Learning Sequencing with Bee-Bot: A Study on Improving Computational Thinking and Motivation for Young Learners in Programming Education

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***Abstract*—This Research-to-Practice full paper presents an exploratory study investigating the impact of using a Bee-Bot educational robot simulator to enhance learning sequencing concepts and student motivation among Macao primary school students.**

Sequencing in computational thinking (CT) is understanding and applying the logical order of steps in problem-solving processes. We introduced a Bee-Bot computer simulator for children to learn sequencing. Our study adopted a pretest-posttest method involving 35 grade two students. The Computational Thinking Test for Beginners (BCTt) was used to assess CT abilities, and the Instructional Materials Motivation Survey (IMMS) was utilized to measure learning motivation.

We found a significant improvement in sequencing ability and more advanced CT concepts (loops and conditions) and a significant correlation between those concepts. Departing from the existing literature, we delved deeper into how Bee-Bot's influence on sequencing extended to more advanced CT concepts.

Moreover, considering the ARCS motivation model, this study examined how Bee-Bot affects learning motivation at the primary education level. After the intervention, the findings revealed that the students showed significantly higher learning motivation, meaning that the different learning activities using the Bee-Bot simulator positively influenced various sub-dimensions of the ARCS model: attention, relevance, confidence, and satisfaction. The correlation between the IMMS scores and the BCTt outcomes further suggested that enhanced motivation positively correlated with better CT abilities.

Keywords—Bee-Bot, Computational thinking, Sequencing, Learning motivation, K-12 programming education

I. INTRODUCTION

The dawn of the 21st century heralded computational thinking (CT) as an essential skill, pivotal not just in computer science but across various domains. CT emphasizes system design, problem-solving, and the development of logical reasoning skills [1]. With core components like sequencing, CT formed the backbone of algorithms and programming logic, essential for developing efficient computer applications [2].

Sequencing in CT involves organizing and ordering steps in a process or set of instructions, which is vital for executing tasks efficiently [2] [3]. It is a crucial skill for young children as it facilitates their algorithm learning and helps them develop a mathematical and scientific understanding of the world [4].

Educational robotics emerged as a promising tool for fostering CT skills in early childhood education. [5] [6].

The Bee-Bot is a bee-shaped programmable robot that offers a hands-on, interactive medium for children to learn sequencing and other foundational CT concepts. It enhances problem-solving, critical thinking, and collaborative learning [7] [8]. As shown in Figure 1, Bee-Bot features arrow keys for inputting commands and directing movements forward, backward, or turning 90 degrees to the left or right. After programming a sequence of commands, children pressed the green GO button to execute the Bee-Bot's path. This hands-on learning tool has been utilized in preschool and primary education to foster the early integration of computational concepts [9].

Fig. 1. Bee-Bot programmable robot

However, the application of Bee-Bot in classrooms, especially those with a high student-to-teacher ratio in Macao, presents challenges due to the need for physical maps for testing. These limitations underscored the need for innovative solutions to sustain educational quality within the practical constraints of classroom settings.

Our study addressed these challenges by introducing a Bee-Bot computer simulator [10] as an alternative to physical robots, thus preserving the pedagogical advantages of Bee-Bot while reducing spatial and equipment constraints. This study proposed to address the four research questions as follows.

(1) How does using Bee-Bot in primary school programming courses affect students' CT abilities?

(2) What is the correlation between different CT dimensions after teaching with Bee-Bot?

(3) How does using Bee-Bot affect learning motivation among primary school students in programming courses?

(4) What is the correlation between CT and learning motivation when teaching with Bee-Bot in primary school programming courses?

Our study revealed significant improvement in sequencing ability and more advanced CT concepts (loops and conditions). We also found a significant correlation between those concepts. Departing from existing literature, we delved deeper into how Bee-Bot influence on sequencing extended to more advanced CT concepts. Moreover, considering the ARCS motivation model, this study examined how Bee-Bot affects learning motivation at the primary education level. After the intervention, the findings revealed that the students showed significantly higher learning motivation, meaning that the different learning activities using the Bee-Bot simulator positively influenced various sub-dimensions of the ARCS model. The correlation between the Instructional Materials Motivation Survey (IMMS) scores and the Computational Thinking Test for Beginners (BCTt) outcomes further suggested that enhanced motivation positively correlated with better CT abilities.

The remainder of the paper is outlined: Section II reviews the literature, focusing on CT and educational robotics applications such as Bee-Bot. Section III describes our research methodology. Section IV presents the findings. Section V discusses the implications of these findings. Section VI concludes the paper with a summary.

