Characterizing Advantages and Challenges for Students Engaging in Computational Thinking and Systems Thinking Through Model Construction

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Abstract: As human society advances, new scientific challenges are constantly emerging. The use of systems thinking (ST) and computational thinking (CT) can help elucidate these problems and bring us closer to a possible solution. The construction and use of models is one of the most widely used tools when trying to understand systems. In this paper, we examine four case studies of student pairs who were engaged in building and using system models in an NGSS-aligned project-based learning unit on chemical kinetics. Using a theoretical framework that describes how CT and ST practices are manifested in the modeling process we examine the progression of students' models during their model revisions and explore strategies they employ to overcome modeling challenges they face. We discuss some suggestions to scaffold students' progression in constructing computational system models and prepare teachers to support their students in engaging in CT and ST practices.

Keywords: modeling, computational thinking, systems thinking

Introduction

Climate change, epidemics, and economic uncertainty are problems whose solutions depend on systems thinking (ST) and computational thinking (CT). Systems thinking is a cognitive approach to problem solving that emphasizes the relationships between the various interconnected elements that make up a system and how the system changes over time (Meadows, 2008). Systems and system models, identified as a crosscutting concept in the Next Generation Science Standards (NGSS) (NGSS Lead States, 2013), are foundational to scientific thinking and are increasingly emphasized as an important component of science education. However, learning materials that effectively integrate ST with disciplinary core ideas remain elusive. Computational thinking has also received increasing attention in science education through the NGSS. Computational thinking describes the cognitive processes necessary to deconstruct a problem or a phenomenon in such a way that it can be solved using an information-processing agent, either a computer or human (Grover & Pea, 2013; Wing, 2006, 2011). Because both ST and CT have only recently been emphasized in the science education discourse (NGSS, 2013), a key challenge for educators is how to integrate ST and CT into multiple STEM curricula. Modeling is a powerful tool for understanding complex systems that engages students with computational thinking and systems thinking. In this paper, we investigate the ST and CT practices students engage in while iteratively developing system models to make sense of a phenomenon.

Theoretical background

Our work is based upon a theoretical framework developed by our research team (Damelin, Stephens, & Shin, 2019), which describes how CT and ST practices are manifested in system modeling (see Figure 1). We reviewed the literature in ST and CT, applying criteria to develop definitions of both, and integrated them to form a contextualized application of ST and CT through the development and use of computationally runnable system models. While this conceptual model demonstrates a theoretical understanding of how students might engage in CT and ST practices through modeling, additional evidence is needed to understand how this occurs in classrooms.

Computational thinking

There is a wide range of perspectives—from a generic approach (Grover & Pea, 2013; The International Society for Technology in Education [ISTE] and Computer Science Teachers Association [CTSA], 2011) to a STEM-centered approach (Weintrop et al., 2016)—on how to describe computational thinking. Based on both of these approaches, we identified several key CT practices. We briefly elaborate on the CT practices we are focusing on in this paper. *Problem decomposition* is defined as the cognitive process of isolating specific features or relationships observed in phenomena by breaking a problem down into smaller sub-problems (Grover & Pea, 2013). The practice of problem decomposition requires capturing essential elements, removing irrelevant elements, and mapping essential elements onto computational solutions for modeling. The *creation of computational artifacts* in the context of system modeling includes developing, revising, and using models by defining the variables of the model and describing the relationships among variables. *Testing and debugging* refer to evaluating the appropriateness of a model based on the explanatory goal as well as the available supporting evidence, and includes detecting faults in a model and fixing them based on model behavior and the presence (or lack) of key ideas related to the phenomenon being modeled (Weintrop et al., 2016). By exploring the range of model predictions based on exhaustive testing of model use, and verifying that the model behaves as expected, frequent testing and debugging through *iterative refinement* leads to model improvements.

Systems thinking

Systems thinking focuses on patterns of events (behaviors over time) and the underlying feedback, accumulation, and delay structures that are responsible for them. We briefly describe the ST practices we are focusing on in this paper. A system can be defined as a single atom, a cell, planet Earth, or a group of galaxies. It is crucial for any investigation to *define system boundaries* according to the question or goal of the model by considering the different components in the system, as well as their appropriate inclusion based on the scale, complexity, and scope of the question being answered. Students must *engage in causal reasoning* to define the relationships between the components to investigate how the web of components and their interactions produce system behavior. *Framing problems or phenomena in terms of behavior over time* is important because systems consist of components that can vary in amount or intensity over time (Meadows, 2008). A system's behavior commonly fluctuates over time and with different inputs.

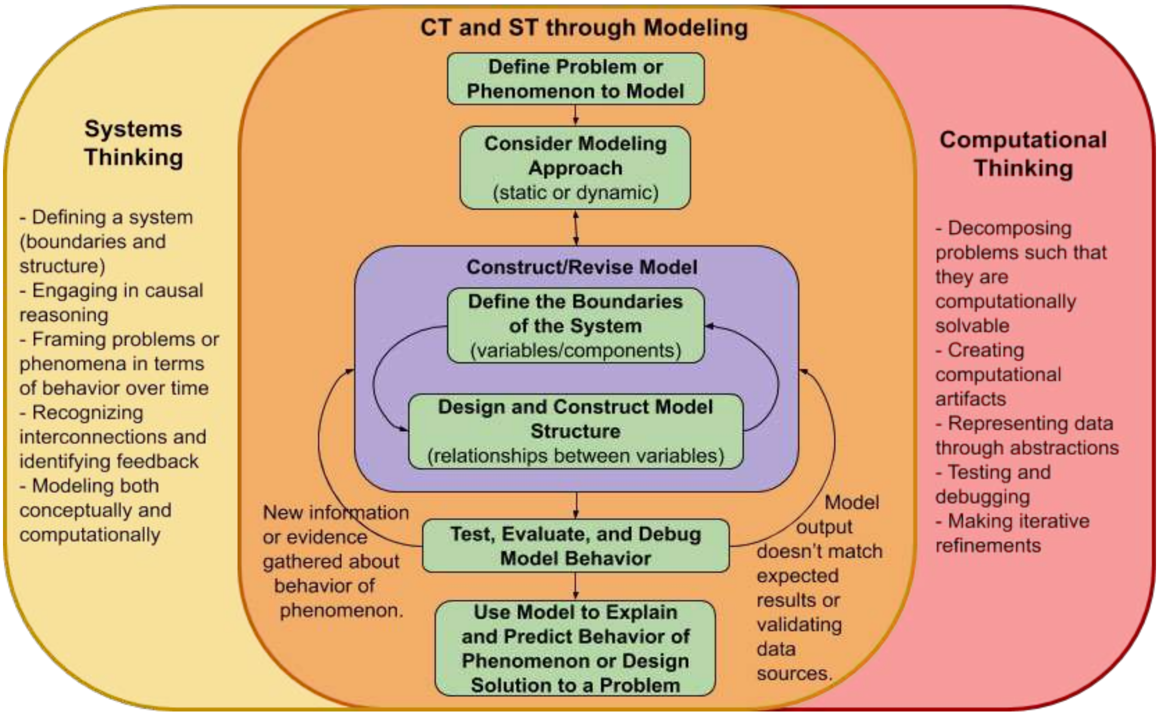


Figure 1. Theoretical framework describing computational and systems thinking through modeling.

CT and ST through modeling

On the right side of the framework are prominent CT practices described in the literature while the left side displays prominent ST practices. The central part of the framework represents a set of modeling practices, which provide a context for operationalizing CT and ST in the process of constructing models (see Figure 1). In this paper, we focus on four of the modeling practices in the framework: (i) *define the boundaries of the system*, (ii) *design and construct model structure*, (iii) *test, evaluate, and debug model behavior*, and (iv) *use the model to explain and predict the behavior of phenomenon or design solution to a problem*.

While engaged in each of these modeling practices students have opportunities to employ one or more CT and ST practices. For example, in a system modeling context, students identify the components that constitute the system and decide which are relevant and should be represented in the computational artifact. This represents the *define the boundaries of the system* modeling practice, marrying both *decomposing problems* from CT and *defining a system* and (potentially) *framing problems or phenomena in terms of behavior over time* from ST.

The *design and construct model structure* modeling practice involves defining the relationships between variables to specify how a change in one variable affects the value of one or more variables with which it is linked. This practice brings together *creating computational artifacts* from CT and both *engaging in causal reasoning* and *recognizing interconnections and* (where appropriate) *identifying feedback* from ST. When setting the relationship between two variables, it is helpful to not only focus on one specific relationship, but also to think about the integration of this effect with the rest of the system. During this process, the modeler may rethink the components in their model, returning to the *define the boundaries of the system* practice. One example of the cyclic nature of engaging in the modeling practices is shown in the framework with curved arrows that link the *design and construct model structure* and *define the boundaries of the system* practices.

One of the major advantages of computational models is that they provide the opportunity to run a simulation of student ideas regarding how a phenomenon works. The act of simulating the model is manifested as the *test, evaluate, and debug model behavior* modeling practice and directly aligns with the CT practice of *testing and debugging*, as well as the *making iterative refinements* CT practice, and additionally involves the ST practice of *modeling both conceptually and computationally.*

Once a model reaches a level of functionality that it seems to correctly model the behavior of the system under exploration, one can engage in the *use the model to explain and predict the behavior of phenomenon or design solution to a problem* modeling practice, which brings together *representing data through abstractions* from CT and *modeling computationally* from ST. Because the model serves as a tool to explain or predict a phenomenon or solve a problem, examining the usability of the model is critical, especially when revising the model and comparing it with other models (Schwarz et al., 2009).

Research question

What are the opportunities and challenges students face as they engage in computational and systems thinking practices in the context of system modeling? More specifically: How do students progress in (i) *defining the boundary of the system*, (ii) *constructing and designing the model*, (iii) *testing, evaluating and debugging*, and (iv) *using the model to make sense of phenomena or to design a solution to a problem*.

Methodology

SageModeler modeling tool

SageModeler is a web-based, open-source tool designed to support student learning by facilitating engagement in systems thinking through building, testing, sharing, evaluating, and revising models (Bielik, Damelin, & Krajcik, 2018, 2019; Damelin, Krajcik, McIntyre, & Bielik, 2017). Supports include a) visual representation of variables and relationships, customizable by the student; b) a simple drag-and-drop interface for constructing a systems diagram; c) the ability to define relationships between components using simple menus, eliminating the need to write complex mathematical equations; and d) the use of an exploratory data analysis environment designed for students.

One of the advanced features of SageModeler is the ability for learners to create time-based dynamic models using aspects of a "stock and flow" system dynamics modeling approach (Zuckerman & Resnick, 2005). Time-based models present a challenge for students as they demand consideration of changes in the system over time, which are affected by the feedback of interconnecting rate-limiting factors (Tadesse & Davidsen, 2019). While SageModeler facilitates easy construction of such models, constructing a *useful* system model of a particular phenomenon still presents a significant challenge for students as we will discuss in the results below.

Development of PBL-aligned curricular materials

A two-week NGSS-aligned chemistry unit using principles of project-based learning (PBL) (Shwartz, Weizman, Fortus, Krajcik, & Reiser, 2008) was co-designed by the classroom teachers and the authors of this paper. The unit focused on the kinetics of chemical reactions. Students were presented with the scenario of a shirt that was stained. A bleach pen was not able to remove the stain in time to wear the shirt. The driving question was: "What can you do to speed up the removal of the stain?" The phenomenon that accompanied the driving question was the gradual fading of food coloring in water when bleach was added. The kinetics unit aimed at students' explaining the phenomenon and giving a solution to the driving question as they progressed in learning three key scientific ideas: 1) A reaction can occur when there are collisions between molecules, 2) increase in temperature increases the frequency of collisions and speeds up the reaction, 3) a higher concentration of reactants increases the frequency of collisions and speeds up the reaction. Students were asked to make a model of the phenomenon using SageModeler to help them answer the driving question. Throughout the unit, students investigated new data to support them in revising their model. They explored various factors that might affect the reaction rate, such as temperature and concentration of reactants and products. The unit was accompanied by an online activity that allowed students to watch science demonstration videos, engage with scientific simulations, answer questions, and build, test, and revise their system models over four iterations. Students also engaged in a hands-on activity in which they collected and analyzed data using a spectrophotometer. They entered the data in a table in SageModeler that allowed them to compare graphs that were generated from their model to graphs generated from their experimental data.

Participants

In the spring of 2019, the chemistry unit was enacted in five classes in a single school in the Midwest U.S. with a total of approximately 100 students. The research population included four 10th grade student pairs from these classes (total = 8 students, 7 females, 1 male) who performed the unit tasks together. The students came from 16 districts and were accepted to a math and science center that accelerates STEM learning at a higher level than is typically available in high school. There were five classes across two science teachers. One teacher had 15 years of teaching experience and the other teacher had 4 years of experience. The teachers participated in professional learning using the modeling tool, which included 10 hours of face-to-face and video chat meetings. The unit consisted of five 80-minute lessons and took approximately two weeks to conclude.

Data sources and analysis

Screencasts

Screencasts of classroom laptops recorded audio discussions and computational operations during three of the unit's five lessons as students developed and revised models (other lessons were dedicated to lab experiments to collect evidence). Screencast recordings were approximately 200 minutes in duration for each group. We used the screencasts to follow students' progress in building, evaluating, and revising their models, focusing on the iteration of the four modeling practices introduced above. We analyzed the screencasts for engagement in CT and ST during each of those modeling practices, using the modeling practices in our theoretical framework. For the first practice, *define the boundaries of the system*, we looked for students' problem decomposition, meaning how students had broken the phenomenon into different variables to represent the progress of a chemical reaction and how its rate is affected by various factors. In regard to the second practice, *design and construct model structure*, we followed students' discussions at points in which they were setting relationships between variables in the model. For the third practice, *testing, evaluating and debugging*, we identified the testing and evaluation of the model as any event in which students ran a simulation of their model and reflected on the outcome of its behavior. We documented who initiated the simulation, as well as students' evaluation following the simulation. Two of the authors in this paper analyzed the screencasts, shared their analysis, and reached full consensus on their decisions.

Student interviews

Semi-structured interviews were conducted with four students, one from each focus group. Each interview lasted approximately 30 minutes. In the interview, students were asked to describe in retrospect their thinking process and strategies for building their final model, to explain how they think the model helped them to answer the driving question, and about their experiences from the unit. Interviews were fully transcribed. Analysis was based on the four modeling practices with an emphasis on the usability of the model. Some of the questions the students were asked included: What was the unit about? Can you tell me about your experience? What is the question you are trying to answer in your model? How do you think your model helps you to answer the driving question?

Student models

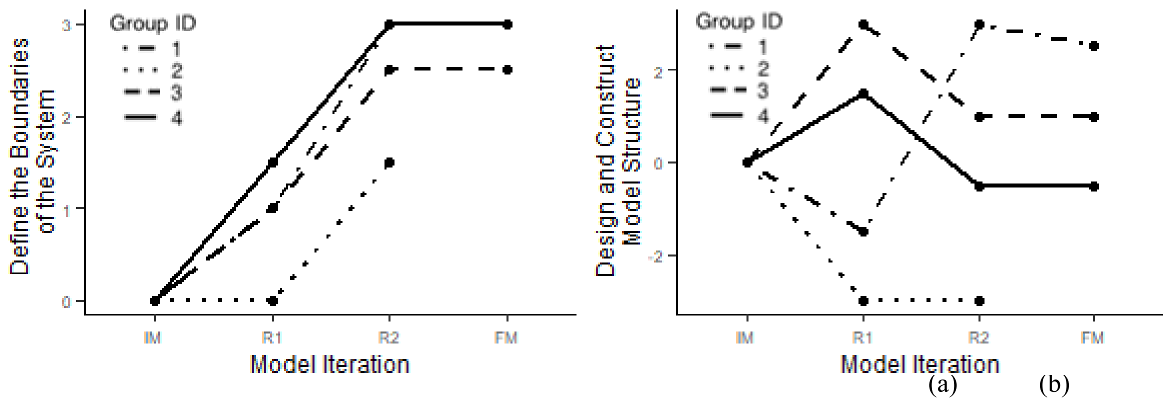
Models were analyzed and scored according to a quantitative rubric from a minus three to a positive three. The rubric targets three of the four focal modeling practices: (i) *define the boundaries of the system*, (ii) *design and construct model structure* and (iv) *use model to explain and predict behavior of phenomena*. The missing modeling practice -- (iii) *test, evaluate, and debug model behavior* -- could not be measured solely through observation of students' models.

Under *define the boundaries of the system*, model variables were scored according to key variables, inappropriate variables, and irrelevant variables. Under the *design and construct model structure*, we assessed the quality of the relationship between variables. Relationships were sorted into categories. Incorrect relationships were given a negative score, while correct relationships received a positive score. The relationships were scored according to the effect the relationship had on the behavior of the model. In the *use model to explain and predict the behavior of phenomena or to design solution to a problem* practice, we looked for the representation of key scientific ideas in students' models and sorted the models into three categories: models that included all key ideas, models that included at least one key idea, and models that did not include any key ideas.

Results

Define the boundaries of the system (variables and components)

Figure 2a shows the progression in students' models in *define the boundaries of the system* practice, which displays a general trend of improvement in all groups. That is, students included more key variables in comparison to inappropriate or irrelevant variables. (Group 2 is missing one revision because they did not complete the unit.)



(a) (b)

Figure 2. Students' progress in (a) the *define the boundaries of the system* practice and (b) the *design and construct model structure* practice. (IM = initial model, R1 = revision 1, R2 = revision 2, FM = final model.).

Design and construct model structure

Figure 2b shows the progression of students' models in the practice of *designing and constructing model structure*. It shows that patterns of progression vary among the groups. The differences in the quality of relationships between variables in students' models change from one revision to the next. As students' progress in the unit their models become more complex, because there are new ideas to implement in the model and, therefore, they are more prone to errors as the number of connections between variables increases.

We examined how students addressed time in their models using the screencast data collected from four groups. If the models are structured correctly, utilizing a special kind of variable we call a "collector" in SageModeler, which accumulates changes from one model calculation to the next, then changes over time become evident in the model behavior. However, all four groups inappropriately included time as a variable in their initial models, explicitly representing an aspect of the model that should be inherent in how it is computed.

During simulation, each variable shows a graph of its value over time. If there is no change over time the simulation will show a flat line (see Figure 3a). To show change over time one needs to set at least one variable to be a collector (see Figure 3b). All focus groups faced challenges in constructing models showing behavior over time, with only one group (Group 1) deleting the time variable and adopting a dynamic approach without explicit teacher instruction. We examined the prompts that led to the eventual deletion of the time variable in each group. From the screencasts, it seemed that the simulations they ran led Group 1 to the conclusion that the time variable does not contribute to their model and, therefore, they decided to take it out.

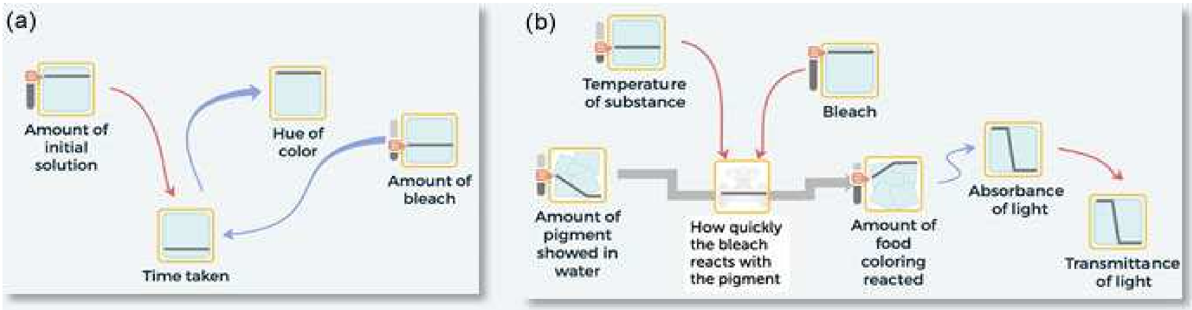


Figure 3. Iterations of student models demonstrating (a) no change over time (Group 2, IM) and (b) a model that includes appropriate types of variables that can accumulate changes over time (Group 1, R3).

Test, evaluate, and debug model behavioral

Table 1 displays the number of times students ran a simulation of their models in Lessons 1 and 2 while building and revising their models. We differentiated between student-driven and teacher-driven initiatives for running the models. Group 1 had the highest number of model simulations, all of which were student driven. Without much support from the teacher they simulated their model almost every time they set a new relationship between variables. The high number of simulations relative to other groups correlates with results that showed higher scores in the three modeling practices examined in their final model. The data from the screencasts indicates that students were less dependent on the teacher after completing their initial model. It is important to mention that teachers' prompts for simulation always occurred after students asked the teacher for support. Also, there was a difference between the two teachers in the way they addressed students' questions. The more experienced teacher of Groups 1 and 2 usually answered with a question, hint, or prompt, and encouraged students to figure out their model on their own, in comparison to the less experienced teacher of Groups 3 and 4, who was more explicit and instructive in his answers, especially in the first lesson.

Table 1: Frequency of simulating the model

Group #	Lesson 1 (initial model construction)		Lesson 2 (first and second model revision)	
	Student-driven	Teacher-driven	Student-driven	Teacher-driven
1	6	0	5	0
2	0	2	3	2
3	0	2	2	0
4	3	2	3	0

We asked one student from Group 1 during the interview about the decision making she and her teammate had engaged in. She said: "Well, we pretty much just decided it. Trial and error. We had these connected here at one point and this connected to this (pointing at the screen). Because at first, we didn't have this valve thing here. We had just a normal relationship. So, just trial and error, and conversations with Mr. H (the teacher)." We can see more evidence for the Group 1 strategy. According to the student, trial and error means running a simulation, evaluating the model, and debugging it, though she did not have an answer as to why she and her partner chose to adopt this strategy, which apparently other groups did not. Even with the persistent self-directed testing exhibited by Group 1, no group's models correlated precisely with their experimental results. Students' experimental results showed an exponential decay trend of absorbance over time graph (an indicator of the rate of reaction) while the equivalent graph generated by their model showed a linear decay. Only students from Groups 1 and 3 provided explanations for the differences between the behavior of the model and their experimental results. Group 3 students attributed the difference to a probable lack of their own proficiency in conducting the experiment, despite correctly collecting data on the phenomenon. They stated that they believed the computer model was more accurate. Group 1 students said they were aware of the difference, but they were unable to overcome the challenges of modeling a phenomenon that exhibited exponential decay, which would have required the implementation of an appropriate feedback mechanism within the model.

Use the model to explain and predict the behavior of phenomenon

Regarding model behavior, Groups 1, 3, and 4 produced a model that demonstrated only the first two key ideas —that concentration of reactants and temperature affect the rate of reaction. