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Empowering Students Computational Thinking through Robotics-enabled STEM Education

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Abstract: The present study aims to conceptualize and develop a comprehensive series of STEM lessons enriched by robotics, meticulously guided by the 5E inquiry model. By skillfully weaving together robotics and STEM education, while adhering to a well-defined pedagogical framework, this research endeavor seeks to bridge the existing gap in the effective amalgamation of CT education within the diverse realms of STEM education. A pilot study conducted in a primary school demonstrated the positive results in CT skills test.

Keywords: Computational thinking, Robotics, STEM, 5E inquiry model

1. Introduction

With the collaborative efforts of teachers, researchers, and educators, the field of STEM education has witnessed a remarkable surge in research activities. Students now have the privilege of engaging in diverse forms of STEM education, notably those enriched with technology-driven components (Tekdal, 2021). In an era characterized by rapid technological advancements and the proliferation of computing tools—such as programming and coding platforms—the integration of these tools into STEM activities has become an inevitable progression (Shute et al., 2017; Chongo et al., 2020). This infusion of computing tools amplifies the advantages of STEM education for students, prominently fostering the development of Computational Thinking (CT) skills—a quintessential 21st-century competency (Barr & Stephenson, 2011). Computational Thinking embodies a systematic approach to unraveling problems and designing systems. It draws upon foundational concepts such as logic, abstraction, pattern recognition, and algorithmic design to skillfully deconstruct and conquer intricate challenges (Wing, 2006; National Research Council, 2010).

Traditionally entrenched in the domain of computer science and computing-related pursuits, Computational Thinking now finds itself pervading a spectrum of STEM contexts (Lee & Malyn-Smith, 2020). Numerous instances underscore the integration of CT skills within STEM education, with coding tools like mBot, Scratch, and app Inventor lending support to this trend. Nevertheless, the seamless amalgamation of CT education into STEM contexts, harmonized by well-crafted pedagogical principles, remains somewhat constrained.

In response, this study endeavors to conceive and develop a comprehensive series of robotics-facilitated STEM lessons, meticulously guided by the 5E inquiry model. By innovatively interweaving robotics and STEM education, while adhering to a well-defined pedagogical structure, this study aims to bridge the existing gap in the effective integration of CT education within STEM domains.

2. Literature Review

Computational Thinking (CT), initially introduced by Papert (1980) and subsequently elaborated upon by Wing (2006), has emerged as a foundational concept. It was initially recognized as a cornerstone within the realm of computer science, involving "problem-solving, system design, and comprehension of human behavior, drawing upon fundamental computer science concepts" (Wing, 2006). The construct of CT was refined by Campbell and Heller (2019) and Yin et al. (2020) to encompass decomposition, abstraction, pattern recognition, and algorithmic thinking. Grover and Pea (2013) further delineated CT skills to comprise elements such as abstraction, pattern generalization, algorithms, logic, problem decomposition, debugging, productivity and performance constraints, parallel thinking, and systematic information processing. Amid the contemporary landscape, CT has solidified its place as a pivotal competency in the 21st century. Consequently, over the past decade, a multitude of theoretical and empirical studies have been conducted to unravel its nuances (Sands et al., 2018). Among these explorations, investigations into CT education within STEM contexts have consistently demonstrated its efficacy in nurturing CT development, bolstering STEM knowledge acquisition, and fostering higher-order cognitive skills, including creativity and problem-solving prowess (Ogegbo & Ramnarain, 2021).

As a captivating pedagogical approach in STEM education, robotics has garnered significant attention due to its inherently interdisciplinary nature. Prior research has underscored the potential of infusing CT education through robotics design to foster robotics literacy, encompassing concepts like simple machines, sequencing, order, and control (Cejka et al., 2006). These facets naturally align with engaging contexts such as environmental exploration, innovative creation, and pragmatic problem-solving. The rapid strides taken in the realms of artificial intelligence and robotics technologies have facilitated the integration of diverse programming tools within AI-driven projects. Yet, the intricate nexus between intelligent robotics technology and the cultivation of computational thinking within the framework of STEM education remains a domain ripe for exploration. In light of this, the current study explored the impacts of robotics-enabled STEM lessons on students' computational thinking and their motivation to engage with these innovative lessons.