II. Literature Review

CT has been increasingly recognized as a crucial skill for the 21st century, emphasizing system design, resolving problems, and comprehension of human behavior by drawing on the concepts fundamental to computer science. Furthermore, CT is significantly correlated with programming performance [11]. Moreover, CT involves problem-solving skills and techniques software engineers use to write programs underpinning computer applications [1]. Among these skills, sequencing was a core component of CT, integral to developing algorithms and programming logic.

Sequencing ability is a complex cognitive skill essential for correctly ordering actions or objects, including scheduling and planning processes [3]. It plays a crucial role in early childhood, as it helps students understand algorithms and view the world through mathematical and scientific perspectives [4]. Additionally, within programming, sequencing refers to the capacity to understand and implement a logical sequence of steps in problem-solving processes [12]. This ability facilitates learning and problem-solving across various contexts.

Sequencing is foundational in programming, where children have to arrange commands in a precise sequence to instruct a robot or computer, fostering logical thinking and planning skills. Children develop sequencing skills by engaging in programming activities crucial for reading comprehension, mathematics [7], and broader cognitive abilities. This development emphasizes the role of programming and robotics in enhancing early educational outcomes, demonstrating the interconnectedness of CT skills with foundational academic competencies. Additionally, sequencing is vital for early mathematics [13] and literacy learning, often integrated into early childhood education through storytelling, ordering activities, and understanding daily routines.

Educational robotics, such as the Bee-Bot, were highlighted for their potential to enhance early childhood education by supporting the development of CT skills, including sequencing [5]. Beyond this concept, CT encompasses other elements, including loops and conditions [14]. As an introductory stage of CT, sequencing provides a foundation for understanding these more complex aspects. Robots like Bee-Bot offer a tangible and interactive medium for students to engage in problem-solving, critical thinking, and collaborative learning [7] [15].

Guidelines for integrating Bee-Bot and similar robotics in educational settings have emphasized the robot's role in fostering a comprehensive understanding of CT [7]. Bee-Bot played a crucial role in demystifying abstract computational concepts by providing symbolized and visualized instructions that prompted learners to direct the robot's movements and design instructions sequentially to execute a series of actions. This resulted in increased accessibility and engagement for young learners, as they could now interact with and understand these concepts more effectively. The literature suggested that educational robotics, through devices like Bee-Bot, significantly contributed to the early development of CT by providing practical, real-world contexts for learning and applying computational skills [7].

Another related research has demonstrated the positive effects of robot programming on children's CT skills, sequencing abilities, and even self-regulation, suggesting a broader impact on cognitive development [16]. Other studies have explored the effectiveness of Bee-Bot in enhancing executive functions and CT in students with special needs, showing that engaging with Bee-Bot helped apply executive functions such as planning and cognitive flexibility [17] [18]. This suggested that Bee-Bot effectively supported the learning of sequencing and other CT skills and the development of crucial cognitive abilities in a broader range of learners.

However, using Bee-Bots in classrooms, particularly in schools with high student-to-teacher ratios, presents several challenges. The physical maps needed to test programs take up considerable space, often not feasible in classrooms with limited resources. Moreover, the time students spend waiting for their turn to test their written programs reduces efficiency and slows down their learning progress. This limitation highlights the need for innovative approaches to maintain educational quality while accommodating the practical constraints of classroom settings, which is a gap not covered by existing literature. Our study addressed this challenge and contributed by utilizing a Bee-Bot computer simulator instead of the physical Bee-Bot robots, thus retaining the pedagogical benefits of Bee-Bot while overcoming the drawbacks associated with physical space and equipment limitations.

Moreover, the existing literature lacked detail on how Bee-Bot's influence on sequencing extended to more advanced CT concepts. Our study delved deeper into the potential relationship between students' mastery of sequencing and their understanding of more complex CT concepts, such as conditional statements (if, if-then-else) and various types of loops (basic loops, nested loops, and while loops).

Furthermore, our study distinguished itself from previous studies by examining the impact of the Bee-Bot on CT and exploring its effects on learning motivation. This dual focus enriched the literature and provided insights into the broader educational implications of Bee-Bot in young learners.

III. Methodology

A. Research Participants

The study was conducted in a Macao primary school involving 35 grade two students aged 7 to 8. They had no prior programming experience before participating in the study.

B. Implementation of Research Design

1) Step 1. Data collection for BCTt pre-test

Initially, students participated in the Chinese version of BCTt pre-test, a 25-item multiple-choice assessment designed to evaluate CT. The BCTt [19] aligns with the CT framework established by Brennan and Resnick [9], targeting primary school students. The reliability of the BCTt was confirmed with a Cronbach Alpha score of 0.860.

The questions in the BCTt primarily focus on identifying the correct sequence of commands that can accurately guide a chick to find its hen. In addition to questions evaluating students' understanding of sequencing concepts (Figure 2), the BCTt also encompasses items that test more advanced CT concepts (Figure 3), including conditions (if, if-then-else) and loops (basic loops, nested loops, and while loops). This comprehensive approach thoroughly assessed CT skills across various dimensions.

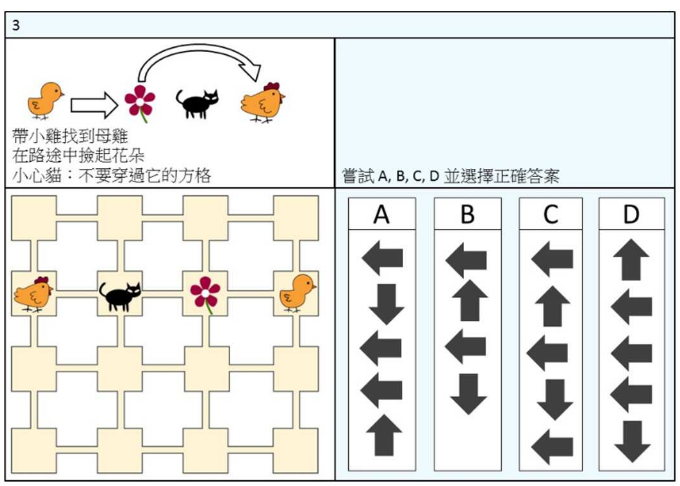

Fig. 2. The sample question for the sequencing concept in BCTt

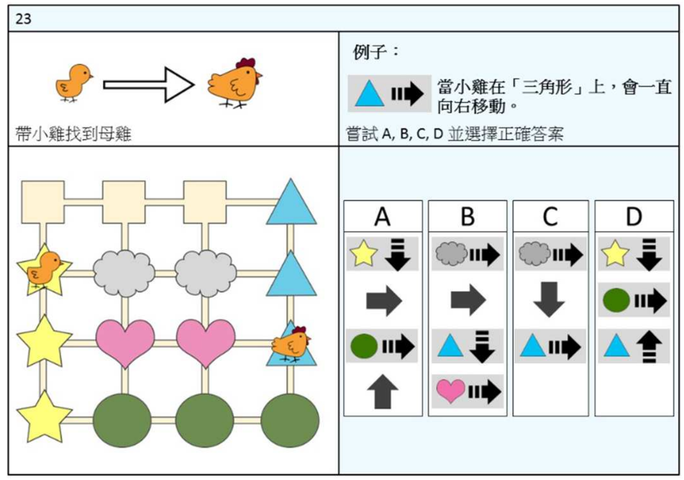

Fig. 3. The sample question for the advanced concepts in BCTt

2) Step 2. Data collection for IMMS pre-test

Before initiating the Bee-Bot teaching experiment, we pre-tested IMMS. The IMMS, grounded in Keller's ARCS model [20], is designed as a five-point Likert scale assessment tool to measure students' motivational responses toward instructional strategies and materials.

This scale comprises 36 items, distributed across four motivational dimensions: Attention (12 items), Relevance (9 items), Confidence (9 items), and Satisfaction (6 items). The IMMS demonstrated its reliability with a Cronbach's Alpha coefficient of 0.921, underscoring its effectiveness in evaluating the impact of instructional materials on student motivation.

3) Step 3. Implementation of Bee-Bot Instruction

The instructional period lasted seven weeks, with two sessions each week for fourteen sessions, each lasting 40 minutes. Since the grade two students had no programming experience, designing a teaching approach that incrementally built their understanding of sequencing was essential. This necessitated a gradual, step-by-step instructional strategy spread over seven weeks to ensure thorough comprehension and retention of concepts.

Initially, we utilized Bee-Bot teaching materials (Figure 4) provided by iClass [21], a learning management system developed in Hong Kong that offers educational resources for information technology and programming, including materials for simulating programming sequences with Bee-Bot. As an introductory exercise, students manually wrote sequencing commands in their textbooks. Sequences are fundamental in programming, helping students grasp the order of operations and the importance of logical thinking in coding. Mastery of sequencing is crucial for effective problem-solving and debugging, as it ensures a clear understanding of the step-by-step execution of commands.

Fig. 4. Bee-Bot teaching materials provided by iClass

Subsequently, teachers introduced various challenges, requiring students to use the simulator [10] (Figure 5) to design instructions for controlling the Bee-Bot 's movement across a map. The simulator was developed by Terrapin, a company that offers a variety of educational products, including the Bee-bot hardware.

