by a computer or human. This means that solving a problem using CT requires a solution that computers or other individuals can understand and execute as intended. In this sense, the utilization of symbols to represent instructions and algorithms to organize these instructions in a specific sequence forms the fundamental basis of CT (Critten et al., 2022). To extend the CT concepts, students should be able to analyze problems or tasks and devise proper solutions (logical thinking), develop step-by-step plans for the solutions (algorithmic thinking), find patterns to make generalizable solutions (pattern recognition), identify the most essential components from similarities and differences (abstraction), and evaluate the effect of solutions and correct any errors (evaluation) (Angeli et al., 2016; Zeng et al., 2023).

To teach students to think like computer scientists, we need to first understand how computer scientists think and perform when solving problems, which has not yet been achieved in the literature on CT education. Many studies have investigated the effectiveness of learning strategies and tools; however, while this is necessary, they often overlook specific learning objectives to be achieved with them. For example, the concept of variables is fundamental for computer scientists to manage data (Samurcay, 1989). However, students often define and utilize variables in inefficient ways that differ from computer scientists' common practices (Grover & Basu, 2017; Kwon, 2017).

Especially when introducing students to the fundamental concepts of CS, their mental models and practices should be understood in relation to those of CS experts. Programmers use program languages to communicate instructions with computers and to collaborate with fellow programmers. A program utilizes a collection of symbols followed by predefined rules. So, it is essential for students to understand that each symbol corresponds to a particular action. Furthermore, they must learn to select the appropriate symbols and arrange them in a specific sequence in order to accomplish a computational task. This can pose a significant challenge for young children due to their cognitive development status and the complexity of the tasks (Andrews & Halford, 2002).

Considering these issues, various age-appropriate pedagogical approaches have been introduced. In particular, block-based programming environments (e.g., Scratch) and tangible robots (e.g., Bee-Bot) have been shown to reduce cognitive load by visualizing text-based code with blocks and illustrating the execution of instructions. These approaches also allow students to easily evaluate their programs by showing their results within the learning contexts. Studies have shown that even kindergarteners can learn to program a robot by entering instructions in order, given proper practices and specific guides (e.g., program Bee-Bot to move a certain path) (Angeli & Valanides, 2020). However, more research is needed to understand the learning trajectories of mastering the concepts and how young children apply the concepts to more complicated tasks (Zeng et al., 2023). From the embodied cognition point of view, these learning environments have limitations in providing embodied learning experiences. This is because no physical referents can be linked to students' sensory-motor information. In the next section, we will review how embodied approaches can support CT learning.

Embodied Learning for CT Education

As discussed, CT involves abstract concepts that are not observable or even felt. This can pose more challenges to young children, who are highly oriented toward sensory-motor information according to their cognitive development (Rijke et al., 2018; Statter & Armoni, 2020). From the embodied cognition perspective, to support students in grounding CT knowledge in their perceptual learning experiences, educators have introduced unplugged activities or robotics (e.g., Kim & Tscholl, 2021; Kwon et al., 2022). These approaches emphasize hands-on activities that encourage students to express their ideas or understandings through their bodily movement (or gesture) or tinkering with physical objects, including robots. Studies have revealed the positive effects of these approaches on students' performances in CT tasks as well as their motivation and engagement in learning (Fofang et al., 2021; Kopcha et al., 2021).

This movement has been extended to VR or AR learning environments where immersive learning experiences are designed for students to interact with virtual objects. The specific affordances of an advanced medium enable adaptive instructional methods that are not possible traditionally. In this sense, researchers emphasize the potential of environments providing immersive learning experiences, which allow students to have a higher feeling of presence and agency (Johnson-Glenberg, 2019). The term "presence" refers to the feeling of "being there," which can be perceived differently according to the degree of immersion and control given to the students and the fidelity of representation of information (Ijsselsteijn & Riva, 2003). In an immersive context, "agency" means the sensation of initiating and directing actions (Moore & Fletcher, 2012). The sense of agency is closely related to the extent to which students exert control over their actions in it.

