Integrating Computational Thinking into Middle School Science: A Search for Synergistic Pedagogy

Whitney Wall Bortz, Aakash Gautam, Kemper Lipscomb, and Deborah Tatar
Virginia Tech/Virginia Tech/University of Texas at Austin/Virginia Tech

Abstract

In recent years, Computational Thinking (CT) has gained status as an essential skill. With little room in K – 12 curricula for new content, an alternative method for providing students opportunities to develop these skills is to incorporate CT into classes that all students take. However, there is not enough research in this context to conclude that integrating CT with other domains truly does deepen learning in both areas. This paper highlights evidence that students *can* learn CT and science in tandem, particularly when pedagogy weaves the two domains into classroom tasks in complementary ways. We describe how the scientific practice of argumentation can act as a synergistic tool, engaging students with both science and CT within the same activity. Quantitative results of a pre/post performance assessment and qualitative analyses of student artifacts demonstrate that argumentation holds potential for simultaneously engaging students with science and CT.

Keywords

Computational Thinking, Science, K-12 Education, Argumentation, STEM, NetLogo

Introduction

As multiple professions now rely on a computationally literate workforce, many argue for providing students with opportunities to develop such skills early on[1,2]. However, integrating computational learning with that of other STEM content areas is relatively new terrain for educators, and new approaches to content require investigative work on the most effective pedagogical approaches in this new domain[3–5]. This paper adds to this conversation by highlighting a particular curricular approach in which scientific argumentation acts as a synergistic tool for the two domains of computational thinking (CT) and science. Through selected student work and data on learning gains, we demonstrate how this approach can help students to make connections between these two content areas and to apply their learning of the two in tandem on classroom tasks.

Integrated Computational Thinking

Starting with Wing's[6] description of *computational thinking* as the habits of mind associated with a computational approach to solving problems, a number of definitions have been proposed, many of which are characterized by lists of components or skills associated with CT[7–9]. While similarities and overlap exist across perspectives on CT, there is no single agreed-upon definition. Definitions of CT also overlap with conceptualizations of other types of thinking, such as a mathematical, engineering, critical, and creative thinking[10], all of which are considered "21st century skills" that should be incorporated into K – 12 learning[11]. Due to the lack of instructional space in K – 12 curricula, one approach to introducing students to CT is to provide opportunities for its development in the context of core disciplines that all students learn, such as in the case of this work, middle-school science. This not only alleviates the pressure on coveted instructional time, it also enhances the learning experience by presenting two domains in a mutually beneficial way. Such interdisciplinary approaches enhance opportunities for engagement with tasks that resemble real world problem solving[2]. Science, in particular, shares pedagogical overlap with CT[12], and the two disciplines are often used in tandem in computational science.

Argumentation

Our intervention included student-generated arguments for modifications made to NetLogo models. Netlogo is a multi-agent programmable modeling environment. Drawing inspiration from the argumentation session phase in Argument-Driven Inquiry[13], students utilized data, scientific core ideas, and CT modeling practices to formulate arguments about modifications made to their NetLogo models. These arguments included a justification of why each modification is valid based on a scientific idea, e.g. conservation of matter, or a CT modeling practice, e.g. abstraction and representation. They then presented these arguments to their peers for feedback, referred to as the "argumentation session"[13]. This phase of our intervention increased student engagement and interaction in interpreting the CT and science content. In this way, argumentation can be thought of as the "+" in CHEM+C.

The *CHEM+C* Approach

The *CHEM+C* intervention consists of three curricular modules, referred to as Computational Chemistry Tasks (CCTs). Each revolves around a simulation of chemistry concepts reported in literature as difficult to learn. Concepts are modeled in NetLogo[15], and include water forming and splitting, the aluminum copper sulfate reaction, and the carbon cycle. Each CCT follows a similar curricular sequence. Students experience an anchoring phenomenon[16], showcasing a chemical reaction. In groups, students then create whiteboards interpreting the chemical reaction observed. They then explore a different representation of the reaction, this time in a computer model. Students are encouraged to approach this simulation as a scientific investigation. In groups, they critique the computer model using a worksheet called a Design Component Chart (DCC), explained more in a later section. Discussions resulting from this activity help students negotiate a change that would improve the model's scientific accuracy. Scaffolded by the teacher, and by collaborating with peers, students then implement the improvement within the NetLogo code.

In the first CCT, all activities are guided by the question "What is happening in a chemical reaction that we do not normally see?" and are centered around the formation and splitting of water molecules. The anchoring phenomenon in this CCT is a physical demonstration of water splitting. To produce this reaction, a battery is submerged in a beaker of water, and a test tube is placed on top of each of the battery's terminals. Epsom Salt ($MgSO_4$) acts as a catalyst that leads to the splitting of water into hydrogen and oxygen, observed as bubbles released into the test tubes. The accompanying computer model simulates this reaction, as well as water forming, at the molecular level (Figure 1). This paper draws from data collected during this first CCT.