In our teaching activities, the difficulty level increased progressively, starting with containing the Bee-Bot to move between two locations (from the first location on the map to the second). Afterward, they were tasked with navigating the Bee-Bot across three locations, eventually four locations, with each step increasing in complexity. This phased approach allowed students to build their skills incrementally, reinforcing each concept before moving on to more complex tasks.

Using the Bee-Bot simulator, each student operated a desktop computer to control their virtual Bee-Bot, equipped with all the buttons on the actual Bee-Bot hardware, enabling students to manipulate their virtual Bee-Bot's movement within the computer.

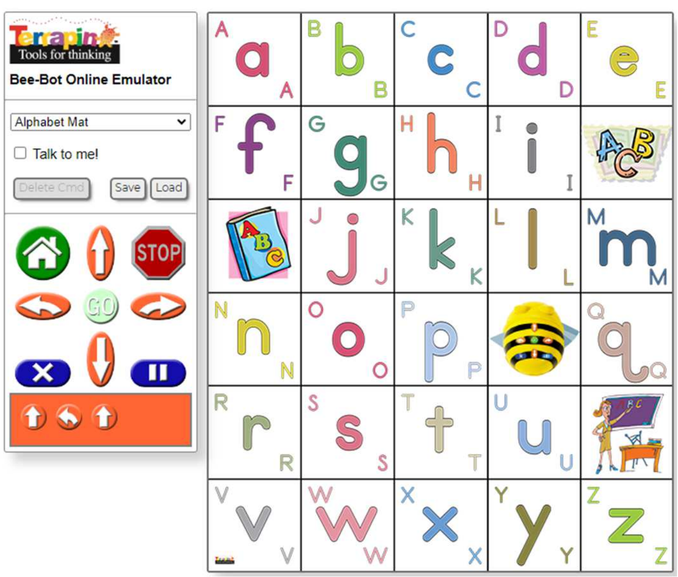

Fig. 5. Bee-Bot simulator

Using the Bee-Bot simulator enabled all students to simultaneously write and test sequencing instructions on their simulators. This approach was beneficial for teachers in identifying students who struggled with programming. Moreover, using the Bee-Bot simulator eliminated the drawback of waiting for turns to test on a physical map when using the Bee-Bot hardware, thus making classroom instruction more efficient.

Moreover, we initiated an interdisciplinary learning activity with the English subject to enhance students' learning interests and diversify the curriculum. In the worksheet shown in Figure 6, Part A required students to identify hidden vocational words on a map, such as Postman, Nurse, etc. Part B had students draw their dream job. In Part C, which focuses on sequencing learning, students used the vocational words found in Part A to direct the Bee-Bot across the map, following the letters of these words.

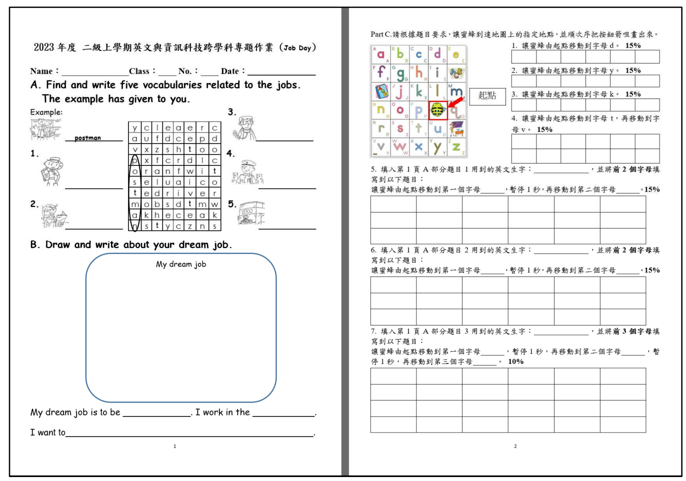

Fig. 6. Bee-Bot interdisciplinary learning worksheet

4) Step 4. Data collection for BCTt and IMMS post-test

Concluding the teaching experiment, we conducted a post-test using the BCTt and IMMS to assess student CT abilities and learning motivation changes following their experience with Bee-Bot.

C. Data Analysis

The data analysis phase was carried out utilizing SPSS software. We first conducted a normality test, verifying the data's adherence to a normal distribution pattern. Following this initial step, paired samples t-tests and Pearson correlation tests were employed to examine variations and correlations in CT and learning motivation.

To enhance the clarity and precision of our findings, we incorporated Python's Seaborn and Matplotlib libraries. These tools were instrumental in generating detailed scatter plots and Pearson correlation heatmaps, providing a comprehensive visual representation of the relationships and trends within the data.

