# Characterizing Computational Thinking in High School Science

**Abstract:** This study identified students' computational thinking (CT) practices and the relationships between their practices-in-use. More specifically, the study explored the CT practices that emerged as a result of students' participation in a two-day high school biology unit featuring exploration of a computational model on predator-prey dynamics. Digitally recorded data were taken from seventy-six students across four classes of one teacher. By applying a grounded analysis to students' written responses to two different assessment items embedded within the unit, we found four practices related to *identifying a model's limitations* and eight practices related to *exploring the model*. Applying a network analysis to responses coded for these practices, we found networks representing common patterns of practices-in-use. This work identifies the informal CT practices that students bring to their learning and models combinations of practices-in-use with varying degrees of complexity.

## Introduction

In recent decades, computational thinking (CT) has become critical in a variety of mathematical and scientific fields (Bailey & Borwein, 2011; Foster, 2006). In turn, STEM education communities have recognized the importance of integrating computation into school curricula (Quinn, Schweingruber, & Keller, 2012; Wilensky, Brady & Horn, 2014). However, computation still remains a separate area of study in most K-12 contexts. Because of this separation, students from groups that have been historically underrepresented in computational fields, such as women and racial minorities (Margolis, 2008; Margolis & Fisher, 2003), are less likely to be exposed to authentic CT practices. Integrating CT into the context of science not only gives all students access to a more authentic image of science, it also increases access to powerful modes of thinking and marketable skills for many careers (Levy & Murnane, 2004).

For these reasons, we believe that integrating CT practices into K-12 STEM curricula is critical for 21st century education. Our group has worked to create curriculum and assessments that develop and evaluate CT practices in the context of STEM content. In the present report, we document and characterize the CT practices in which students engaged as a result of their participation in one of our computationally-enriched science units. We then explore particular combinations of practices the students used synergistically in order to address tasks within the unit.

## Theoretical Framework

Our perspective on computational thinking is motivated by Wilensky and Papert's (2010) Restructuration Theory, which demonstrates that the representational form in which knowledge is embodied significantly influences how it may be understood. Restructuration Theory builds on a long history of psychological and historical research that has argued that representational forms shape human knowledge and understanding, both at the individual and societal level (e.g., Goody, 1977; Olson, 1994; diSessa, 2001). In light of this theory, we argue that the representational affordances of computational tools are changing the way knowledge can be constructed, expressed, and understood across disciplines. However, the character of computational thinking is not yet well understood, nor is how to create curricula and assessments that develop and measure these practices (Grover & Pea, 2013).

Our group addressed a small slice of the challenge and characterized the nature of computational thinking in the STEM disciplines. On the basis of interviews with computational STEM researchers, we developed an operational definition of computational thinking as a set of practices and organized these in the form of a taxonomy (Anonymous, 2015). The taxonomy categorizes CT practices in STEM in terms of four major strands: *Data Practices*, *Modeling and Simulation Practices*, *Computational Problem-Solving Practices*, and *Systems Thinking Practices*. We have since used this taxonomy to inform our development of learning objectives, curricula, and assessments that foster and evaluate students' development of computational thinking practices in STEM subjects at the high school level.

The taxonomy outlines CT practices we hope students will develop. It informs our design of curriculum and assessment by establishing explicit learning objectives. When designing curriculum, it is also important to consider the prior knowledge students bring to their learning. diSessa (1993) has argued that students develop more expert knowledge through the reorganization and refinement of prior knowledge. He further argued that knowledge is a complex system of smaller elements. In the novice knowledge system, elements are loosely interconnected and cued variously for sense-making depending on context. In the expert knowledge system, elements are more reliably connected and cued more consistently in contexts where they are productive. Learning (and the transition from novice to expert) occurs through the reorganization and refinement of the networks of elements in the knowledge system. The novice knowledge system is therefore viewed as a resource rich with potentially productive building blocks for the construction of more expert knowledge networks. Research within the KiP program has documented elements of naïve knowledge in a variety of forms including (but not limited to) intuitions for why things work the way they do (diSessa, 1993), naïve epistemologies (Hammer & Elby, 2002), and competencies for representational practices (diSessa & Sherin, 2000).