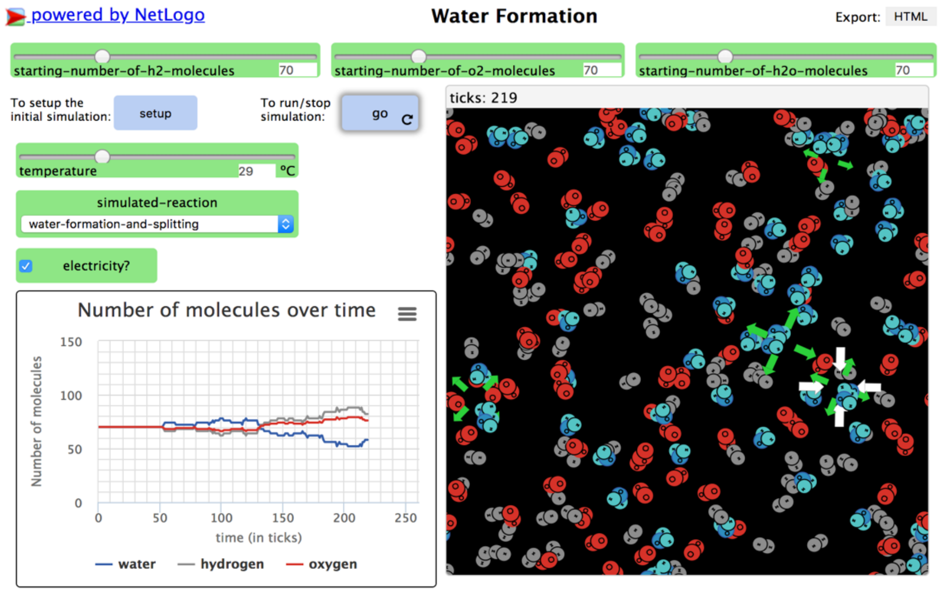


Figure 1. Screenshot of the NetLogo Simulation of Water Formation and Splitting

Data Sources and Analysis

Data analyzed represent the experiences of 180 students from 17 eighth-grade science classrooms in a low-to-moderate socio-economic-status (SES) public middle school in Texas. While this paper draws heavily from qualitative analyses of student-generated artifacts, we frame these within quantitative results from scores on a pre/post performance assessment consisting of tasks requiring applications of both science and CT. The student artifacts were generated during two classroom tasks that utilized argumentation. In the first classroom task, students completed DCCs, worksheets that asked which aspects of the simulation were scientifically accurate, inaccurate, or missing. Prior to working on the DCC, the students had explored the *NetLogo* simulation, and were given a "science fact sheet" describing key science concepts modeled in the simulation. Worksheet data were transcribed into excel and coded by two members of the research team. Of these coded excerpts, the first author selected 17 quotes that represented science and CT learning as complementary. All four authors discussed and analyzed quotes, narrowing the data for inclusion in this short paper to five quotes.

The second set of student artifacts analyzed were images of group generated white boards used by students to plan the change they would implement in the code in order to improve the model. Boards listed properties assigned to the object, $MgSO_4$ (Epsom Salt) that would be added. Groups provided a rationale for each property, presented these boards to the class, and received feedback from their peers. The first author selected ten images in which the groups' white board provided a clear rational for the object's properties. Three authors then discussed each image and collectively selected the four images that best represented synergistic use of science and CT learning to support their decisions. The following section describes our findings in detail.

Results

Results of the pre/post performance assessment suggested learning gains. Students could earn a maximum of 53 points on the assessment. A Mann Whitney U test indicated that overall summative post-test scores (Mdn= 18) were significantly ($p < 0.001$) greater than pre-test scores (Mdn= 4) with an effect size of 0.825. Still, the median score on the posttest suggested that students continued to struggle with the science and CT in this integrated context, and related pedagogical considerations are discussed elsewhere[17]. However, these learning gains supply only a partial picture of the effects of the potential of this intervention.

Qualitative analyses of classroom artifacts revealed that the activities utilizing argumentation afforded opportunities for students to apply CT and science learning in tandem. Table 1 presents selected responses from students on the DCCs. In this activity, students applied science knowledge in both interaction with and critique of the computer simulation, thus engaging in both science and CT. Critiquing the model required an understanding of how it worked and also an understanding of the science modeled. Weintrop et al.[18] proposed a taxonomy of applications of CT in mathematics and science instruction consisting four categories of practices: data practices, modeling and simulation practices, computational problem solving practices, and systems thinking practices. Table 1 links students' responses to particular CT practices from this taxonomy.

Furthermore, the artifacts contained evidence of students' "knowledge in pieces" (KiP)[19], fragmented ideas that have not yet been woven into a coherently integrated structure aligned to scientific truth. diSessa[20] asserts that articulating and encountering these ideas in multiple scientific contexts assists students with such construction. Furthermore, unveiling these ideas provides formative feedback to the teacher on how such ideas could be rewoven in order to promote deeper understanding of a concept[20].

Table 1. Students' Displays of Knowledge in their Judgements of the Model's Accuracy

Student Responses to "What is scientifically accurate about the model?"	**Highlighted CT practice from Weintrop et al.'s[18] taxonomy**	**Science "Knowledge in Pieces"[19]**
"The model properly shows that the temperature does affect the molecules because when the temperature is heated, the molecules move faster and collide often."	Systems Thinking: Understanding the Relationships within a System	Student observed that temperature affects molecules, and heat results in faster movement and more collision. (Student's understanding is incomplete, but contains fragments of scientific truth)
"The white arrows represent the molecules coming together, and I can choose if they come together by turning on the electricity."	Modeling and Simulation: Using Computational Models to Understand a Concept; Assessing Computational Models	Student determined that the white arrows indicate water forming. Also observed that electricity must be present for this to occur. (This reveals a partial understanding of the role of electricity in the chemical reaction)

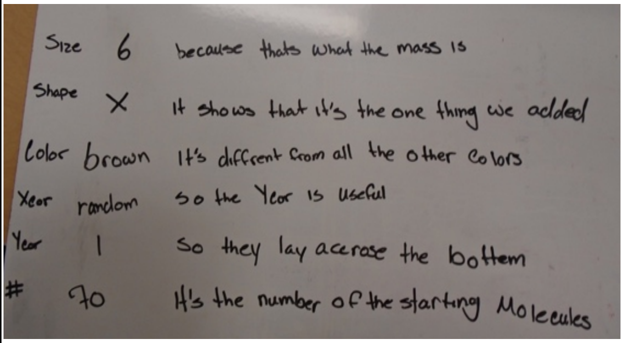
"When molecules collide, they don't always react, because on this simulation, molecules are colliding all over the place, but a chemical reaction doesn't occur."	Modeling and Simulation: Using Computational Models to Understand a Concept; Assessing Computational Models	Observation of collision without reaction affirmed student's prior knowledge that collision does not guarantee reaction.
"The speed the molecules are moving at by moving the temperature because we changed the temperature from hot to cold a lot."	Modeling and Simulation: Using Computational Models to Understand a Concept; Assessing Computational Models	Student utilized the controls in the models interface to systematically investigate how changing the conditions in the simulation affected the science modeled.
"2 H_2O forming, because in real life, they can only form in 2, not isolated."	Modeling and Simulation: Using Computational Models to Understand a Concept Systems Thinking: Understanding the Relationships within a System	Student connected the observed reactions in the simulation to the balanced equation for the formation of water, as two water molecules are present in the product.

Table 1 demonstrates how an activity requiring students to construct an argument engaged students in computational practices while also unveiling facets[21,22] of their science understanding, what diSessa calls KiPs[19].

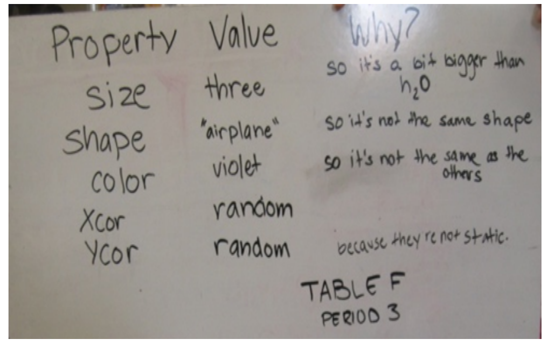
We found similar evidence of the role of argumentation in student-generated whiteboards. Figure 2 presents three examples of group white boards on which students listed chosen properties for the object to be added($MgSO_4$) and a rationale for each. In this activity, students used science to support these decisions. In accordance with Weintrop et al.'s[18] taxonomy, this activity engaged students in two key Computational Problem Solving Practices: "Choosing Effective Computational Tools" (using aspects of the simulation to explore), and "Creating Computational Abstractions". Here, students fuse understandings of both domains to choose computational objects that both accurately represent the science and also suit the computational system. Their boards provide their rationales.

In Example 2A, students allowed the number of atoms to dictate the molecule's size. While slightly different from the concept of *mass*, as their board states, we consider this KiP that lies on a trajectory toward a deeper understanding of the science. In Example 2B, students again considered the number of atoms which choosing size, and as a result, chose for $MgSO_4$ to appear bigger than H_2O. In addition, they set "xcor" and "ycor" (variables of position) as "random", suggesting engagement with concepts of Brownian motion[23].

