Computational Thinking in Practice: How STEM Professionals Use CT in Their Work

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Introduction

Conducting scientific research without computing is now almost unthinkable. Due to recent advances in high-speed computation and analytical methods, science is becoming an increasingly computational endeavor. These advances have, in turn, created a growing need to educate students as future scientists, engineers, and mathematicians who understand how to make use of computational tools and methodologies to achieve scientific goals. Computational skills extend beyond programming to include a larger set of skills broadly captured by the concept of computational thinking (Wing, 2006). The importance of bringing computation to science education is particularly evident from the inclusion of “Computational Thinking Practices” in the Next Generation Science Standards (NGSS Lead States, 2013). To better understand the scope of computational thinking (CT) within STEM disciplines, we interviewed 17 professional STEM practitioners. The goal of this study was to identify the characteristic CT practices that are most important for STEM professionals across a range of disciplines. By interviewing scientists, the definition of CT in STEM is grounded in CT practices as they are used in the real world. In this way, we are drawing on a social-cultural research tradition that makes “a distinction between the laboratory, where cognition is studied in captivity, and into the everyday world, where human cognition adapts to its natural surroundings” (Hutchins, 1995, p. xiv). Similar projects have taken this approach for understanding CT among STEM professionals (Malyn-Smith & Lee, 2012). Our work extends this approach by emphasizing the implications of CT practices on shaping high school math and science classrooms.

Perspectives and Motivation

Though still a relatively young and emerging set of disciplines, computational sciences are now ubiquitous in all aspects of STEM professions (ACM/IEEE-CS Joint Task Force on Computing Curricula, 2013). STEM fields have seen a renaissance in experimental approaches primarily due to the availability of more powerful computers, accessibility of new analytical methods, and the development of highly detailed computational models in which a diverse array of components and mechanisms can be incorporated (Augustine, 2005). The advances in computing allow researchers across disciplines to envision new problem-solving strategies and to test new solutions in both the virtual and real world (Wing, 2006). These advances have in turn created a pressing need to educate students in computational methods and techniques to support the rapidly changing landscape of research across the STEM disciplines (Henderson, Cortina, & Wing, 2007, p. 195). Towards this end, a growing body of research has argued for, and documented success associated with, bringing computational thinking into science classrooms (Guzdial & Soloway, 2003; Hambrusch, et al., 2009; Jona et al., 2014; Sengupta et al., 2013; Wilensky, Brady, & Horn, 2014). The importance of CT practices and their role in education is becoming increasingly recognized (National Research Council, 2011), however, defining exactly what this skill is comprised of remains an open question (Grover & Pea, 2013). The goal of this study is to understand and define what constitutes computational thinking within STEM disciplines and what form it should take in school STEM classrooms. This study is part of our larger effort to prepare future generations of scientists by embedding CT into high school STEM curricular materials.

We addressed the challenge of defining computational thinking for STEM by creating a taxonomy consisting of 22 CT practices (Weintrop et al., 2016). In creating the first iteration of our taxonomy, we primarily drew on multiple resources including: (1) exemplary educational activities involving computational thinking in STEM; (2) existing concept inventories and standards documents and other computational thinking literature; and (3) feedback from other STEM researchers, teachers and curriculum developers, and STEM professionals whose work heavily relies on computation. Figure 1 shows our taxonomy broken down into four main categories: data practices, modeling and simulation practices, computational problem solving practices, and systems thinking practices. Each category is composed of a subset of five to seven practices. (Weintrop et al., 2016) reports our approach of infusing CT into STEM coursework and also presents our taxonomy along with detailed descriptions of each element of the taxonomy.

As the next phase of this study, we are currently in the process of refining and extending our taxonomy, drawing on multiple new resources. The two main resources for this process are: (1) data collected at schools where our CT activities and assessments have been implemented and tested over the past three years; and (2) interviews with STEM professionals whose work relies on computation. In this paper, we present findings from our interviews that inform the next iteration of our taxonomy. The goal of these interviews is to validate and improve the first iteration of our taxonomy and its emerging categories, as well as to provide supplemental data on the nature of computational thinking as it happens in authentic scientific settings.

Methods and Data Sources

To better understand the nature of CT practices in STEM disciplines, we conducted semi-structured clinical interviews with 17 STEM practitioners (5 females and 12 males). These interviews were carried out with 6 academic faculty from mathematics and science disciplines, 9 graduate students pursing degrees in STEM disciplines, one post-doctoral researcher, and one scientist from industry. The practitioners' expertise covered various STEM disciplines including physics and astronomy, biology, biochemistry, materials science, chemistry, computer science, earth and planetary sciences, and transportation engineering (see figure 3 for a breakdown of participants' STEM backgrounds). Seven of the 9 doctoral students were fellows in an NSF GK-12 program that linked STEM graduate students (who used computation in their research) with high school teachers to develop classroom-ready activities. These participants were particularly valuable as they had firsthand experience translating their CT practices into high school educational contexts.