Such networks of novice and expert knowledge systems can be visualized and analyzed through network analysis tools. In general, network analyses trace the flow of information, uncover prominent patterns in networks, and detect the effects of such patterns. In social network analysis, for example, researchers examine patterns among people's interactions, where the nodes of the network represent people and links among the nodes represent how strongly certain people are connected (Freeman, 2006). To measure connections among CT practices, however, the nodes do not represent people, but rather represent the knowledge and skills of one individual. These nodes are essentially elements identified in discourse (e.g. written documents, conversations, or actions). The links in this type of network represent the individual's associations between nodes, or to what extent the different elements work alongside each other. In effect, this creates a discourse network that allows us to analyze the connections among CT practices.

One tool for developing such discourse networks is *Epistemic network analysis* (ENA) (Shaffer et al., 2009; Shaffer, Collier, & Ruis, 2016; Shaffer & Ruis, 2017). ENA measures when and how often students make links between domain-relevant elements during their work. It accomplishes this by measuring the co-occurrences of discourse elements and representing them in weighted network models–meaning when someone repeatedly makes a link between elements, the weight of the link between those elements is greater. Furthermore, ENA enables researchers to compare networks both visually and through summary statistics that reflect the weighted structure of connections (Collier, Ruis, & Shaffer, 2016). Thus, researchers can use ENA to not only model discourse networks, but also quantitatively compare the discourse networks of various individuals and groups of people.

In this study, we take a KiP lens to students' activity in the context of our curriculum and chart the space of the informal computational thinking practices in which they engage. We then use ENA to model the relationships between students' practices in the context of instructional tasks. The specific research questions we address are: (1) What is the character of students' CT practices that emerge in the context of one curricular unit? and (2) How are the practices connected when students use them to accomplish a particular task within the unit?

## Methods

We approached our research questions by analyzing data from the fifth iteration of a design-based research cycle (Collins, Joseph, Bielaczyc, 2004). The implementation spanned the 2016-2017 school year and was tested in eight classrooms across three partner high schools in a large Midwestern city. Over the course of the school year, students ranging from grades 9 – 12, participated in three CT science units, each unit approximately two days in length. In order to understand the character and connectedness of CT practices that students enacted in our curricular units, we conducted a fine-grained analysis of a smaller sample of student work produced in the context of a single high school biology unit which focused on predator-prey dynamics and ecosystem stability. For this preliminary analysis, we chose to investigate the work of the students belonging to one participating biology teacher.

### Unit Description

The ecosystem stability unit is a 2-hour unit designed to engage students in CT practices within the *Modeling and Simulation* strand of our taxonomy in the context of traditional biology content. For this unit, students explored population dynamics in a NetLogo (Wilensky, 1999) simulation of an ecosystem consisting of three organisms (grass, sheep, and wolves) (Wilensky, 1997). Students investigated the population-level effects of parameters for individual organisms (such as initial population and reproduction rate) by running the simulation with different values for each organism. Through their exploration, the students learned about the complex population dynamics that emerge from the interactions between individual organisms. In this way, students both learned about factors affecting the balance of an ecosystem and developed practices related to using and assessing computational models (e.g. *exploring a model by changing parameters*; *identifying simplifications made by a model*).

### Participants and Data Collection

The unit was implemented during the fall of 2016 in the five regular biology classes of Ms. Buckthorn, a 9$^{th}$ grade biology teacher at Greenboro High School. Seventy-six 9$^{th}$ grade students participated in the unit. Ms. Buckthorn's students were representative of the students at Greenboro (44% White, 29.4% Black, 18% Hispanic, 5.6% Asian, 2.4% Native American, Pacific Islander, or Bi-Racial; 40.5% low-income; 4.2% English Learners; 12% IEP students).

Data were collected in the form of student responses to assessment items embedded in the curricular unit. Student responses to two particular prompts were coded for this analysis. The first prompt was "*Describe 3 limitations of using a model like this to make predictions about what could happen in the real world*." This prompt was designed to engage students in CT practices related to *identifying the simplifications made by a model*, a practice within the *Modeling and Simulation* strand of the taxonomy. These practices are important to students' epistemological development, as they relate to their understanding of a computational model as a tool that is both powerful and limited with regards to the construction of new knowledge.

The second prompt followed a challenge that asked students to adjust parameters to stabilize the system (i.e., keep both the wolf and sheep populations from going extinct). This prompt had two parts: "*Which specific variable(s) did you change and how did you change them?*" and "*Explain why you made these changes. How do you think these changes helped to stabilize the ecosystem?*" It was designed to engage students in CT practices related to *exploring a model by changing parameters*, a practice also organized within the *Modeling and Simulation* strand of the taxonomy. These are very basic practices but they play an important role in students' (and scientists') abilities to learn about the relationship between particular parameters and system behavior at the macro-level.

We addressed our first research question by using a qualitative approach to characterize the nature of students' CT practices. We addressed our second research question by using a quantitative approach to explore the relationships between these practices. We began by applying a grounded analysis to students' written responses to identify and characterize their CT practices within the *Modeling and Simulation* strand of the taxonomy under the general practice *identifying model limitations* or *exploring a model by changing parameters*. We used these practices as the basis of coding schemes which we applied to student responses to the two questions from the curricular unit. Two researchers coded a subset of ten student responses from the data as a training set and calculated their inter-rater reliability using Cohen's Kappa. If the researchers had a kappa higher than .60, they split the dataset and coded the remainder of the responses. Cohen's Kappa statistics are reported in the findings for each code below.

In order to quantify the connections between practices-in-use, we used Epistemic Network Analysis (ENA). In this context, ENA essentially measures when and how often students make connections between CT practices during their work by measuring the co-occurrences of these practices. The co-occurrences are then represented as a weighted network model where the nodes represent the coded practices and the links represent whether or not these practices co-occur. The network representation allows for an examination of two aspects of student work: (1) the density of the networks, which shows how many connections a student is making and thus, how broadly they are able to connect practices and (2) the thickness of the links, which tells us what types of connections students are making more frequently than others. Additionally, ENA allows for the comparison among multiple student networks because it fixes each practice in the same Cartesian space for all students. The location of each node is determined by a singular value decomposition (SVD) and an optimization routine that minimizes the distance between the centroid of the network representation and the projected point that represents the network under the SVD rotation. Although ENA also provides other features such as an interpretable multi-dimensional projection space and offers a variety of confirmatory statistical analyses, in this study, we used only the basic weighted network topology to conduct an exploratory analysis of the various student patterns of CT practices-in-use.

## Findings

Our findings focus on students' CT practices for *identifying model limitations* and *exploring a model by changing parameters*. We present our findings for research question 1 by characterizing student CT practices. We then present our findings for research question 2 by exploring the connections between practices-in-use.

### Research Question 1: Characterizing Student CT Practices

Through a grounded analysis, our team identified four CT practices relevant to *identifying the limitations of a model* in students' responses to prompt 1: "*Describe 3 limitations of using a model like this to make predictions about what could happen in the real world*." We identified eight CT practices relevant to *exploring a model by changing parameters* in students' responses to prompt 2: "*Which specific variable(s) did you change and how did you change them*? *Explain why you made these changes. How do you think these changes helped to stabilize the ecosystem*?" We present these CT practices and characterize and illustrate each with examples from the data.

## Identifying Model Limitations

**Identifying general limitations.** Thirty-six students (47%, Cohen's Kappa = .61) addressed prompt 1 by noting general inaccuracies or missing factors as limitations of the model. For example, one student wrote: "This model may not be accurate, and it does not factor in outside variables." This suggests these students are aware that the wolf-sheep model is an approximation of reality, but they have not engaged in careful thinking to identify particular inaccuracies or missing factors.

**Identifying visual representational limitations.** Nine students (11%, Cohen's Kappa = 1) noted visual inaccuracies as limitations of the model. One student wrote: "It isn't 3-D." This suggests that these students understand that the model is not an accurate depiction of reality. The model used presented a 2-D projection of the environment which is certainly an approximation of the true reality. However, this is not a "meaningful" limitation compared to other limitations that students mentioned, as in this case, this approximation does not influence the interactions between the elements of the model and therefore does not influence the outcome of any given simulation trial. In other words, wolf and sheep are confined to movement about the Cartesian plane and the addition of a third dimension would not influence any outcomes of this model.

**Identifying completeness limitations.** Forty-five students (60%, Cohen's Kappa = .65) offered specific elements or factors that were missing from the model. One student listed three missing or incomplete aspects of the model: "1. You only have two animals, 2. You don't have an entire country, 3. You only have one thing a sheep can eat." These students recognize that the wolf-sheep model is an approximation of reality. They have compared it with the real world and identified factors that are found in the real world but missing from the model. It is probable they believe these factors are somehow important to the model and would change the outcome of a simulation trial. Limitations such as these are important for scientists to identify, because they help them interpret their results and recognize their limitations.

**Identifying procedural limitations.** Ten students (13%, Cohen's Kappa = .75) noted differences between the interactions or behaviors encoded in the model and those they expected to find in the real world. One student wrote: "The moving of the animals is random, they run out of energy which isn't very similar to the real world, the real world is unpredictable." Limitations such as this are extremely important for scientists to recognize, as they are related to how successful the model is at approximating reality. Procedural limitations of the model influence the outcome of a simulation run in an important way: if the simulation does not reproduce patterns found in real-world data, something about the encoded theoretical model is *wrong* and needs to be revised.

## Exploring a Model by Changing Parameters

**Varying a parameter.** Sixty-eight students (92%, Cohen's Kappa = 1) noted the specific parameters they changed. One student wrote: "We changed every single variable until we found the closest one until the sheep kept spiking so we changed the reproduction rate and they became more balanced." It is not surprising that so many students engaged in this practice, as they were directly prompted by the lesson to do so. Tinkering with a model by varying parameters is, however, an activity fundamental to exploring a model.

**Testing a parameter.** Forty-six (62%, Cohen's Kappa = 1) students noted the range of values (or specific values) they tried for different parameters. One student wrote: "We changed both sheep and wolf reproduction, sheep reproduction from 4% to 3%, and wolf reproduction from 4% to 9%. We changed the initial wolf population from 50 to 55. We changed the wolf gain from food from 20 to 25." This is evidence that they tested specific parameter values. This is a more particular instantiation of varying a parameter that the student executes with perhaps greater intentionality (e.g., they might intend to investigate the relationship between a parameter and system behavior by comparing extremes). This is a more systematic approach to exploring a model than a tinkering approach.

**Describing effects qualitatively.** Forty-nine students (66%, Cohen's Kappa = 1) qualitatively described how the system responded when they changed particular parameters. One student wrote: "These changes, such as raising the reproduction rate of wolves grew the wolf population and by result lowered the sheep population." It is important to attend to outcomes of the simulation when tinkering with or testing parameters, in order to notice relationships between cause and effect. Simple qualitative characterizations of the relationships within a system are a foundation for constructing more detailed or mathematical relationships. A simple qualitative almost gestalt understanding of a cause-effect relationship can be a powerful tool for reasoning about system dynamics and for conveying the big ideas about the relationships within a system to others (in the scientific world these "others" might be collaborators or members of the scientific community at-large).

**Describing effects quantitatively.** Six students (8%, Cohen's Kappa = 1) included quantitative information from the simulation when describing how the system responded to their changes to parameters. One student wrote: "I lowered the reproduction rates of both wolves and sheep to 1%. I started with 90 sheep and 50 wolves. The sheep had 2 for their gain from food and the wolves had 40." This suggests that these students were attending to particular evidence in the data and trying to describe the relationships they saw in a more precise and mathematical way. Note that while this practice is similar to "Testing a parameter," it requires students to attend to model outcomes, not just input parameters.

**Describing the evolution of a system over time.** Ten students (14%, Cohen's Kappa = 1) described how the system progressed over time. One student wrote: "I actually didn't change anything and just clicked go, after watching the graph and the animation for 884 ticks it seemed to be stable, grass goes up sheep begin to go up, sheep go up wolves go up. grass goes down sheep go down and wolves will go down too." This is an important part of exploring a simulation: letting it run and observing how it changes over time. Complex systems such as the one represented by this ecosystem model, are dynamic systems–they exhibit patterns of change over time. Important changes can only be observed if simulations are run over a long enough period, and describing behavior as it changes over time can lead to recognizing important patterns.

**Explaining reasoning.** Forty-nine students (66%, Cohen's Kappa = .60) provided explanations for why changing a particular parameter resulted in a system outcome. One student wrote: "I made these changes because the sheep population was growing too large. This caused the wolf to eat more, then reproduce more. Then eventually the sheep would die off, causing the wolfs to die off." Explanations such as this convey the students' reasoning and suggest that they are not only attending to cause and effect, but that they are going one step further and trying to make sense of the relationship between cause and effect – a fundamental activity of science.

**Strategizing.** Thirty-nine students (53%, Cohen's Kappa = .74) wrote responses that showed evidence of goal-directed or planned behavior. One student wrote: "I changed the reproduction rate because the wolves started to spike so I figured the wolf reproduction was too high." This suggests the student was drawing on a hypothesis about the relationship between reproduction rate and population size to make decisions about changing parameters, strategically.

**Comparing across multiple trials.** Fourteen students (19%, Cohen's Kappa = .62) gave responses that were evidence they ran the simulation over multiple trials and compared results across those. One student wrote: "I changed the reproduction rate for each organism and changed the initial amount of each. It was difficult to get the things exactly right but I got close my closest was 228 ticks." When exploring a model to learn more about the dynamics of, or test a hypothesis regarding, a complex system, it is important to observe more than one simulation run. This is because complex systems are inherently random and the results of changing a parameter vary over different simulation trials. A pattern of cause-effect relationships will hover around an average tendency, but this average tendency may not be exactly embodied in one (or several) simulation trials. So, if a student only runs one trial, they may have a misguided impression of a pattern in system behavior. It is also a good idea to run multiple trials in order to systematically compare the effects of different parameter values on system behavior.

## Research Question 2: Exploring Connections Between CT Practices

Using ENA, our team identified the most frequent and most sophisticated individual student networks of CT practices using students' responses to prompt 1 and prompt 2. To answer research question 2, we characterize and exemplify each network of students' CT practices with data.

### Identifying Model Limitations

The first question asked students: "*Describe 3 limitations of using a model like this to make predictions about what could happen in the real world*." Thirty-nine students (53%) had discourse networks which consisted of zero connections (not pictured). Eleven students (15%) had discourse networks which consisted of one link between General Issues and Completeness (Figure 1). We interpreted a link between General Issues and Completeness as a student claiming the model was incomplete and then listing general issues related to a lack of completeness. For example, one student responded, "In the real world there are more variables like day to day weather, other predators, hunters and so many other things that could affect their habitat." This student claimed the model was incomplete ("In the real world there are more variables like day to day weather...") and concluded with a general statement ("...and so many other things that could affect their habitat.").

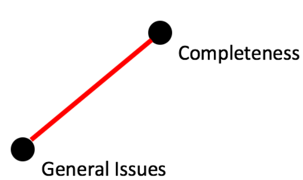

Figure 1. The second most frequently occurring discourse network for prompt 1 which consists of one connection between General Issues (Identifying general limitations) and Completeness (Identifying completeness limitations). Nine students had this network.