Immersive learning environments utilizing VR or AR technologies provide students with the sense of presence and agency in various methods, including allowing them to generate gestures that represent reasoning or quantitative operations (Lindgren et al., 2019), play an agent, allowing first-person perspectives, or observe other agents' behavior, allowing third-person perspectives, to understand a complex system while playing (Peppler et al., 2020), see abstract scientific concepts visualized by 3D models (Sahin & Yilmaz, 2020), and carry our physics laboratory experiment by manipulating virtual objects (Thees et al., 2020). Literature has shown that these embodied learning experiences facilitated by immersive learning environments bring positive learning outcomes in both attitudinal as well as cognitive aspects (Fan et al., 2020; Garzón et al., 2020; Kwon et al., 2024).

It is noteworthy that the effects of embodied learning are highly associated with the degree of congruency that maps students' embodiment and the content to be learned (Johnson-Glenberg & Megowan-Romanowicz, 2017). If students cannot make a connection between their bodily experiences and cognitive processes, we may not expect positive learning outcomes. In this vein, exploring the degree of congruency that students perceive is crucial to advancing our knowledge in immersive embodied learning. Although there is growing research on this topic in various subjects, there is still a lack of studies examining students' learning experiences within immersive learning contexts where embodied learning activities aim to enhance CT skills and practices.

Method

Participants

We collaborated with two teachers from a public elementary school in a mid-sized city in the Midwestern United States. A total of 44 students, aged 7–9, comprising 20 first-grade and 22 second-grade students, were recruited. Only a few participants had limited previous experience in programming a robot, and none had learned CT within a mixed-reality environment. This study was approved by the Institutional Review Board (IRB) at the researchers' institute. Written informed consent was obtained from all participants' parents or legal guardians prior to their participation in the study.

Mixed-Reality Learning Environment

The researchers developed a mixed-reality learning environment where students can understand and practice CT concepts (symbols and sequences) while navigating a chessboard-like ground to accomplish CT tasks. On a five-by-five grid (covering a 92 ft^2 area), where each cell coordinated locations of an agent and objects, students were instructed to move (forward or backward) or turn (right or left in 90°) like a robot to find a path toward a goal (see Figure 1). Virtual objects were visualized through AR technology at the center of each cell. These objects represented mission items to collect, obstacles to avoid, or the destination to reach (see Figure 2). The AR technology detected students' bodily movements based on the coordination of the board and provided feedback simultaneously.

Four symbols (🠅: Move Forward, 🠇: Move Backward, ➡: Turn Right, and ⬅: Turn Left) were introduced to the students. Each symbol was presented on the students' handheld tablet screen in association with their bodily movements. For instance, if students moved toward the next cell in front, the system displayed the Move Forward symbol and said, "You just moved forward." As students moved or changed directions, the symbols were listed in order at the bottom of the screen, which represented the sequence of symbols. In this article, we will refer to the mixed-reality learning environment as "the application" for convenience.

Figure 1. A student moving on the physical board while seeing virtual objects through the screen.

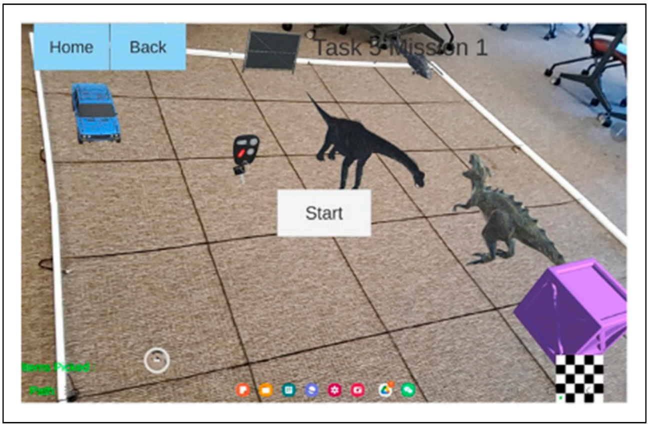

Figure 2. Virtual objects shown on the tablet screen.

Intervention

The intervention unfolded in three phases over four days, scheduled within the regular school day, with the presence of a teacher, an assistant teacher, and four researchers. The teachers took charge of explaining and demonstrating each intervention phase, while the researchers facilitated group activities and addressed technological issues.

In the first phase, a walk-through of the application occurred. The teacher introduced the learning activity by demonstrating movements on the board (including four allowed movements and restrictions like moving diagonally), the use of a tablet to view virtual objects, and tasks to accomplish. The teacher guided students in handling the tablet, explaining how to navigate the interface, adjust views to explore the virtual objects, and interact with the application's features. Students were also shown how to interpret feedback within the application, with time allocated for them to explore the tablet's functions before beginning the tasks. This helped students become familiar with operating the tablet and understand CT tasks in the application, while also acquiring CT concepts such as the meaning of symbols and how to organize them into sequences.

The second phase constituted the main learning session, where students engaged in embodied learning activities to acquire CT skills, which refers to the ability to apply CT concepts in their practices. Each student individually performed a CT task with teacher support. Using the application, students carried out the CT task by collecting mission items while avoiding obstacles and arriving at the destination. Immediate feedback was provided through the application, including symbols for each movement, accumulated symbols (sequence), and guidance or warnings related to mission items or obstacles. The augmented information provided the player with a first-person perspective on the CT tasks. As this learning session occurred in a classroom with other students observing individual performances, the tablet screen was live-streamed through a classroom projector. During this phase, students associated their bodily movements with symbols and organized them toward a common goal, which was the main learning objective of this intervention.

The third phase involved programming a robot. Beebot was chosen for our study due to its codes aligning with the symbol systems learned in the second phase. The Beebot board, where programming tasks took place, simulated the surface features of the mixed-reality learning experiences. As shown in Figure 3, students programmed Beebot to navigate a specific path toward a goal, mirroring the activities from the second phase. This served as a transfer task, requiring students to apply the CT skills to robot programming. In this group activity, each group consisted of four to five students and had the guidance of a researcher. This arrangement allowed students to take turns programming Beebot and observe their peers' performances.

Data Collection

The data for this study encompassed the assessment of CT competency, perception of CT, and performance in robot programming. To assess CT competency, a test consisting of 12 multiple-choice questions was developed (see Figure 4). The test was administered both before and after the intervention in a paper-and-pencil format. CT competency was measured in three aspects: CT concepts, tasks to perform, and the configuration of directions. Regarding CT concepts, four questions tested the meaning of symbols represented on a board, while eight questions checked the results of organized symbols (sequence). In terms of tasks to perform, each of the three questions

Figure 3. Programming Beebot on the board.

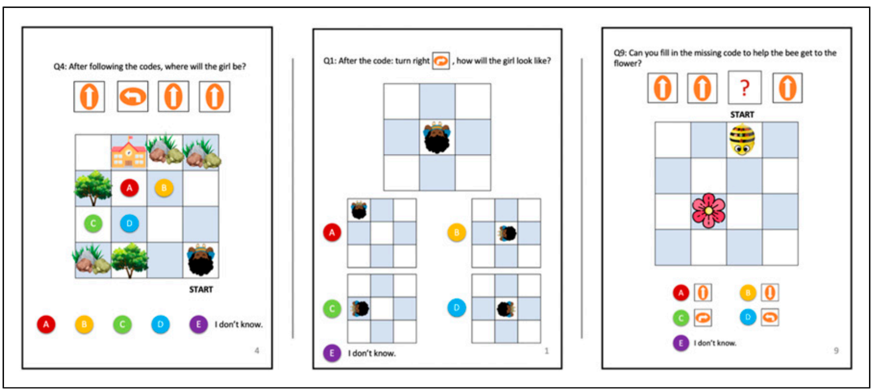

Figure 4. Sample questions of the CT Test.

assessed the identification of symbol meaning, anticipation of code outcomes, completion of missing code, and the development of code for a given task. Regarding the configuration of directions, we evaluated how students would figure out directional inconsistencies given three different initial directional pieces of information. As illustrated in Figure 5, there could be three different initial directions: one type consistent with the students (a robot facing upward), one type opposite to them (a robot facing downward), and two types 90° inconsistent with them (a robot facing left or right sides).

