Bringing Computational Thinking Into High School Mathematics and Science Classrooms

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Abstract: Computation is reshaping modern science and mathematics practices, but relatively few students have access to, or take, courses that adequately prepare them for the increasingly technological nature of these fields. Further, students who do study computational topics tend to not reflect the greater student body, with female and minority students being disproportionately underrepresented. To address these issues, we investigate the approach of embedding computational thinking content into required high school mathematics and science coursework. Using data from a 3-year implementation, we present results showing differences in attitudes towards computing by gender, while also finding similar gaps do not correlate with aptitude. Using pre/post measures, we then show female participants expressed improved confidence with computational thinking and interest in STEM careers. Additionally, we report a dosage effect, where participating in more activities resulted in greater learning gains, providing evidence in support of embedding computational thinking enhanced activities across high school curriculum.

Keywords: computational thinking, high school mathematics and science, broadening participation

Introduction

Computation is changing the landscape of modern scientific and mathematical fields. Computational tools, practices, and methods are reshaping the way mathematicians and scientists conduct their work. This is true in research laboratories, in industry, and increasingly, in educational settings as well. Given the growing computational presence across mathematics and science contexts, the question faced by educational institutions is how to prepare learners for the increasingly computational nature of these disciplines. Our answer to this question is to bring computation and computational thinking enhanced activities into existing mathematics and science classrooms. As such, we have pursued a course of research working to integrate computational thinking (CT) into high school mathematics and science contexts through the creation of CT enhanced curricula across four primary STEM subject areas: biology, chemistry, physics and mathematics. Our conceptualization of CT as it relates to mathematics and science takes the form of a taxonomy that delineates a series of specific practices grouped into four, overarching categories: data practices, modeling and simulation practices, computational problem solving practices, and systems thinking practices (Weintrop et al., 2016). In this paper, we provide data showing the positive effects of distributing CT across the curriculum and across classrooms, as opposed to limiting exposure to a single classroom or a single unit. These effects include improved attitudes towards, and confidence in, computing as well as increased interest in pursuing careers in STEM disciplines. Additionally, based on data from the final year of a three-year study, we report a dosage effect; showing that students who encountered more CT enhanced activities performed better on posttests designed to measure learners' CT abilities. Collectively, these findings lend support to the effectiveness of embedding CT in existing mathematics and science classrooms as an approach to improving attitudes towards the field, engaging diverse and historically underrepresented populations in computing, and preparing students for the computational futures that await them regardless of the professions they choose to pursue.

Practical motivation

A primary motivation for introducing CT practices into science and mathematics classrooms is in response to the increasingly computational nature of the disciplines as they are practiced in the professional world (Education Policy Committee, 2014; Foster, 2006; Malyn-Smith & Lee, 2012; Weintrop et al., 2016). Computation is now an indispensable component of STEM disciplines (Henderson, Cortina, & Wing, 2007). This rise in importance of CT and its constituent skills and practices has been recognized both by those creating standards for mathematics and science classrooms (National Governors Association Center for Best Practices, Council of Chief State School Officers, 2010; NGSS Lead States, 2013) as well as by computer science education organizations (ACM/IEEE-CS Joint Task Force on Computing Curricula, 2013). Bringing computational tools and practices into mathematics and science classrooms gives learners a more realistic view of what STEM fields are and better prepares students for STEM careers (Augustine, 2005; Gardner, 1983).

Preparing students for the modern STEM landscape is not the only reason to bring CT into STEM classrooms. From a pedagogical perspective, the thoughtful use of computational tools and skillsets can deepen learning of STEM content (Guzdial, 1994; National Research Council, 2011; Repenning, Webb, & Ioannidou, 2010; Sengupta et al., 2013; Wilensky, Brady, & Horn, 2014; Wilensky & Reisman, 2006). The reverse is also true – namely, that science and mathematics provides a meaningful context (and set of problems) within which CT can be applied (Hambrusch et al., 2009; Jona et al., 2014; Lin et al., 2009; Wilensky et al., 2014). This differs markedly from teaching CT as part of a standalone course where the assignments tend to be divorced from real-world problems and applications. This reciprocal relationship—using computation to enrich STEM learning and using STEM to enrich computational learning—is at the heart of our motivation to bring CT and STEM together.