IV. RESULTS

A. Analysis of CT

The distinction in BCTt scores before and after the experiment was assessed using a paired samples t-test.

TABLE I. PAIRED SAMPLES T-TEST RESULTS OF BCTT

Dimension	Test	Mean	Sd	Se	t	p
Sequence	Pre-test	4.74	1.52	0.26	-3.89	0.000
	Post-test	5.69	0.63	0.11		
Loop	Pre-test	3.80	1.18	0.20	-3.19	0.003
	Post-test	4.43	0.88	0.15		
Nested Loop	Pre-test	3.37	2.14	0.36	-5.00	0.000
	Post-test	5.00	1.57	0.27		
If	Pre-test	0.83	0.75	0.13	-2.07	0.047
	Post-test	1.14	0.73	0.12		
If Then Else	Pre-test	1.11	0.80	0.13	-2.09	0.044
	Post-test	1.46	0.78	0.13		
While	Pre-test	1.26	0.85	0.14	-4.58	0.000
	Post-test	1.86	1.00	0.17		
Overall	Pre-test	15.11	5.26	0.89	-7.19	0.000
	Post-test	19.57	4.07	0.69		

As demonstrated in Table I, the results reveal significant changes in the BCTt scores across various dimensions of CT.

Sequence: The pre-test scores had a mean of 4.74 (SD = 1.52), which increased to a post-test mean of 5.69 (SD = 0.63). The paired sample t-test yielded a value of -3.89, with a significant p-value of 0.000 (< 0.05), indicating a statistically significant improvement in the Sequence dimension following the experiment.

Loop: In this dimension, the pre-test mean was 3.80 (SD = 1.18), which rose to a post-test mean of 4.43 (SD = 0.88). The t-test result was -3.19, with a significant p-value of 0.003 (< 0.05), signifying that the students' understanding of loops significantly improved after the experiment.

Nested Loop: The pre-test scores showed a mean of 3.37 (SD = 2.14), increasing to a post-test mean of 5.00 (SD = 1.57). With a t-value of -5.00 and a p-value of 0.000 (< 0.05), this dimension experienced a substantial improvement.

If: The scores increased from a pre-test mean of 0.83 (SD = 0.75) to a post-test mean of 1.14 (SD = 0.73), with a t-value of -2.07 and a p-value of 0.047 (< 0.05), indicating a significant enhancement in understanding conditional statements.

If Then Else: This dimension increased from a pre-test mean of 1.11 (SD = 0.80) to a post-test mean of 1.46 (SD = 0.78), with a t-test result of -2.09 and a p-value of 0.044 (< 0.05), reflecting significant progress.

While: The mean scores improved from 1.26 (pre-test) to 1.86 (post-test), with a t-value of -4.58 and a p-value of 0.000 (< 0.05), showcasing a notable advancement in comprehension of while loops.

The total BCTt scores increased from 15.11 (SD = 5.26) to a post-test mean 19.57 (SD = 4.07). The paired samples t-test showed a value of -7.19 with a significant p-value of 0.000 (< 0.05), underscoring a significant overall enhancement in CT skills after the experiment.

In summary, the paired sample t-test results of the BCTt revealed a significant improvement in students' CT skills across all tested dimensions after participating in the Bee-Bot teaching experiment. Notably, while the Sequence dimension showed a substantial increase, more advanced CT concepts such as Loop, Nested Loop, and While exhibited even more significant enhancements, highlighting the effectiveness of the instructional approach in deepening students' understanding of complex programming constructs. Although the dimensions of If and If Then Else also showed improvement, these increases were relatively minor, suggesting that while students have progressed in understanding conditional statements, mastering these concepts may require additional focus or tailored instructional strategies.

Overall, the results underscored the positive impact of integrating hands-on programming activities, like those offered by Bee-Bot, on young learners' development of CT, suggesting that such practical, interactive teaching methods can significantly boost foundational programming skills.

B. Correlation between the dimensions of CT

The Pearson correlation test results presented in Figure 7 highlight notable associations between various CT dimensions.