The perception of CT in the context of mixed reality was evaluated through a survey comprising twelve statements. The questionnaire consisted of three constructs: (1) self-efficacy, (2) attitude toward CT, and (3) confidence in CT. Table 1 presents the statements for the three constructs. Considering the age of students, the researchers simplified responses into two options (yes = 1, no = 0).

To evaluate how students apply CT concepts in programming tasks, we observed students' Beebot programming performance individually conducted after the

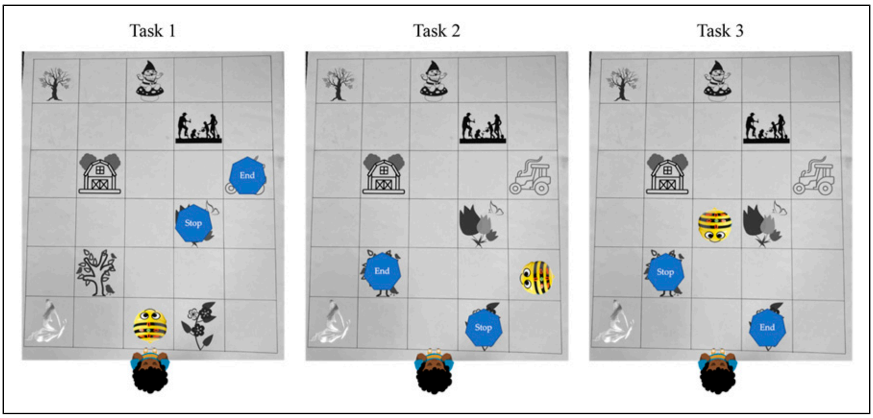

Figure 5. Three Beebot programming tasks having different initial directions. Note: In Task 1, students shared the same directional orientation with Beebot, while in Task 2 and 3, they had different orientations. The character at the bottom of the board represents a student.

Table 1. Survey Statements Measuring the Perception of CT

Self-efficacy	1. I can program paths with my body movements in AR.
	2. I can explain my ideas of codes (sequences) to my friends with body movements in AR.
	3. I can understand codes (sequences) created by others.
	4. I can fix errors by changing my positions or directions in AR.
Attitude toward CT	5. I think programming with AR is useful to learn.
	6. I think programming paths with AR is easy to do.
	7. I like programming paths with AR.
	8. I want to learn more about programming with AR.
Confidence in CT	9. I know how to break down a task to make it easy.
	10. I know how to program bee-bot using codes.
	11. I know how to use codes to create a step-by-step path.
	12. I know how to solve other problems with my experiences of using codes.

intervention. In three tasks, the students were asked to program Beebot to navigate from a starting point to the endpoint, with an additional required stop in between. To test students' ability to handle directional information while programming Beebot, each task presented different directional orientations of Beebot as shown in Figure 5. If students failed a task, they were allowed to try up to two additional attempts.

Analysis

The current study employed statistical analyses to examine if there were any changes in CT competency after the intervention. A one-way multivariate analysis of variance (MANOVA) was conducted to test the difference between pre- and post-tests across the three aspects of CT competency. Descriptive statistics of students' perceptions of CT were calculated.

Students' Beebot programming performance was evaluated based on the success of CT task. To be successful, a student should program Beebot to pass the Stop (first mission) and arrive at End (second mission) as shown in Figure 5. Considering the complexity of the tasks, the moment of failure was also evaluated (before or after the first mission). As students were allowed to try the test up to three time, the number of trials was measured. To identify error types, the researchers employed inductive thematic analysis (Braun & Clarke, 2006) and categorized errors according to their shared reasons and patterns. While analyzing the programming performance, the researchers also made a note of students' voluntary embodiment (e.g., hand gestures demonstrating Beebot movements) as necessary.

Results

CT Competency

The learning gains after the intervention had been assessed regarding the CT concept (symbol and sequence), tasks to perform (identifying the meaning of symbols, anticipating the outcome of a given code, completing a missing code, and developing a code for a given task), and the initial direction of an agent (up, down, and right or left). Table 2 presents the descriptive statistics of the assessment.

A MANOVA was conducted with the time of tests as an independent variable and with the measures of each category as a dependent variable. The MANOVA on the CT concepts revealed significant differences between the tests, Wilks' $\lambda = .13, F(2, 45) = 149.5, p < .001, \eta_p^2 = .87$. Follow-up univariate analysis indicated that students demonstrated significant learning gains after the invention in both symbol, $F(1, 46) = 4.95, p = .031, \eta_p^2 = .10$ and sequence, $F(1, 46) = 34.12, p < .001, \eta_p^2 = .43$.

The MANOVA on the task type revealed significant differences between the tests, Wilks' $\lambda = .12, F(2, 45) = 76.80, p < .001, \eta_p^2 = .88$. Follow-up univariate analysis indicated that students demonstrated significant learning gains after the invention in

Table 2. Descriptive Statistics of Learning Evaluation.

	Pretest		Posttest				
Measure	M	SD	M	SD	F	*p-value*	η_p^2
CT concepts							
Symbol (4)	1.79	.954	2.19	1.096	4.95	.031	.097
Sequence (8)	2.19	1.676	4.00	2.011	34.12	<.001	.426
Tasks							
Meaning (3)	1.79	.954	2.19	1.096	4.95	.031	.097
Outcome (3)	.30	.587	1.36	1.092	36.62	<.001	.443
Missing (3)	1.02	.872	1.49	.953	10.37	.002	.184
Arrange (3)	.87	.947	1.15	.722	3.22	.079	.065
Direction							
Up (4)	1.74	1.170	2.32	.837	8.55	.005	.157
Down (4)	1.30	.749	1.85	1.083	11.10	.002	.194
Horizontal (4)	.94	.942	2.02	1.406	28.39	<.001	.382

Note. The numbers in parentheses represent the number of questions, which is equal to the highest score that can be obtained.

identifying the meaning of symbols, $F(1,46) = 4.95, p = .031, \eta_p^2 = .10$, anticipating the outcome of a given code, $F(1,46) = 36.62, p < .001, \eta_p^2 = .44$, and completing a missing code, $F(1,46) = 10.37, p = .002, \eta_p^2 = .18$. However, students did not demonstrate a significant learning gain in developing a code for a given task, $F(1,46) = 3.22, p = .079, \eta_p^2 = .07$.

The MANOVA on the initial direction of an agent revealed significant differences between the tests, Wilks' $\lambda = .09, F(2,45) = 145.9, p < .001, \eta_p^2 = .91$. Follow-up univariate analysis indicated that students demonstrated significant learning gains after the invention in configuring upward agent, $F(1,46) = 8.55, p = .005, \eta_p^2 = .16$, downward agent, $F(1,46) = 11.10, p = .002, \eta_p^2 = .19$, and horizontal agent, $F(1,46) = 28.39, p < .001, \eta_p^2 = .38$.

Overall, the findings suggest the positive effects from the learning activities on students' understanding of CT concepts. Considering the difficulty of tasks, students demonstrated significant improvement in identifying the meaning of symbols, anticipating the outcome of a given code, and completing a missing code. However, for the most challenging task -- developing a code for a given task -- they did not show statistically significant improvement. Regarding the initial direction of an agent, students performed best when facing the same direction as the agent (upward). When students had different directional perspectives from the agent, they performed poorer. However, even in these cases, students demonstrated significant learning gains after the learning activities.

Perceptions of CT

Students' attitudinal aspects were collected after the intervention (see Table 3). Overall students expressed high self-efficacy regarding CT ($M = .95, SD = .122$), positive attitude ($M = .80, SD = .177$), and great confidence ($M = .94, SD = .141$).

Beebot Programming Performance

The Beebot programming performance of students was assessed based on individual tasks, with successes and failures (see Table 4). Students achieved initial success rates of 46.7%, 30.0%, and 46.7% for Tasks 1, 2, and 3, respectively. This indicates that approximately half of the students (14 out of 30) successfully completed Tasks 1 and 3 on their first attempts. Moreover, Task 2 proved more challenging, with only 9 out of 30 students succeeding on their initial try.