A third motivation for bringing CT into STEM classrooms is to reach the widest possible audience and address the longstanding issues of underrepresentation of women and minorities in computational fields. Despite numerous ongoing local, regional, and national campaigns targeting women and underrepresented minorities, the numbers continue to drop in STEM (National Science Board, 2012) and computer science (Klawe and Levenson, 1995) enrollments. Among the reasons for these trends, researchers have identified a lack of interest and confidence (Margolis, Fisher, & Miller, 2000), limited visibility of positive role models (Townsend, 2002), and lack of positive experiences with both computer science and in STEM fields more broadly (AAUW, 1994; Miliszewska, Barker, Henderson, & Sztendur, 2006). Currently, only a fraction of high school students have the opportunity to take a computer science course due to a lack of qualified teachers, inadequate facilities, or a lack of student interest. Embedding CT activities in STEM coursework directly addresses the issue of students self-selecting into (or out of) computational learning experiences. It also avoids practical issues of fitting new classes into overcrowded schedules and finding teachers to teach them. Collectively, these aspects of the relationship between CT and STEM, paired with the ability to reach diverse audiences and work within existing educational infrastructure, makes the embedded CT design a potentially powerful and effective approach to bring CT to diverse learners.

Theoretical perspective

Efforts to incorporate computational thinking into high school curricula have been hampered by shifting and underspecified definitions of what constitutes CT skills and practices. Our definition of CT is framed within two core theoretical constructs: 1) Wilensky and Papert's concept of restructuration (Wilensky & Papert, 2010) and 2) diSessa's framework for computational literacy (diSessa, 2000). Wilensky and Papert's work defines a structuration as the knowledge content of a domain as a function of the representational infrastructure used to express it. A restructuration is a shift in representational infrastructure in a domain, which inevitably changes the practices in that domain and the ways we teach and learn the domain. For example, a major restructuration of arithmetic took place around the turn of the first millennium with the shift from Roman to Hindu Arabic numerals. The place value construct embedded in Hindu-Arabic numerals radically reshaped what was possible to do with numbers and shifted, for example, multiplication and division, from an activity that only small number of highly trained specialists were capable of, to a nearly universal practice. We believe that computational representations are already beginning to have a major restructurational effect on STEM disciplines (e.g. Abelson & DiSessa, 1986; Blikstein & Wilensky, 2009; Noss & Hoyles, 1996; Sengupta & Wilensky, 2009; Wilensky & Reisman, 2006) and that through embedding CT practices in mathematics and science contexts we can prepare learners for this shift.

diSessa notes that for a representational infrastructure to become universal it has to specialize to several social niches. So for example, print literacy specializes to the niches of poetry and romance novels among many others. Similarly, we see computational representations as specializing to a variety of niches, each with its own conventions (in contrast to a single monolithic set of practices). The unifying theme amongst all our CT activities is exploring the ways we can use computational representations to make significant shifts in the way students learn, think and practice science and mathematics. Thus, we developed a taxonomy (Figure 1) to frame our work that describes and organizes the various 'niches' of computational representations and practices in mathematics and science disciplines (Weintrop et al., 2016). Through the taxonomy, we begin to identify commonalities and patterns across these practices that we can then leverage to design educational activities to grow students' proficiency in, and understanding of, these new computational representations in various STEM disciplines. Building proficiency in these new forms of representations is what we mean by *computational thinking in mathematics and science.*