3. Research Questions

Based on the above research background, this study aims to design a robot-enabled STEM program to develop students' computational thinking skills and enhance their learning motivations, Specifically, the research questions are as follows:

1) To what extent does robotics-enabled STEM education impact students' computational thinking knowledge?

2) To what extent does robotics-enabled STEM education influence students' learning motivations?

4. Methodology

4.1 Participants

To ascertain the sample's representativeness and accessibility, the study employed the purposive sampling method. This approach involved selecting all Grade 4 students from a local primary school in Hong Kong, renowned for its emphasis on ICT education. Prior to commencing the intervention, requisite permissions were secured from both the students' parents and the students themselves, ensuring voluntary participation. Subsequently, a total of 56 students, aged approximately 11 years on average, were chosen from four distinct classes.

4.2 Instruments

4.1.1 Computational Thinking skill Test

Drawing upon the works of Shute et al. (2017) and Curzon et al. (2019), an assessment of students' computational thinking skills was executed through a carefully designed test. This evaluative tool encompassed 20 questions, each necessitating students to articulate their problem-solving approach. The comprehensive problem-solving process comprised five distinct stages of computational thinking: identification and representation of strategies for problem resolution, decomposition of problems into manageable segments and identification of critical information, recognition of patterns, trends, and regular inferences, and a final review of the adequacy of the problem-solving solution. The scoring system allocated up to 5 points to each question, reflecting the progression through these stages (Table 1). Consequently, the maximum achievable score was set at 100 points. To ensure the validity of the assessment, the test questions underwent meticulous screening and correction by both frontline teachers and subject matter experts prior to its formal administration.

Table 1. Dimension Classification of the Student Motivation Questionnaire

Component	Definition	Score
Algorithmic thinking	*Identifying and representing routines to solve a problem or task, like ordered, step-by-step instructions*	*1*
Decomposition	*Breaking down one problem, algorithm or process into smaller parts such that the partial results can be later integrated to more easily solve or understand the whole problem*	*2*
Abstraction	*Identifying essential elements of a problem or process; this involves simplifying and hiding detail*	*3*
Pattern recognition	*Inferring and identifying patterns, trends or regularities in a certain problem or process*	*4*
Evaluation/ debugging	*Reviewing the adequacy of solutions or elements to a problem*	*5*

4.1.2 Learning Motivation Questionnaire

The students' motivation was assessed using a questionnaire consisting of 13 questions, categorized according to the framework developed by Glynn et al. (2011) (as presented in Table 2). This questionnaire comprises a range of motivation-related aspects, including 3 items related to intrinsic motivation, such as "I find the prospect of working with robots intriguing," 3 items reflecting extrinsic motivation, such as "Acquiring knowledge about robotics will benefit my learning and future growth," 4 items concerning self-determination, such as "I am committed to investing substantial effort into learning robotics," and 3 items gauging self-efficacy, such as "I hold the belief that I performed well in the robotics activity." Respondents were requested to provide their responses on a 5-point Likert scale, spanning from "strongly agree" to "strongly disagree." In ensuring the reliability and validity of the questionnaire, a preliminary test of the questions was administered. This validation process yielded favorable results, with a Cronbach's alpha coefficient of 0.781 and a Kaiser-Meyer-Olkin (KMO) measure of 0.870, indicating strong internal consistency and reliability.

Table 2. *Dimension Classification of the Student Motivation Questionnaire*

Dimension	Item
Intrinsic motivation	I think it is interesting to work with robots.

	I think knowledge of computer engineering, mathematics, physics and mechanical sciences is necessary to master robotics.
	Winning events and competitions is very important to me.
Extrinsic motivation	Understanding robotics technology will help my learning and future development.
	Participating in robotics activities will improve my academic performance.
	I think I will be able to use what I have learned from the robotics activities in other courses.
Self-determination	My future career dream is to become a scientist
	I intend to put a lot of effort into learning robotics.
	I will gather information from different sources, such as math and physics, to use in robotics activities.
	If I have a problem, I will continue to try and solve it by reading the material without anyone's help.
Self-efficacy	I am able to express and explain my ideas to my team
	I believe that I have done a good job in robotics activities.
	I participate actively in team activities.