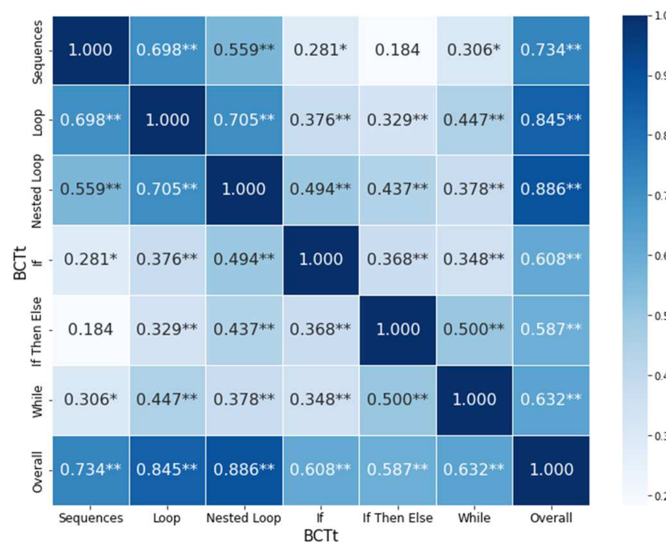

Fig. 7. Pearson correlation heatmap for BCTt

** denoted that the correlation is significant at the 0.01 level
* denoted that the correlation is significant at the 0.05 level

The ability in sequences showed strong correlations with Loop (0.698**) and Nested Loop (0.559*) abilities, indicating a significant association where enhancements in sequencing are linked with higher capabilities in these more complex CT areas.

Although correlations between sequences and the If (0.281*) and While (0.306*) constructs were lower, they remained significant, suggesting that proficiency in sequencing is related to understanding these areas as well.

Furthermore, a strong correlation was observed between sequences and the overall BCTt score (0.734**), highlighting the significant association of sequences with overall CT proficiency. This suggests that sequences play a central role in CT, correlating strongly with a broader set of computational skills.

Overall, the strong correlations observed between sequences and other CT dimensions suggest an association that a thorough understanding of sequencing is linked to mastering more sophisticated computational areas. This emphasizes the importance of sequencing as a foundational skill associated with developing a more profound proficiency in CT among young learners.

C. *Analysis of Learning Motivation*

The distinction in IMMS scores before and after the experiment was assessed using a paired samples t-test. Table II shows significant improvements in the IMMS scores across the four dimensions following the experiment.

TABLE II. PAIRED SAMPLES T-TEST RESULTS OF IMMS

Dimension	Test	Mean	Sd	Se	t	p
Attention	Pre-test	3.34	0.55	0.09	-4.65	0.000
	Post-test	3.74	0.50	0.08		
Relevance	Pre-test	3.29	0.56	0.10	-4.88	0.000
	Post-test	3.86	0.58	0.10		
Confidence	Pre-test	3.14	0.41	0.07	-5.03	0.000
	Post-test	3.63	0.60	0.10		
Satisfaction	Pre-test	3.32	0.75	0.13	-5.59	0.000
	Post-test	4.13	0.62	0.10		
Overall	Pre-test	3.27	0.49	0.08	-6.12	0.000
	Post-test	3.81	0.48	0.08		

Attention: The mean pre-test score was 3.34 (SD = 0.55), which increased to a post-test mean of 3.74 (SD = 0.50). The paired samples t-test reported a value of -4.65, with a highly significant p-value of 0.000 (< 0.05), marking a significant improvement in the Attention dimension after the experiment.

Relevance: In this dimension, the pre-test mean was 3.29 (SD = 0.56) and rose to a post-test mean of 3.86 (SD = 0.58). The t-test outcome was -4.88, with a highly significant p-value of less than 0.000 (< 0.05), indicating a significant enhancement in students' perception of Relevance following the Bee-Bot experiment.

Confidence: The mean score for Confidence advanced from a pre-test average of 3.14 (SD = 0.41) to a post-test average of 3.63 (SD = 0.60). The t-value was -5.03, with a significant p-value of 0.000 (< 0.05), demonstrating a substantial increase in student Confidence.

Satisfaction: Pre-test scores for Satisfaction had a mean of 3.32 (SD = 0.75), improving to a post-test mean of 4.13 (SD = 0.62). The t-test yielded a value of -5.59, with a p-value of 0.000 (< 0.05), reflecting a significant rise in student Satisfaction.

The overall scores increased from a pre-test mean of 3.27 (SD = 0.49) to a post-test mean of 3.81 (SD = 0.48). The t-test result was -6.12, with a p-value of less than 0.000 (< 0.05), emphasizing a significant general enhancement in IMMS scores after the intervention.

In summary, post-experiment IMMS scores significantly increased across all dimensions, reflecting enhanced student motivation following the intervention. The results indicated that navigating Bee-Bot across maps captured the students' interest, thus improving their attention and satisfaction. The incremental difficulty of tasks allowed students to understand basic concepts before learning more challenging ones, which appeared to boost their confidence.

Additionally, the interdisciplinary worksheet incorporated vocational words and allowed students to draw their dream jobs, which brought real-world relevance to the learning experience and improved the relevance dimension. This study highlights the effectiveness of hands-on, interactive programming activities, like those provided by Bee-Bot, in significantly enhancing foundational programming skills and motivation among young learners, making the content more accessible and engaging.