The interview protocol included questions about participants' background, current program of research, the role of computers in their research, different computational challenges they faced in their work, and a discussion of the computational tools, simulation packages, and programming languages they relied on in their work. Each interview lasted approximately one hour and was video recorded, transcribed and coded by two researchers. We recruited the participants through referrals from STEM researchers and faculty in computational research.

In this paper, we focus on a subset of interview protocol to answer the following research question: *what CT practices are used in authentic scientific research settings*? To study this question, we coded the interviews and examined which of the CT practices included in the taxonomy are used in the interviewees' work. The findings from these interviews feed into our larger goal of defining what constitutes computational thinking within STEM disciplines to revise our taxonomy of CT practices (Weintrop et al., 2016).

Preliminary Findings and Discussion

Two researchers conducted an exhaustive coding of the interview transcripts in order to identify CT practices of our taxonomy. In this process, each researcher read through the transcripts and recorded lines with identified taxonomy elements. Here, we are only interested in studying CT practices used by STEM practitioners in their work and hence we focused on the portion of each interview where the interviewees described their current research. We did not log the instances in which taxonomy elements appeared in the interviewees' talk about previous research, research by colleagues, or their opinion about computational STEM research. For this subset of interview transcript, we found 494 instances of CT practices in total. Instead of counting the number of times each element of taxonomy was identified in one interview, we did a binary count of the practices for each interview. This made our analysis more robust considering the semi-structured nature of the interviews. The binary counts showed whether a certain taxonomy element appeared in one interview (1) or not (0).

Figure 2 illustrates a bar graph that summarizes the frequencies of all CT practices featured in the taxonomy. Each color corresponds to each taxonomy main category as shown in Figure 1 and the height of each bar shows in how many interviews the practice was identified. The graph shows that all elements in our taxonomy have been identified in the interviews, with the *analyzing data (da.4)* practice being identified in all 17 interviews (the most frequent practice) and the *communicating information about a system (st.4)* practice being identified in only 4 interviews (the least frequent practice). Moreover, the most frequent CT practice in each of the four categories are: *analyzing data (da.4)* in data practices (17 interviews); *using computational models to test and find solutions (ms.2)* in modeling and simulation practices (11 interviews); *programming (ps.2)* in computational problem solving practices (16 interviews); and *defining systems and managing complexity (st.5)* in systems thinking practices (10 interviews).

We then studied the identified codes with respect to the interviewees' field of research. We first grouped the interviewees' field of research into four disciplines: (1) physics, astrophysics, and earth sciences; (2) biology and chemistry; (3) computer science; and (4) engineering and materials science. Then, for each research discipline, we calculated the frequencies of practices identified in each taxonomy main categories. Figure 4 shows a bar graph that compares the percentages of CT practices among research disciplines. We found that each main category of CT practices is identified with approximately same percentage across different disciplines: around 30% use data analysis, 20% use modeling and simulation, 30-35% use computational problem solving, and 15-20% use systems thinking.

Moreover, we characterized the use of CT practices with respect to the role of computation in the interviewees' research. Here, we grouped interviewees' research into four categories: (1) purely computational research; (2) research that combines computation with experimentation; (3) research relying more on experimentation; and (4) purely theoretical research. Figure 5 illustrates the percentages of CT practices (in each taxonomy main category) that are used in different categories of research. We found that the use of *data practices* is more frequent for STEM researchers whose research relies more on experimentation than computation. Our findings also suggest that by increasing the role of computation in research, there is more use of *systems thinking practices* and *modeling and simulation practices*. Finally, we found that theoretical researchers mainly draw on *computational problem solving* practices in their work.

Conclusion

The overarching goal of this study is to bring current CT-infused STEM educational efforts in line with the increasingly computational nature of STEM research practices. Towards this end, we conducted interviews with STEM practitioners in various fields to understand the nature of computational thinking as it happens in authentic scientific research settings and to revisit and verify a first iteration of our definition of CT in form of a taxonomy. This exploration gives us greater insight into how scientists use computers in their everyday work and what CT practices are used in scientific research settings. The findings from these interviews help us identify what practices are important to include in high school math and science learning contexts. By understanding what modern science looks like in practice, and using that to inform the design of classroom activities, we can better prepare today's students for the modern STEM landscape that awaits them.

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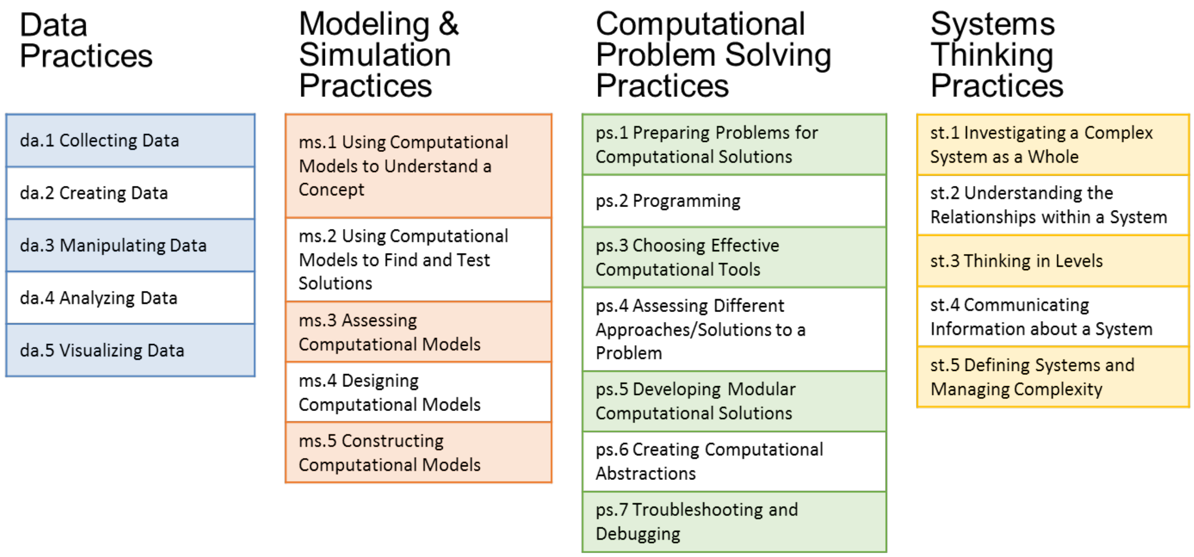

Figure 1. Computational thinking in mathematics and science taxonomy (Weintrop et al., 2016)

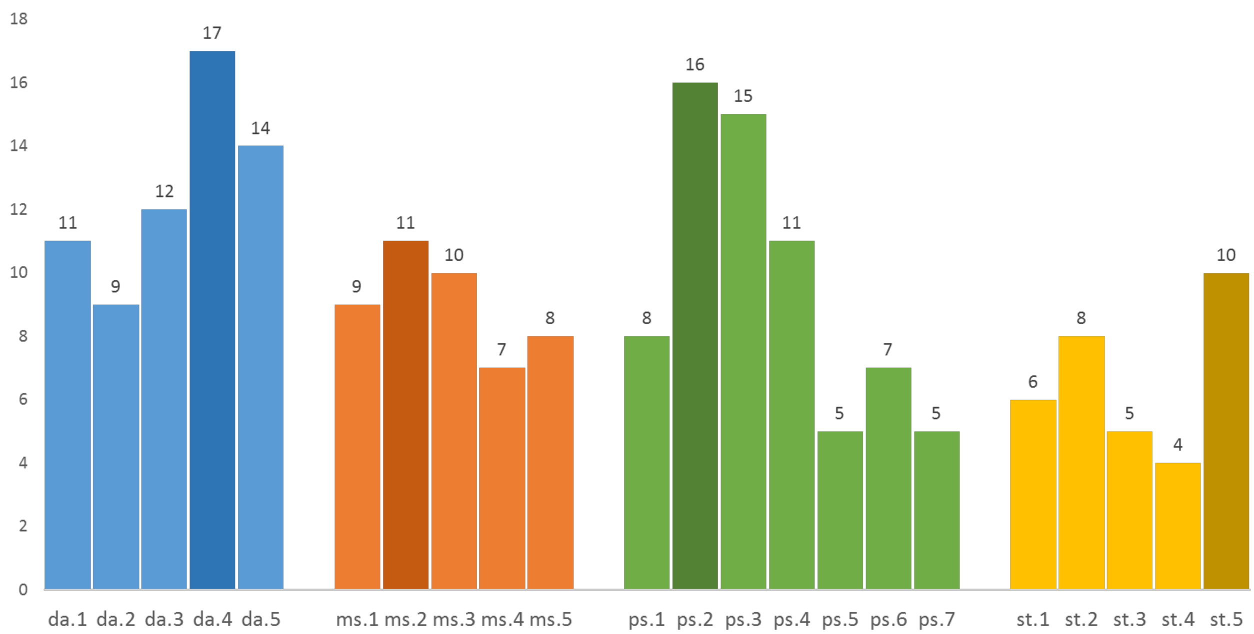

Figure 2. A bar graph illustrating the frequencies of all CT practices identified in the interviews. Each color corresponds to each taxonomy main category: data practices (blue); modeling and simulation practices (oranges); computational problem solving (green); and systems thinking (yellow). For each category, the most frequently observed practice is highlighted by a darker color.