4.2 Robotics-enabled STEM Curriculum

Collaborative efforts between educators and researchers culminate in the design and execution of Computational Thinking (CT)-focused STEM lessons, synergistically bolstered by the utilization of VEX Robotics toolkits. Specifically, the VEX Robotics toolkit, recognized for its educational value, offers an array of block-based coding tools tailored to students from kindergarten to grade 12. This inclusive approach translates into an "interactive, programmable robot that bridges the realms of Computer Science and Computational Thinking, transcending digital screens to become a tactile experience for Pre-Primary students." Guided by the established 5E inquiry model, the lessons seamlessly align with existing VEX activities available at https://education.vex.com/stemlabs/go/activities. The incorporation of the 5E inquiry model ensures an engaging and comprehensive learning process encompassing engagement, exploration, explanation, elaboration, and evaluation. Therefore, this study drew on the existing activities of VEX GO and modified them according to their characteristics and the cognitive characteristics of grade 4 primary students to form the final robot-supported STEM curriculum. The lesson plan can be found in Table 3, where students constructed an Astronaut Vault. The course lasted for 5 classroom hours. By intertwining CT principles with robotics education through the VEX Robotics toolkit and grounding the pedagogical approach in the 5E inquiry model, the collaborative endeavor seeks to foster an immersive and impactful STEM learning journey.

Table 3. *Exemplar of lesson plan*

5E Inquiry phase	Student Activities
Engagement	Students are introduced the lunar rover through watching videos and answer the related questions about lunar rover.
Exploration	Student are asked to work with their classmates to build an astronaut vault which could speed quickly toward an object and stop before hitting it. They are discussing the design ideas and build the model
Explanation	Students are invited to present their design and do demonstrations, with further explaining how it works.

Elaboration	Student are further elaborate their design based on teacher feedback and other group's comments.
Evaluation	The students answer the questions about CT knowledge and skills in the activities.

4.3 Data Collection and Analysis

The dataset for this study comprises three distinct categories: the pre-test and post-test results measuring students' computational thinking skills, the pre-test and post-test outcomes gauging students' motivation through a questionnaire, and unstructured interviews conducted with the students. To ensure data collection consistency, the students' computational thinking skills and motivation to learn questionnaires was administered by their classroom teachers both prior to and following the intervention. Furthermore, unstructured interviews were carried out with three selected students under the guidance of a facilitator, who then recorded the collected data.

The ensuing data analysis encompasses both quantitative and qualitative methodologies. Initially, the students' computational thinking skills test results and their academic motivation outcomes underwent descriptive statistical analysis in SPSS. This encompassed the computation of total mean scores, standard deviations, and paired sample t-tests to ascertain the disparities between students' pre-intervention and post-intervention scores. Additionally, variations in each facet of academic motivation was visually represented using line graphs generated in EXCEL. Lastly, the interview transcripts from the students were analyzed to glean profound insights into their computational thinking skills and motivation to learn.

5. Results

5.1 Computational Thinking skills

An examination of descriptive statistics pertaining to students' total scores in computational thinking skills, both in the pre-test and post-test (refer to Table 4), revealed a notable trend: the students' post-test scores surpassed their pre-test scores. Evidently, this signifies a discernible enhancement in the students' overall computational thinking skills following the intervention.

Table 4. *Scores of the pre-test and post-test*

Test	*M*	*SD*	*SE*
Pretest Score	67.717	6.298	.865
Posttest Score	81.422	6.387	.894

Subsequently, a paired samples t-test was employed to analyze the pre-test and post-test results of the students' computational thinking skills assessment. The outcomes indicated a substantial disparity between the students' pre-test and post-test scores ($p < .05$), affirming a noteworthy improvement in their computational thinking skills subsequent to the intervention.