Students were allowed to solve the problems up to three times after initial failures. The success rates, inclusive of multiple trials, increased to 63.3%, 43.3%, and 53.3% for Tasks 1, 2, and 3, respectively. Analyzing the number of trials undertaken revealed that, on average, students attempted 1.26, 1.31, and 1.13 times before successfully solving the problems. Notably, some students attempted three times, but none achieved success on the third trial. This suggests that once students encountered initial failure, they faced considerable difficulty in solving the problems if unsuccessful in their second attempts.

The analysis of errors in Beebot programming tasks among students revealed two main types: turn-related errors and move-related errors (see Table 5). Turn-related errors occurred when students directed Beebot in the wrong direction (Incorrect Turns) or neglected to turn when required (Missed Turns). These errors were the most frequently observed, accounting for 58% and 22% of Incorrect Turns and Missed Turns, respectively. The remaining errors were associated with Beebot's movements, including instances of adding unnecessary or omitting necessary forward and backward motions, constituting 16% of the total errors.

Considering that there were two targets to pass, we analyzed when the errors occurred: before or after passing the first target. Among the 78 errors, excluding the three categorized as 'other,' 53 (68%) errors occurred after passing the first target, and

Table 3. Descriptive Statistics of Attitudinal Aspects.

Construct	M	SD
Self-efficacy	.948	.122
Attitude toward CT	.803	.177
Confidence in CT	.935	.141

Note. Forty-two students responded to the survey, with each construct's range extending from zero (negative) to 1 (positive).

Table 4. Performances on Each Task.

	Task 1	Task 2	Task 3
# of success at first trial	14	9	14
# of success in total	19	13	16
# of trials to success	1.26	1.31	1.13

Note. The total number of students was 30.

Table 5. Types and Ratios of Errors per Problem.

Type of error	Task 1	Task 2	Task 3	Grand total
Turns	17 (70.8%)	29 (87.9%)	19 (79.2%)	65 (80.2%)
Incorrect turns	14 (58.3%)	19 (57.6%)	14 (58.3%)	47 (58.0%)
Missed turns	3 (12.5%)	10 (30.3%)	5 (20.8%)	18 (22.2%)
Moves	5 (20.8%)	4 (12.1%)	4 (16.7%)	13 (16.0%)
Incorrect moves	3 (12.5%)	2 (6.1%)	2 (8.3%)	7 (8.6%)
Missed steps	2 (8.3%)	2 (6.1%)	2 (8.3%)	6 (7.4%)
Other	2 (8.3%)	0 (0%)	1 (4.2%)	3 (3.7%)
Total	24 (100%)	33 (100%)	24 (100%)	81 (100%)

25 (32%) occurred before. This revealed that students made more errors after solving the first task, which implies that the complexity of the task negatively affected their performance. In other words, as the tasks became more complex, students made more errors accordingly.

Discussion

The study aimed to investigate the impact of embodied activities on comprehending the concepts of symbols and sequences, and subsequently, on programming a robot by applying these concepts. The results revealed that students exhibited significant knowledge gains across various dimensions, including CT concepts, tasks to perform, and directional orientations. In terms of attitudinal aspects related to CT, students expressed high self-efficacy, a strong positive attitude, and robust confidence after engaging in the learning activities. Moreover, the study identified specific types of errors made by students during the robot programming phase, which would provide valuable insights into understanding student CT learning. In this section, we will discuss the meaning of the findings and suggest their implications for designing embodied learning experiences within the context of CT.

Embodied Learning Activities for CT

The integration of embodied learning activities within the AR learning environment has proven to be effective in understanding CT concepts and applying them to CT tasks. In this study, these immersive learning experiences were designed to instill a sense of presence and agency among students (Johnson-Glenberg, 2019). The AR-based learning environment, by seamlessly integrating virtual objects into the physical space, provided students with interactive embodied learning experiences. In this context, students were able to map their bodily movements to the CT concepts being taught. This congruency between physical actions and abstract concepts contributes to their deeper understanding (Hald et al., 2015; Odermatt et al., 2021). The AR-based learning environment also offered real-time feedback which allowed students to assess their performance immediately during the CT tasks. The positive outcomes facilitated by the immersive embodied learning experiences are consistent with prior research, highlighting the benefits of embodied learning for CT (Agbo et al., 2023; Zhang et al., 2023).