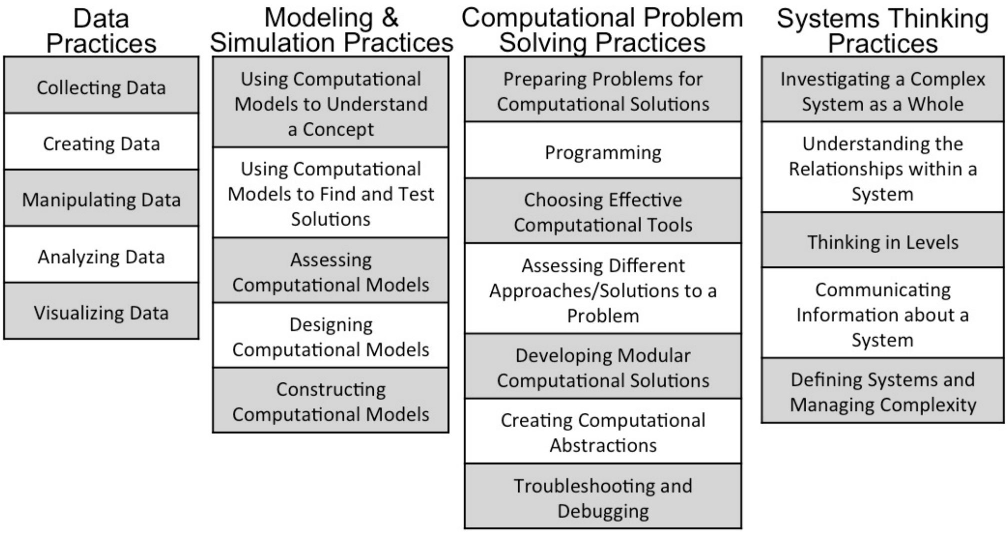

Figure 1. The computational thinking in mathematics and science practices taxonomy.

Methods and data sources

The data we present in this paper were collected as part of a larger, 3-year study investigating the effectiveness of the embedded CT in mathematics and science strategy. Over the course of the project, 58 teachers attended professional development workshops from 38 schools. The data we present are from 11 classrooms in a Midwestern city that participated in the third year of the project. As part of the study, pre/post attitudinal and CT skills assessments were administered along with classroom observations and teacher interviews. The attitudinal surveys were modeled after other similar efforts to measure student attitudes in STEM and computer science contexts (Adams et al., 2006; Dorn & Elliott Tew, 2015). The pre/post skills assessments were designed as part of the larger project and were designed to assess students' abilities to employ CT practices, as opposed to content knowledge of a given scientific or mathematical domain (Weintrop et al., 2014). The assessment are hosted online and ask students to use various computational tools (including interactive data visualizations, computational models and simulations, and dynamic data management widgets) to answer open ended and multiple choice questions relating to the four CT in mathematics and science categories shown in Figure 1.

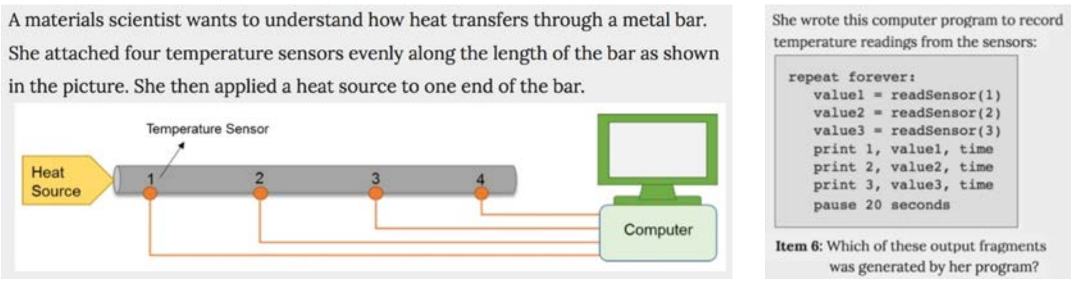

Figure 2. A sample multiple choice question from a CT skills assessments.

The CT-enhanced lesson plans that were taught as part of this study were designed by members of the research team in collaboration with graduate students working in STEM fields as part of an educational outreach program. The lessons were designed in conjunction with in-service mathematics and science teachers and later taught in their high school classrooms. An important part of this outreach program is for graduate students to bring their own research into high school classrooms, both showing high school students what cutting edge research looks like and to bring diverse, practicing scientists into the classroom to confront the misconception that all scientists are old, Caucasian men wearing lab coats. The graduate students and teachers who contributed lesson plans were vetted through professional development training on what CT means in mathematics and scientific contexts. Lessons were created for high school mathematics, biology, chemistry, and physics classes and included subjects as diverse as US census data, radioactivity, black holes, and video games. Lessons usually lasted two or three class periods and, when possible, used the same computational tools that the scientists themselves use in their work. For example, one lesson plan called DNA sequencing had students study and apply the shotgun algorithm that was used to sequence the human genome, and then introduces them to BLAST, an online search tool that scientists use to explore the conservation of, and differences in, DNA sequences of different organisms. With this activity, we bring together scientific content, CT (in the form of algorithms and working with data), as well as having students use modern computational tools, bringing authenticity to the activity. A longer description of some of the activities in this study and how the incorporate CT can be found in (Weintrop et al, 2016).