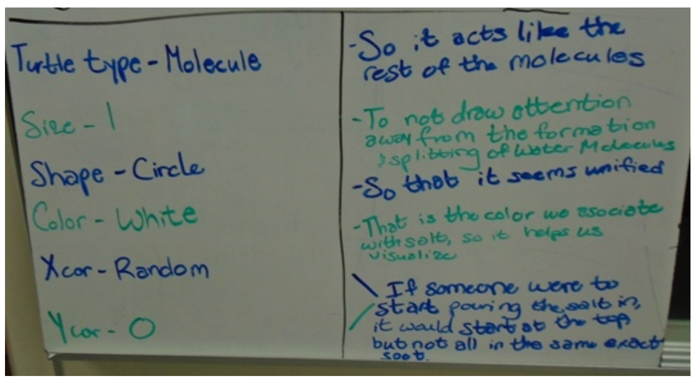
Example 2C shows an application of data abstraction by the students. They assigned this new molecule a "turtle type" (a data object type) of "molecule" so that it would "act like" the rest of the molecules. This demonstrated their understanding that established behaviors of other molecules in the code will now be abstracted to this new object, due to the kind of object that it is. An interesting diversion in this example from the others is that in spite of this molecule being larger in nature, the group chooses to make their $MgSO_4$ smaller than the other molecules. Their reasoning is that this foregrounds the scientific representation of the chemical reaction – a compromise similar to those made by actual scientists and computer scientists. Models prioritize representations of specific phenomena and cannot be expected to holistically represent scientific reality[24]. Therefore, these students demonstrated an understanding of two critical CT practices: abstraction and representation.



Example A: Students' choose the molecule's size based on the number of atoms in contains.



Example B: Students' positioning of objects reflects an understanding of molecular movement.



Example C: Students apply data abstraction in the assignment of turtle type. Their chosen molecule size prioritizes the main purpose of the model.

Figure 2. Student-Created Whiteboards Provide Rationale for Changes to the Simulation

Conclusions and Future Work

Integrating CT with other STEM areas is a relatively new practice, and investigations of whether integration is effective and best pedagogical approaches for doing so are ongoing. Our analyses reveal that student learning *can* occur simultaneously in CT and science, and infusing instruction with argumentation can play a role in the success of integration. Our examples show students drawing upon understandings of science while exploring and critiquing a computer simulation. We also observed students making decisions about computational modeling that were driven by both CT and science. Whether nascent or sophisticated, students' articulated understandings of the science through such classroom tasks show components of KiP. Articulating ideas can deepen learning on its own, but this also generates formative feedback for the teacher. Moreover, argumentation may also be useful to the integration of other "21st century skills", such as engineering thinking, and we encourage further research on the synergistic use of this pedagogical strategy.

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Whitney Wall Bortz

Dr. Bortz is a former K – 12 mathematics teacher whose research focuses on STEM education and assessment in both K – 12 and higher education. She holds a Ph.D. in Education from Queen's University in Belfast. She is currently a Postdoctoral Research Fellow at Virginia Tech where she works on two NSF-funded projects. Alongside colleagues in computer science, she has investigated the integration of computational thinking into science education. In the Department of Engineering Education she works with a team looking at funding models in STEM graduate programs and related experiences and career outcomes of graduate students.

Aakash Gautam

Aakash is a graduate student at Virginia Tech. A part of his research involves collaborating with teachers to design educational technology systems that facilitate teaching practices with the focus on improving interactions with students.

Kemper Lipscomb

Kemper Lipscomb is a PhD candidate in STEM education at the University of Texas at Austin and a former K-12 science teacher. Her research examines how students investigate and explain scientific phenomenon. Her current work focuses on students' participation in modeling, computational thinking, and argumentation practices in the context of collaborative scientific investigations. She has published articles and books relating to these issues. She assists in teaching science and science education courses at the undergraduate level, with a teaching philosophy rooted in theories of learning that stress the importance of shared experience, collaboration, and metacognition.

Deborah Tatar

Deborah Tatar (Ph.D. Psychology, Stanford) is Professor of Computer Science and, by courtesy, Psychology at Virginia Tech. Previously, she was a Cognitive Scientist at the Center for Technology in Learning at SRI International, a member of the research staff at Xerox PARC and a Senior Software Engineer at Digital Equipment Corporation. Her research is concerned with the integration of technology into face-to-face contexts, especially middle school classrooms. Her focus has been on mathematics and science but always prioritizes interpersonal interaction and the ability of the teacher to operate effectively in the environment. She was the Principle Investigator on the CHEM+C project.