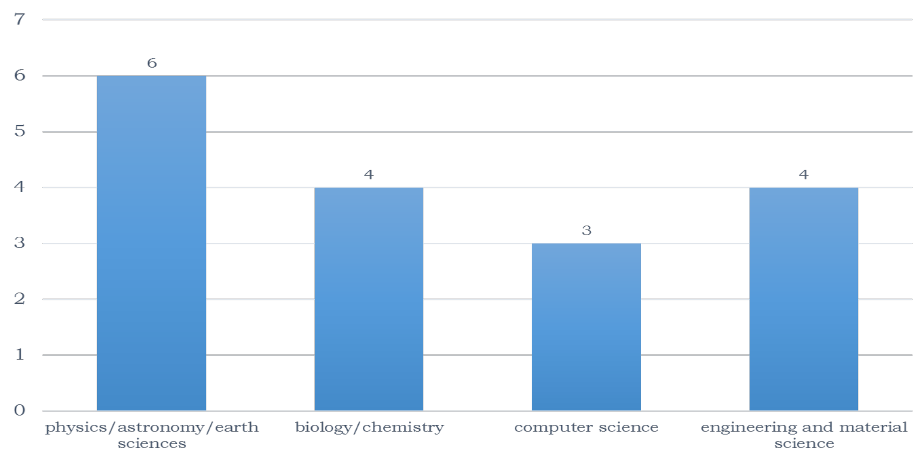

Figure 3. Breakdown of interviewees' backgrounds by STEM field

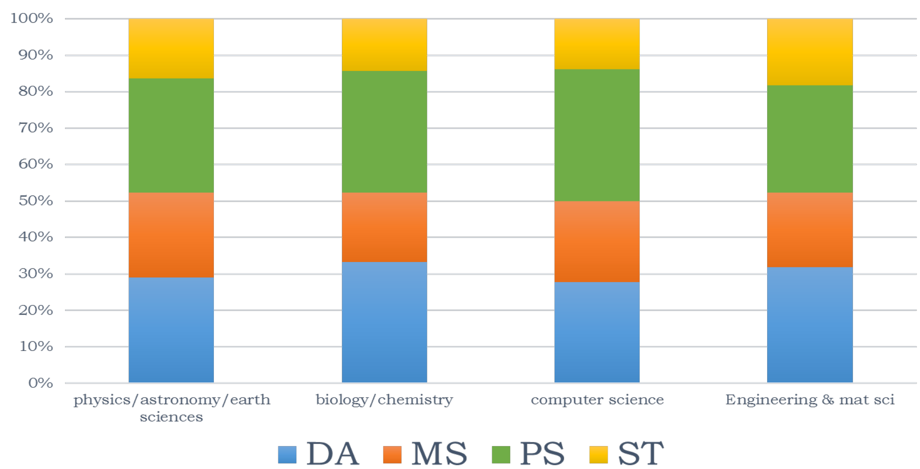

Figure 4. Breakdown of CT practices (in percentage) by interviewees' research disciplines.

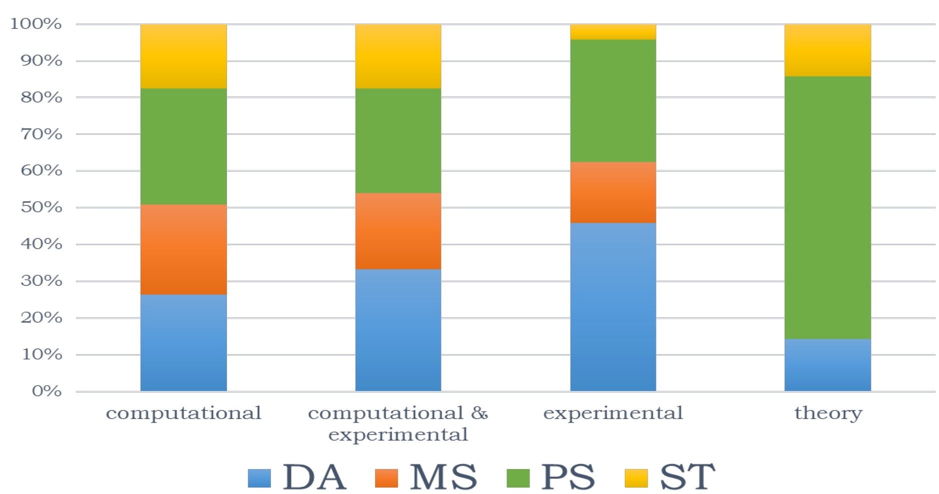

Figure 5. Breakdown of CT practices (in percentage) by interviewees' type of research with respect to the role of computation. DA: data practices; MS: modeling and simulation practices; PS: computational problem solving practices; and ST: systems thinking practices.