Of the remaining students, two had the most connected and most sophisticated network which consisted of links among General Issues, Completeness, and Procedural Limitations (Figure 2). For example, one student provided a variety of limitations of the model: "Nature isn't a perfect system so it won't be completely accurate. There is more than one type of predator and more than one type of prey. Weather isn't taken into account in this model." This student identified procedural limitations ("Nature isn't a perfect system"), provided a general statement related to such procedural limitations ("so it won't be completely accurate"), and then claimed that the model was incomplete ("There is more than one type of predator and more than one type of prey. Weather isn't taken into account").

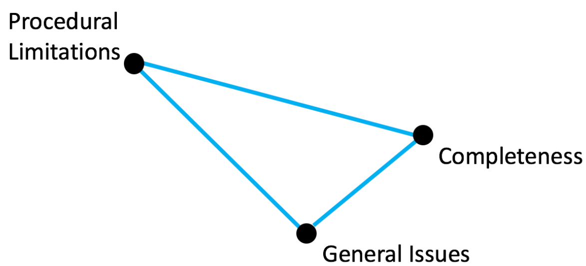


Figure 2. The discourse network with the most connections for prompt 1 which consists of connections among General Issues (Identifying general limitations), Completeness (Identifying completeness limitations), and Procedural Limitations (Identifying procedural limitations). Two students had this network.

### Exploring a Model by Changing Parameters

This question had two parts and asked students: "*Which specific variable(s) did you change and how did you change them?*" and "*Explain why you made these changes. How do you think these changes helped to stabilize the ecosystem?*" Ten students (13%) had discourse networks which consisted of zero connections (not pictured). Eight students (11%) had discourse networks which consisted of one link between Varying Parameters and Testing Parameters (Figure 3). For these eight students, this link occurred in the first part of the question; these students did not make any links in the second question. We interpreted a link between Varying Parameters and Testing Parameters as being able to vary parameters and then provide specific values for testing. For example, one student responded, "the variables that we changed was the grass regrowth time to 50" which coded for both Varying Parameters and Testing Parameters. For the second part of the question, the same student responded, "Because the grass is like the most important part to keep the system alive," which did not contain any co-occurrence of codes and thus, did not appear in the network representation.

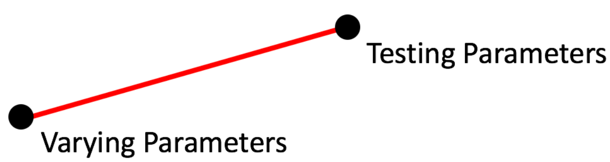


Figure 3. The most frequently occurring discourse network for Q2 which consists of one connection between Varying Parameters (Varying a parameter) and Testing Parameters (Testing a parameter). Eight students had this network.

Out of the remaining students, one had the most connected and most sophisticated network which consisted of links among Comparison, Reasoning, Describing Effects Qualitatively, Strategy, Varying Parameters, and Testing Parameters (Figure 4). This student linked between Varying Parameters and Testing Parameters in the first part of the question. In the second part of the question, the student again connected between Varying Parameters and Testing Parameters (which is why this link is thicker in the network representation), but also added Comparison, Reasoning, Describing Effects Qualitatively, and Strategy. The student's response to the first part was, "I changed the initial number of sheep to 150 and the initial number of wolves to 75," and his response to the second part was "I made these changes from trial and error. I switched them so that the wolves and sheep wouldn't die out so quickly, so giving them a greater initial population helped, while the reproduction percentage kept the populations balanced." The student explained the use of a "trial and error" strategy "so that the wolves and sheep wouldn't die out so quickly," which was a qualitative description of the effects and a comparison of the predator and prey populations. The student's reasoning for those actions were that "a greater initial population helped, while the reproduction percentage kept the populations balanced."

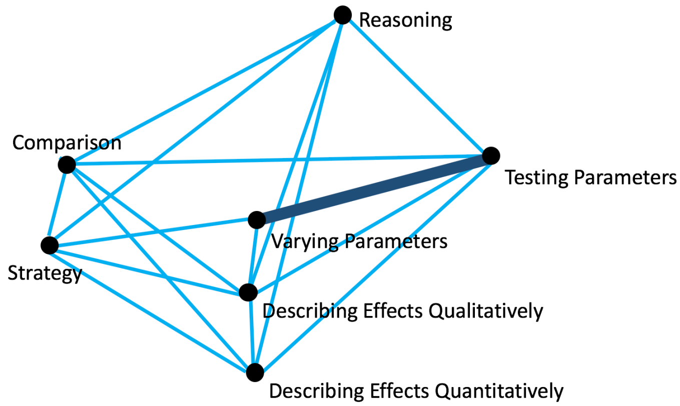


Figure 4. The network with the most connections for prompt 2 which consists of connections among Comparison (Comparing across multiple trials), Reasoning (Explaining reasoning), Describing Effects Qualitatively, Strategy (Strategizing), Varying Parameters (Varying a parameter), and Testing Parameters (Testing a parameter). Only one student had this network.

## Discussion

In this study, we examined student responses to two prompts given in one CT science unit which introduced students to predator-prey dynamics through exploration of computational models. Through a grounded analysis, we identified emergent student CT practices and classified them within the *Modeling and Simulation* strand of our theoretical taxonomy of CT practices in STEM. We then analyzed patterns of co-occurrences of these practices-in-use and represented these co-occurrences as discourse networks using ENA. Such networks allowed us to shed light on characterizing student CT practices in terms of the relationships among students' CT practices-in-use and varying levels of expertise regarding their synergistic use. Our results showed that students brought a variety of informal CT practices to accomplishing tasks within a computational biology unit and that they drew on multiple practices while working on particular tasks within the predator-prey unit.

We found that students engaged in practices relevant to *identifying model limitations*, including identifying general, representational, completeness and procedural limitations. We found that the majority of students noted general model limitations and missing elements, while very few students noted inaccuracies regarding visual representations or inconsistencies between the behavior of model elements and that of their real-world counterparts. We found that students engaged in practices relevant to *exploring a computational model*. These practices included varying parameters by tinkering, testing particular parameters, describing the effects of changing parameters in both qualitative and quantitative terms, describing the evolution of a model over time, explaining their reasoning for a system's behavior in response to changing a parameter, approaching their exploration of a model strategically, and comparing simulation results across multiple trials. All students varied parameters and most tested specific parameters. The majority of students qualitatively described the relationship between changing a parameter and its effect on the system behavior and explained their reasoning for why the cause-effect relationship made sense. A majority of students also showed evidence of approaching their exploration of the model strategically. Taken together, these findings suggest that participating students brought many informal practices to their learning that can be developed into more sophisticated CT practices (Smith, diSessa & Roschelle, 1994).

Our network analysis revealed a range of complexity in students' patterns of practices-in-use, from students who drew on very few practices to students who drew on numerous practices to respond to a particular sense-making task. The supporting qualitative analyses of these network topologies indicated that students with more highly connected networks (i.e., students who drew on more practices to accomplish a task) provided more sophisticated, detailed responses to the assessment prompts. This suggests that as students develop more complex and meaningful patterns of practices-in-use, they may develop more highly and meaningfully connected representations of understanding (diSessa, 1993). We argue that the networks we presented represent patterns of practices-in-use at varying levels of expertise and could be used to model and understand developmental trajectories of student expertise with CT practices. In addition, we provide general tools for identifying student CT practices (i.e., our taxonomy of practices) and an approach for modeling the connections between students' practices-in-use (i.e., our ENA method).

Next steps for this work include revising our units in the tradition of design-based research to engage and develop students' informal CT practices and encourage students to draw on them in meaningful connection other practices. We will also examine the students of other teachers and units using the approach described here, with the aim of characterizing the space of CT practices in the other strands of our taxonomy (i.e., *Data Practices, Computational Problem-Solving Practices, and Systems Thinking Practices*). Finally, we will analyze student pre- and post-assessment scores to determine which patterns of CT practices-in-use are correlated with learning gains.

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