Student Learning of Computational Thinking in a Robotics Curriculum: Transferrable Skills and Relevant Factors

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Abstract: This poster presents findings from the implementation of a robotics curriculum emphasizing applying computational thinking (CT) to solve both programming and everyday reasoning problems. Utilizing an online CT instrument as the pre-and-post measure, students' performance, improvement, and process data were analyzed. Results show that the curriculum helped students improve CT in both scenarios. While student self-determination was positively correlated to their score gains, other factors (gender, class, familiarity with problem settings) were not.

Introduction

Since Papert (1980) coined the term computational thinking (CT), it has gradually gained its momentum as an important learning goal. Wing (2006) made it clear that CT should be considered as a foundational skill students need to develop in and out of schools. However, scholars have yet to achieve a widely acknowledged definition; different explanations on what CT entails were proposed (Barr & Stephenson, 2011; Grover & Pea, 2013). Most of these interpretations framed CT in a problem-solving process and emphasized its power to transfer across tasks and domains (Wing, 2006; CSTA, 2011). Current practices of teaching CT in programming contexts have difficulty in preparing students to transfer problem-solving skills to other non-programming contexts. Moreover, it is difficult to assess CT gain for younger students with minimum prior programming experience.

In order to fill these gaps, we developed a robotics programming curriculum with an emphasis on CT as applicable to everyday settings together with an instrument in accordance with this connotation. We hope that by completing our robotics curriculum, students gain knowledge and skills that could be applied to solving not only programming but also everyday-reasoning problems. We are also interested in if certain student knowledge and characteristics (such as their familiarity with certain problem contexts) factor into their initial performance and learning gains. Two research questions guided our study: (1) Does the robotics programming curriculum improve students' CT in both programming and everyday reasoning contexts? (2) What student characteristics are relevant in explaining their initial performance and learning gains?

Methods and results

Based on experience gained from two pilot runs, we finalized a robotics curriculum for upper elementary school students using an autonomous, programmable humanoid robot platform NAO, with emphasis on both robot basics and application of learned concepts to solve everyday reasoning problems. The curriculum was implemented in a Title I elementary school in southeast United States. All the fifth grade classes (6 classes; 125 students) adopted the curriculum. Each class spent about two hours each day on the curriculum for 5 consecutive days.

Based on our framework of CT (Chen et al., 2017) adapted from the CSTA (2011) definition, our current online CT assessment could record students' answers to and actions with items. It has two types of scenario: robotics programming (programming a robotic arm to draw and a robot to move) and everyday reasoning (cooking, booking flight tickets, and doing laundry). The same assessment was used as the pre-and-posttest for this study. Students' familiarity of everyday settings involved in the assessment was asked in the pretest. And they were asked to complete a science motivation questionnaire adapted from Glynn et al. (2011) in the posttest. The assessment took students about 30-60 minutest to finish. In total 107 completed responses of both pre-and-posttest were analyzed.

In order to answer the first research question, paired t-test was used to calculate the statistical significance of learning gain. Results ($t(106)=-5.15$, $p=0.0000$, $d=0.24$) revealed that students did statistically significantly better, with low to medium effect sizes, in posttest than pretest. Moreover, they gained more in everyday reasoning items ($t(106)=-4.97$, $p=0.0000$, $d=0.36$) than programming items ($t(106)=-3.60$, $p=0.0002$, $d=0.18$). Also, fine-grained process data can provide insight into better understanding of student application of CT in problem solving. For example, some students' score gain from pretest to posttest could be validated and score lose explained. And calculation of problem solving time based on action timestamps revealed that whereas score increase might be due to students' improved CT skills that enabled them to spend more time in solving this item, score decrease seemed to be caused by students' unwillingness to spend enough time in posttest. Their reluctance might be directly related to the boringness of writing lines of code.

To answer the second research question, two-sample t-test was used to test the gender differences in pretest and score gain. Neither a statistically significant difference was found between male and female students in pretest ($t=-0.17$, $df=103.72$, $p=0.86$), nor in score gain ($t=-1.13$, $df=102.51$, $p=0.26$). This indicates that gender did not have an effect on students' initial performance and gains after this curriculum. In addition, appropriate correlations were calculated to examine the possible relationship between student familiarity with everyday reasoning and programming settings and their pretest performance and gains. These results show that students' familiarity with and experience in both everyday scenario and programming settings did not associate significantly with their pretest performance and gains from pretest to posttest. Also, only self-determination is significantly and positively correlated with score gain ($r=0.197$, $t(105)=2.06$, $p=0.041$). One-way ANOVA was used to test class differences and their relationship with student pretest score and gains. The results show statistically significant difference among classes in terms of pretest score ($F(5,101)=9.079$, $p=0.000$). However, no significant difference was found for score gains among the six classes ($F(5,101)=1.446$, $p=0.214$). This result shows that although the students from different classes started with different pretest performance, they gained similarly from the curriculum.

Conclusion
This study summarized our effort to evaluate student progress in acquiring CT skills from participating in our robotics programming curriculum. The results showed that students benefited from the curriculum in solving both programming and everyday reasoning items as well as relevant student features in determining their initial performance and CT gain as indicated by their pre-and-posttest scores. This study also revealed the potential of using logged data to understand students' application of CT in problem-solving process toward a better understanding of their learning gain.

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