5.2 Learning Motivation

Descriptive statistics were applied to the students' pre-test and post-test motivation scores, with the findings outlined in Table 5. The results unveil varying degrees of advancement in the four dimensions: intrinsic motivation, extrinsic motivation, self-determination, and self-efficacy, following the intervention. Among these dimensions, post-intervention self-efficacy registered the highest mean score, closely followed by intrinsic motivation. This pattern underscores how the intervention notably bolstered students' confidence in ICT-related learning and fostered a heightened willingness to propel their learning through personal initiative.

Table 5. Students' learning motivations of the pre-test and post-test

Test	Dimension	*M*	*SD*	*Skewness*	*SE*	*Kurtosis*	*SE*
Pretest	IM	3.71	1.09	-1.124	0.319	0.748	0.628
	EM	3.63	1.18	-0.850	0.319	0.042	0.628
	SD	3.14	1.1	-0.067	0.319	-0.557	0.628
	SE	3.81	1.11	-1.045	0.319	0.731	0.628
Posttest	IM	4.01	1.06	-1.369	0.322	1.600	0.634
	EM	3.83	1.14	-1.149	0.322	0.814	0.634
	SD	3.43	1.16	-0.388	0.322	-0.439	0.634
	SE	4.04	1.08	-1.271	0.322	1.458	0.634

Note: IM: Intrinsic Motivation; EM: Extrinsic Motivation; SD: Self-Determination; SE: Self-efficacy

Paired-sample t-tests were subsequently conducted for each individual dimension as well as the overall mean, aiming to ascertain any distinctions between the pretest and posttest conditions. The findings are presented in Table 6. When analyzing the overall mean, the posttest total score significantly exceeded that of the pretest ($p < .05$). This substantial discrepancy points towards a marked elevation in students' overall motivation to learn subsequent to the intervention. Further examination of each dimension showcases noteworthy trends. Intrinsic motivation, self-determination, and self-efficacy displayed notable increments post-intervention, exhibiting statistically significant improvements. However, the variation in extrinsic motivation—pertaining to external incentives like monetary rewards or other external inducements—was relatively modest between the pre-test and post-test stages. This suggests that post-intervention, students' motivation wasn't largely driven by external factors. Instead, the intervention primarily centered on bolstering their learning confidence and cultivating a genuine interest in the subject matter itself.

Table 6. *Paired t test of students' pre and posttest of learning motivations*

Pair	*t*	*p*
IM	-1.926	0.039*
EM	-1.244	0.219
SD	-1.575	0.041*
SE	-1.573	0.021*
Total	-1.816	0.045*

Note: IM: Intrinsic Motivation; EM: Extrinsic Motivation; SD: Self-Determination; SE: Self-efficacy

5.3 Interviews

At the end of the intervention, three randomly selected students were interviewed to further confirm the effectiveness of the robot-assisted STEM programme. Insights from the interview data indicated that students consistently agreed on the benefits of integrating robotics into the STEM curriculum. The integration of robotics into the STEM curriculum was praised by students for infusing an inquiry-based and problem-solving approach, which promoted computational thinking skills.

Students confirmed the effectiveness of these classes in promoting problem solving skills by asking "Question 1: Do you think robot-assisted STEM classes have helped you with your problem-solving skills?" Students confirmed the efficacy of these courses in promoting STEM knowledge and competence.

Student A: It was okay, I learned general patterns of problem solving in the classroom activities.

Student B: I clearly grasped the content of the course, which will help me solve problems in the future.

Student C: It was helpful in developing my computational thinking skills because I need to solve a lot of problems on my own.

For "Question 2: After listening to the whole lesson, did you find the STEM programme more interesting?" They became interested in the STEM curriculum through robot-assisted STEM learning. In addition, as the intervention culminated, the students became more and more emotional-enthusiastic about the upcoming STEM course and renewed their resolve to take the related academics seriously.

In response to "Question 3: How well do you feel you are listening in STEM classes now compared to before?" Overwhelmingly, respondents reported that the classes hold their attention and provide a way for them to participate more effectively in the classroom. Students agreed that they performed better and were more attentive in STEM classrooms that leveraged robotics.