One of the main benefits of utilizing embodied learning for abstract concepts is the enhanced comprehension of concepts and application to problem-solving tasks (Keefer et al., 2014), which forms different cognitive styles (Allen et al., 2024). The analysis of the tests revealed that students performed better in tasks with the same directional orientation (Up) than in those with the opposite directional orientation (Down). Notably, the findings indicated that students significantly improved their performance even in tasks where they had different directional orientations that required higher cognitive effort. These findings suggested that embodied learning has ultimately led to positive learning outcomes. However, differences in task performance emerged based on the task difficulty, as determined by directional orientation.

Interestingly, the differences disappeared in the robot programming tasks, where students could represent CT tasks with their gestures. When figuring out directional information in the paper-and-pencil tests, the utilization of embodied cognition could be limited for students. While programming the robot, however, they could simulate spatial information onto their hand gestures, which had been observed often. This type of utilization of embodied cognition allowed students to perform well in the tasks where they needed to intentionally figure out the directional information, as well as in tasks where they could intuitively see directional information.

These findings suggest the effects of embodied activities during learning CT concepts and highlight the significance of leveraging embodied cognition when carrying out CT tasks. The study also found that the learning experiences were associated with positive attitudinal responses from the students. To deepen our understanding of embodied learning in virtual environments, further analysis of immersive embodied learning experiences is essential. This includes examining how students perceive virtual information in association with their movements and how they ground CT concepts in their bodily actions.

Cognitive Challenges and Embodied Strategies

The analysis of robot programming performance revealed the types of errors students made and the contexts in which these errors appeared. Not surprisingly, students made more errors as the tasks became more complex, which added more intrinsic cognitive load (Van Merriënboer & Sweller, 2005). The low success rates after unsuccessful trials suggested that the initial failures were not mere mistakes but rather a result of insufficient skills or knowledge related to the complexity of the tasks. This implies students' performance on the CT tasks could indicate their mastery of the learning objectives.

Considering the cognitive tasks students carried out while programming a robot, they were required to trace the changes in the robot's location and direction according to the codes they entered. Here, the CT tasks involved converting spatial information (including direction and distance) into codes (Qiu et al., 2019). The frequency of error types indicated that cognitive tasks dealing with directional information were more challenging than those involving distance information. At this point, it is interesting to examine how students utilized the embodiment they experienced.

A close examination of student performance during robot programming tasks unveiled that some students employed embodied learning strategies to figure out spatial information. For example, using an index finger to count the number of cells was an effective means to convert distance information through a hand gesture. Turning one's left hand toward the proper direction, mimicking the robot's turn, helped a student process directional information. Additionally, we observed less effective methods of embodiment, such as pointing to cells without accompanying turning gestures, which failed to explicitly represent directional information (turning right or left). This insufficient embodiment often resulted in errors: turning in the opposite direction.

The results of the current study indicate that embodiment, when adopted appropriately, can enhance cognitive function and facilitate problem-solving performance, in line with existing literature (Macedonia, 2019; Zhong et al., 2023). However, due to the limitations of the research design, we did not investigate how embodiment was voluntarily utilized by students or how it could be trained, including factors influencing its effectiveness in problem-solving tasks. Future studies exploring these aspects, such as voluntary utilization or training to employ embodied strategies, can contribute significantly to the embodied learning literature.

Conclusion

As the advance of technologies has allowed mixed-reality experiences, the potential of embodied learning activities utilizing immersive learning has gained more attention in the education field. However, there is still a lack of studies exploring their educational effects and suggesting instructional design principles to implement embodied learning strategies in K-12 settings. In this context, the current study contributes to the literature by revealing the positive impacts of embodied learning activities within a mixed-reality learning environment. It also deepens our understanding of embodiment in learning CT by analyzing the errors students made while carrying out CT tasks. This study calls for future research that closely examines students' embodied learning experiences, their learning trajectories, and the utilization of embodiment in problem-solving to further advance our understanding in this regard.

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Ethical Statement

Ethical Approval

The study was approved by the Internal Research Board of Indiana University (No. 2101346045).

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