D. *Correlation between CT and Learning Motivation*

The scatter plot in Figure 8 shows a positive correlation between IMMS and BCTt scores. The trend line, illustrated in blue, indicates that as the IMMS score increases, the BCTt score also tends to increase.

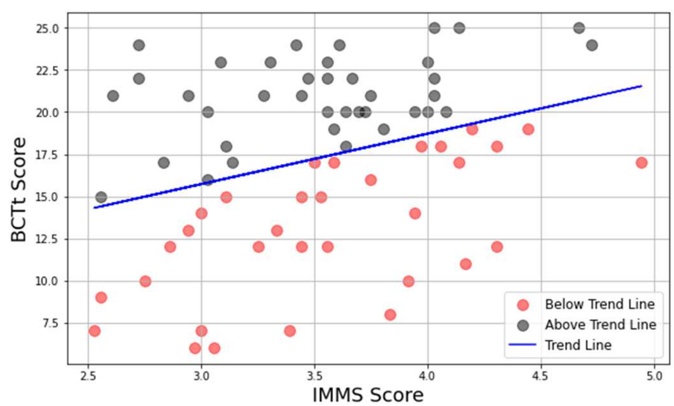

Fig. 8. Scatter plot for IMMS and BCTt

The red data fall below the trend line, suggesting that these observations have a BCTt score lower than expected at that IMMS score level. Conversely, the black points are above the trend line, indicating a higher BCTt score than expected for the given IMMS score. The distribution of points on both sides of the trend line suggests variability in the data. However, the trend line's overall upward trajectory supports a positive correlation between the two variables.

To further analyze the relationship between CT and learning motivation, Pearson correlation tests were conducted. The results, displayed in Figure 9, reveal strong interconnections between different dimensions of the IMMS. For instance, Attention was strongly correlated with Relevance (0.696**), Confidence (0.767**), and Satisfaction (0.677**), showing that higher levels of Attention within the ARCS model were associated with higher levels across the other dimensions of motivation.

Furthermore, the various components of IMMS exhibited varying degrees of correlation with the BCTt scores. The correlations between BCTt and Attention (0.325**), BCTt and

Relevance (0.275*), and BCTt and Confidence (0.337**) were significant, indicating a strong association between these ARCS components and BCTt scores.

However, the correlation between BCTt and Satisfaction (0.185) was not significant. This may be due to the nature of the satisfaction construct, which could be influenced by external factors not captured by the instructional materials and the learning process measured by IMMS and BCTt.

The overall IMMS score demonstrated a significant correlation with BCTt (0.319**), indicating that a student's overall motivation, as measured by IMMS, was strongly correlated with their performance on BCTt. This suggested that higher learning motivation, fostered through Bee-Bot instruction, is associated with improved CT abilities, as reflected by the BCTt scores.

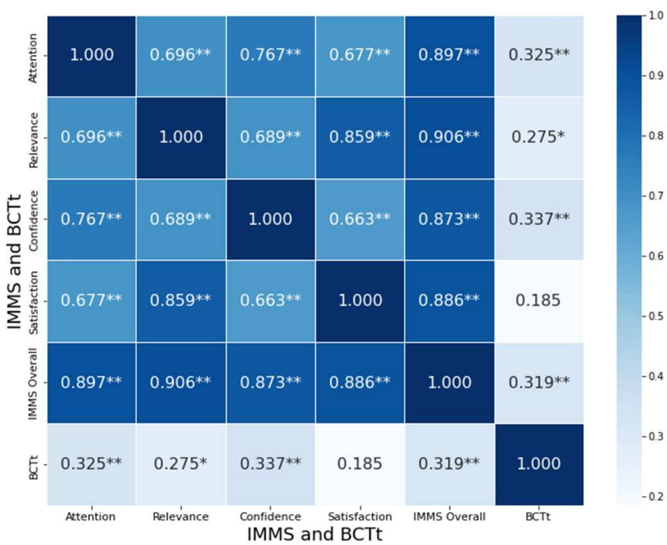

Fig. 9. Pearson correlation heatmap between PCTS and BCTt

** denoted that the correlation is significant at the 0.01 level
* denoted that the correlation is significant at the 0.05 level

V. Discussion

A. RQ1) How does using Bee-Bot in primary school programming courses affect students' CT abilities?

The BCTt analysis results indicated that using Bee-Bot in primary school programming courses significantly enhanced students' CT skills across various dimensions, including sequences, loops, and conditions.

Using Bee-Bot significantly enhanced students' sequencing skills. The study's findings indicated a substantial increase in sequencing ability, with students' mean scores on the BCTt significantly rising after the intervention.

Moreover, the Loop dimension (Basic loop, nested loop, and while) saw notable enhancement. Although the dimension of conditions (if and if then else) also improved, these were less pronounced than others, indicating that while students made progress in understanding conditional statements, achieving proficiency in these areas might have required more focused or specialized instructional approaches.

Overall, this study underscored the significant positive impact that Bee-Bot had on developing foundational programming skills among young learners.

B. RQ2) What is the correlation between different CT dimensions after teaching with Bee-Bot?

The Pearson correlation analysis highlighted significant correlations between various dimensions of CT. There was a notable correlation between the ability in sequences and both Loop and Nested Loop abilities, suggesting a linkage in proficiency across these CT areas. Although lower, correlations with the If and While constructs were also significant, indicating that proficiency in sequences was also associated with understanding these areas.

Additionally, there was a significant correlation between sequences and the overall BCTt score. These findings emphasized the importance of sequences as a foundational skill in CT, which is crucial for fostering an understanding of more complex concepts among young learners, mainly when using tools like Bee-Bot in educational contexts.

C. RQ3) How does using Bee-Bot affect learning motivation among primary school students in programming courses?

The study demonstrated that post-experiment IMMS scores significantly increased across all measured dimensions: Attention, Relevance, Confidence, and Satisfaction.

The results suggested that navigating the Bee-Bot across maps significantly captured students' interest, which contributed to increased attention and satisfaction. Additionally, the incremental difficulty of the tasks effectively scaffolded learning, allowing students to build confidence as they progressed from simpler to more complex tasks. Including vocational vocabulary and opportunities for students to engage with content related to their dream jobs added real-world relevance, further boosting their motivation.

Overall, this study underscored the value of integrating interactive and applied learning strategies in teaching foundational programming skills to young learners, enhancing both their skills and motivation with the Bee-Bot intervention.

D. RQ4) What is the correlation between CT and learning motivation when teaching with Bee-Bot in primary school programming courses?

The study revealed a positive correlation between IMMS scores and BCTt scores through a Scatter plot and Pearson correlation test, indicating that higher levels of student motivation were associated with better CT abilities.

This relationship was evident across various dimensions of the IMMS, where components such as Attention, Relevance, and Confidence showed significant correlations with BCTt scores. Notably, the correlation with Satisfaction was not significant, suggesting that this dimension might have been influenced by external factors not captured by the instructional materials.

The overall significant correlation between the general IMMS score and BCTt scores further underscored the importance of motivation in fostering CT skills, highlighting the effectiveness of motivational and educational strategies in enhancing foundational programming competencies.

VI. Conclusion

Our study demonstrated significant enhancements in sequencing ability and a deeper understanding of more advanced CT concepts, such as loops and conditions. Additionally, we found a substantial correlation between these concepts. We also explored how the influence of Bee-Bot on sequencing extends to more advanced CT concepts.

Moreover, considering the ARCS motivation model, this study examined how Bee-Bot affected learning motivation at the primary education level. After the intervention, the findings revealed that the students showed significantly higher learning motivation, meaning that the different learning activities using the Bee-Bot simulator positively influenced various sub-dimensions of the ARCS model. The correlation between the IMMS scores and the BCTt outcomes further suggested that enhanced motivation positively correlated with better CT abilities.

Our study contributed to educational technology and programming by introducing a Bee-Bot simulator to address the practical challenges of using physical robots in constrained spaces. This innovative approach expanded the educational utility of Bee-Bots and facilitated a deeper engagement with advanced CT concepts such as conditions and loops. The findings enhanced our understanding of the pedagogical impacts of Bee-Bots, particularly in developing computational skills and fostering motivation among young learners.

Regarding future work, we propose exploring more creative teaching methods with Bee-Bot to deepen students' understanding of sequencing and other CT concepts. Additionally, investigating other programming tools suitable for young students could provide further insights into enhancing sequencing concepts. By integrating diverse educational technologies, we aim to continually improve the effectiveness of programming education for young learners, ensuring a solid foundation in computational thinking and motivation.

In conclusion, our study demonstrated that the Bee-Bot teaching experiment significantly enhanced young learners' CT abilities and motivation. The positive changes observed in CT skills and motivational levels post-intervention affirm the value of integrating interactive, hands-on programming activities in early education. Our findings advocated for the broader adoption of educational robotics like Bee-Bot in primary education, emphasizing the importance of engaging instructional materials and innovative teaching methods in cultivating the next generation.

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