Student A: He likes the way the class is taught compared to before and listens attentively in every class.

Student B: I am interested in robotics, so I am more motivated than before.

Student C: Sometimes I get sleepy in class, but now I try to stay awake and concentrate on the STEM lessons.

Overall, this instructional approach served as a catalyst for student enthusiasm and motivation in the STEM field of study. It not only enriched students' current learning experiences, but also fostered their continued interest in future STEM projects.

6. Discussions

This study entailed the design and implementation of a robot-enabled STEM program, structured upon the 5E model, with the primary objective of enhancing students' computational thinking skills and fostering motivation to learn. Significant advancements in students' computational thinking skills were observed post-program intervention, signifying a tangible improvement as a result of the intervention. This observation aligns with prior research indicating that STEM programs incorporating computational thinking elements contribute positively to the computational thinking skills of pre-service teachers (Çiftçi & Topçu, 2023), as well as similar findings in the context of robotics-enhanced STEM summer camp activities and game design for children from diverse regions (Chiang et al., 2022; Leonard et al., 2016; Shang, 2023). The current study reinforces these findings, affirming that a robot-enabled STEM program effectively enhances computational thinking among primary school students in Hong Kong. This pedagogical intervention, brimming with inquiry and problem-solving processes, propels students to collaboratively tackle real-life issues. This immersive engagement fosters a deeper appreciation for the intricacies of problem-solving, thereby nurturing their computational thinking prowess (Shute et al., 2017; Barak & Assal, 2018).

Turning to the aspect of student motivation, the preponderance of prior research indicates that robot-enabled STEM programs distinctly elevate students' self-efficacy, learning attitudes, and enthusiasm for learning (Gomoll et al., 2016; Sisman et al., 2021; Üçgül et al., 2022). This study's findings reaffirm these conclusions, while also delving deeper to explore the program's influence on self-determination and extrinsic motivation. The results underscore that, upon intervention completion, students displayed substantial enhancements across intrinsic motivation, self-determination, and self-efficacy. Nonetheless, concerning extrinsic motivation, the mean scores witnessed growth, yet the variance from the pre-intervention phase did not attain statistical significance. This could be attributed to the program's intrinsic nature, which aims to cultivate enjoyment and interest by immersing students in inquiry and problem-solving activities, consequently boosting their self-efficacy in addressing challenges (Barak & Assal, 2018). As a result, future iterations of the course might consider incorporating immediate classroom assessments to amplify external motivation in alignment with their learning objectives.

7. Conclusions

This study devised a robot-enabled STEM program rooted in the 5E instructional model. Through a comparative analysis of students' computational thinking skills and motivation prior to and following the intervention, significant insights emerged. The study revealed that the integration of robotics within STEM education holds the potential to foster considerable enhancements in students' computational thinking skills. Moreover, the infusion of robotics into STEM curricula yielded positive outcomes, ameliorating students' intrinsic motivation, self-determination, and self-efficacy.

This realization underscores the prospect for educators to leverage similar STEM programs in the future. By orchestrating comparable initiatives, teachers can ignite students' fascination for STEM learning, nurture adept problem-solving abilities, consequently augmenting their computational thinking proficiencies. In doing so, a harmonious advancement of students' STEM literacy can be achieved.

Nevertheless, this study is not without its limitations. Although it validated the efficacy of robotic-enabled STEM courses in bolstering intrinsic motivation, self-determination, and self-efficacy, the discernible impact on students' external motivation was not statistically significant between pre- and post-tests. This aspect presents an avenue for future refinement. A potential approach involves the integration of immediate classroom assessments, strategically aimed at amplifying external motivation.

In conclusion, this research underscores the transformative potential of robot-enabled STEM initiatives. By harnessing the power of robotics within the framework of STEM education, educators can foster a well-rounded development of students' computational thinking skills, intrinsic motivation, and self-determination, thereby paving the way for a comprehensive advancement of students' STEM literacy.

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W13

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