The attitudinal data we present are drawn from surveys that were administered to students in participating classrooms at the beginning and the end of the school year. A total of 704 attitudinal surveys were completed (475 pre and 229 post) with 49.7% of the surveys being filled out by female students. The survey primarily used a 5-point Likert scale and asked students to respond to statements such as "I feel comfortable working with computers" and "I am interested in pursuing a career in engineering." For the CT skills assessment results, a total of 1,022 assessments were completed by 549 students during the 2013-2014 school year. In particular, as we are interested in student trajectory over the course of the year, we focus on the 152 students who took both pre and post tests along with additional assessments during the year, providing a timeline of students' progress over the course of the year.

Results

This section presents findings from both the attitudinal and CT skills assessments conducted as part of this study. In the discussion that follows, we bring these two sets of findings together and reflect on the strategy of embedding CT in mathematics and science that we are investigating.

Attitudinal outcomes

One of our motivations for embedding CT in STEM is to address issues of students self-selecting into or out of elective computer science courses. As a result of our approach, all students enrolled in conventional science and mathematics classes are exposed to CT, thus addressing issues of low numbers of female and minority students taking computer science. Of the 549 students who took an assessment, 49% (271) self-identified as Hispanic, 37% (203) as African American, 15% (83) as white, and 10% (53) as Asian. Of this same sample, 52% were male while 48% were female. These breakdowns are representative of the larger student populations of the schools where these studies took place. The diversity of students taking our assessments and the equality with respect to the gender of students provides evidence that the approach of bringing CT into STEM classes is an effective way to introduce a broad and diverse set of students to CT.

Comparing the responses given on the pre survey between male and female students, we see disparities that match those reported in other studies on gender and STEM and computer science fields (Dryburgh, 2000; Stake & Nickens, 2005). Female students were significantly less interested in the STEM fields, felt CT was less important, and reported being less comfortable with computers than their male counterparts. When asked about interests in possible future professions, female students were significantly less interested in careers in computational sciences, engineering, mathematics, and computer science. Finally, female students were less confident in all 20 questions pertaining to CT in mathematics and scientific contexts. A portion of these results can be seen in Table 1.

Table 1. Average responses given on a 5-point Likert scale for questions on the pre-attitudinal survey.

Statement	Avg. Female Response	Avg. Male Response	T-Statistic
I think being a scientist is a possible career for me.	2.760	3.102	$t(474) = 3.099, p < .002$
I think being a mathematician is a possible career for me.	2.502	2.911	$t(474) = 3.717, p < .000$
I am interested in a career in engineering	1.747	2.711	$t(474) = 10.96, p < .000$
I am interested in a career in mathematics	1.755	2.077	$t(474) = 3.617, p < .000$
I am interested in a career in computer science	1.581	2.301	$t(474) = 8.326, p < .000$
Generally, I feel comfortable using computational tools.	3.297	3.610	$t(474) = 3.850, p < .000$
Generally, I feel comfortable working with computers.	3.799	4.130	$t(474) = 3.976, p < .000$
I am used to using computational tools.	3.079	3.463	$t(474) = 4.298, p < .000$
I am interested in learning more about computers.	3.188	3.715	$t(474) = 5.675, p < .000$
Computational thinking comes naturally to me.	2.913	3.260	$t(474) = 4.739, p < .000$

At the end of the school year, the attitudinal survey was re-administered to see if students' perceptions of and attitudes towards CT changed after being exposed to our CT in STEM activities. Responses in the post-test show significant gains on questions relating to interest in pursing careers in science $t(349) = 2.018$, $p < .05$, enjoyment related to using computational tools for schoolwork $t(439) = 2.905$, $p < .05$ and the learning benefits of doing so $t(349)=2.531$, $p < .01$. Most importantly, female students showed positive gains on 19 of the 20 questions pertaining to confidence in CT in STEM questions. This shift highlights the effectiveness of CT learning experiences situated within STEM for female students.

Skills assessment outcomes

A preliminary analysis of student responses shows no significant difference in performance between students based on gender. Looking at the subset of responses to our General CT in STEM skills assessment set that can be automatically scored, we see that the 161 females had an average score of 2.21 out of 5, while the 192 male students had an average score of 2.27 out of 5, a difference that is not statistically significant $t(352) = .377$, $p = .706$. This suggests at the outset of the year, there was no significant difference in CT aptitude by gender, which is especially interesting when taken together with the findings from the previous section showing that confidence differed significantly by gender.

When we look at how students perform on the post assessment compared to the pre assessment, we find no significant difference in the scores. These results were unexpected based on expectations from studies showing repeated encounters with learning technologies improving student comfort level and competencies (Delen & Bulut, 2011) and based on teacher feedback on student engagement and content learning from the CT activities in early pilot studies. As part of our program, we conduct post-implementation surveys, interviews and monitoring. Upon closer analysis, we realized that many of the participating teachers had not taught the minimum three required CT lessons in their courses that were expected as part of the program requirements and teaching agreement. Instead, many teachers taught only a single CT-enhanced lesson in their classrooms. Given this fact, it is less surprising that students did not have a lasting improvement over the course of the year from the single encounter with the practices we were assessing. The silver lining of this situation is that it gave us the ability to investigate the effects of repeated exposure to CT lessons. While the reasons for the lack of compliance varied across teachers and partner schools, and included various justifications and roadblocks ranging from personal to institutional, they served as a representative survey of challenges teachers face when incorporating computing resources into classes that historically have not relied on such technologies.

As we are investigating a whole school model where students are exposed to CT in difference classes and applied in multiple content areas, we are particularly interested in understanding how student who received multiple exposures to CT lessons performed. To examine the possible benefits of multiple exposures to CT in mathematics and science practices over the course of the school year, we look at student pre/post test gains broken down by the number of CT enhanced lessons each student encountered. Table 2 shows the results of this analysis. Students who were exposed to only a single CT event (1) regressed over the course of the year, showing no improvement; while students who were exposed to two CT lessons over the course of the year showed a small increase in their performance, but not at a significant level. In contrast to the first two categories, students who participated in three CT events showed positive gains on our CT in mathematics and science assessments. These findings suggest that the more CT enhanced lessons a student participated in, the larger the student gains between the pretest and posttest.

Table 2: Average student score by number of assessment events taken before the posttest. "1 CT Event" indicates that the student only took the pretest and the posttest with no other assessments.

	1 CT Lesson (N = 50)	**2 CT Lessons (N = 24)**	**3 CT Lessons (N = 77)**
Pretest	4.60	5.17	4.87
Posttest	3.78	5.21	5.12
Gain	-0.82	0.04	0.25

To validate this preliminary analysis, we ran a 2-way ANOVA with sex and number of events as independent variables. There was a significant main effect of event number with no interaction for posttest score ($p = 0.000$). There was also a marginally significant main effect of event number for gain (pretest / posttest difference) ($p = 0.066$). Bonferroni post-hoc tests revealed that students with two or three events performed significantly better on the posttest than students with one event ($p < 0.01$). However, for gains, only students with three events were marginally significantly better than students with one event ($p = 0.075$).

There are a number of potential explanations for this outcome. One possible way to explain this dosage effect is a time-on-task outcome. Students who spent longer working on CT enhanced mathematics and science activities performed better on the end-of-the-year post assessments. While this is a very plausible explanation and we would be happy with this outcome, the data suggests that there is more going on than just exposure, as the one and two CT event students show no significant gains. A second possible explanation is that the improved performance is not only due to seeing the material more frequently, but also due to being exposed to varied contexts in which the material is presented. For example, in a year-long physics course, learning and applying CT practices in lessons about electricity, projectile motion, and conservation of energy, might better support learners in developing deeper intuitions and a more flexible understanding of the widely applicable CT practices included in the lessons. Taken a step further, by having students engage with CT practices across both mathematics and science courses, and year-after-year, students' computational thinking abilities may further improve. The analysis of our 3rd year of this study provides positive indications of these hypotheses and we are currently designing a follow-up study that will give us the ability to more precisely study the impact of the embedded CT in mathematics and science approach, with the goal of more clearly being able to attribute these learning gains to the synergy of exposure across different STEM subject areas.

Discussion

With this work, we explore one possible strategy for introducing students to CT through the design of CT enhance activities designed to fit within existing mathematics and science classrooms. This approach seeks to bring CT to wide audiences while at the same time putting in-service teachers in positions to be successful by situating new CT concepts alongside familiar content. To date, this approach has been successful on both of those two fronts. As we show above, embedding CT in required classes enables us to reach all students, directly confronting issues of students self selecting into (or out of) computing learning opportunities. At the same time, the reaction from teachers to this project has been especially positive due to its timing in relation to the adoption of the Next Generation Science Standards, which includes CT as one of eight central scientific practices.

One of the more important findings from this work is the replication of previous findings that show females, on average, having lower confidence with respect to CT, paired with the finding that females show no difference in aptitude. The fact that female students at the start of the year were less confident with respect to computational practices as well as less interested in pursuing careers in computational fields speaks to the need to devise low-barrier entry points into computational learning experiences. This underscores the importance of bringing CT, and computational learning opportunities more broadly, into contexts where all students are present. Our approach of integrating CT with mandatory coursework is one such approach that is yielding positive results with respect to engaging all students in computational learning opportunities. Similarly, the results showing female students have increased confidence with respect to CT and a growth in interest in various computing and STEM careers shows this approach can be successful at cultivating a positive computational and scientific identity.

A second important outcome from this work is finding a dosage effect among students who had multiple exposures to CT enhanced STEM activities. While this could potentially be explained as time-on-task finding (i.e. students spending longer on a topic yield better results), we find the explanation that grounding CT learning experiences in diverse contexts across mathematic and scientific fields to be more compelling. Teasing apart exactly how much of the dosage effect gains can be accounted for by these two explanations is work we intend on pursuing in the future. Computational thinking as a set of practices is not bound to a specific content area, therefore, by having students employ these practices to various types of problems and in diverse content areas, we can reinforce the broad applicability of these skills while both providing students concrete contexts to employ them. This also provides opportunities for teachers to lead discussions and prompt for student reflection about the relationships between CT practices and the contexts in which they can be applied. Encountering multiple CT activities and repeated exposure to CT practices and tools not only reinforces the validity and broad utility of the computational strategies used by modern STEM professionals, but also provides learners with opportunities to become more comfortable and familiar with the tools themselves. Furthermore, our findings suggest that repeated exposure to CT activities is an effective instructional strategy for reinforcing student computational problem solving practices.

Bringing CT into high school classrooms not only provides an effective strategy for introducing diverse populations of learners to important 21st century skills, it also shifts perceptions of what it means to participate in modern mathematics and scientific endeavors. Showing that computation is not just a skillset reserved for those who seek to pursue computer science gives learners a more accurate view of what it means to practice contemporary mathematics and science. Furthermore, in showing the diverse applicability of both CT and computational tools, we can begin to shift how students view computing and how and when computation can be leveraged in pursuit of various goals. We are currently looking to extend the work we present here towards this goal by shifting from STEM to STEAM and looking at ways to bring computing into arts and humanities classes in the same way we have brought it into mathematics and science contexts. In broadening our approach in this direction, we seek to further demonstrate to students the diverse applicability of CT and show how professionals across a very diverse set of fields utilize computing in their work.

Conclusion

As computational methodologies, tools, and practices continue to drive scientific and mathematical discovery, it is becoming increasingly important for learners to understand how to interpret, and build on, findings that rely on such technologies. This is important not only for those students interested in pursuing careers in mathematics or scientific fields, but for all learners in order to participate in society as scientifically and mathematically, literate citizens. Over the last three years, we have been pursuing an approach to introduce high school learners to these critical computational thinking practices by designing CT enhanced lessons that fit within existing mathematics and science curricula. With this work, we show that this approach is effective at reaching diverse audiences and being easily adopted by in-service teachers. Further, we present data that reveals a dosage effect, showing that the more CT in mathematics and science activities learners are exposed to, the better they perform on our CT practices assessment. Our findings suggest that creating more activities, and finding more ways to enhance existing lesson plans with computational thinking practices, will further improve learners CT in mathematics and science abilities. Our hope is that through taking this approach, we can better prepare today's students for the computational future that await them.

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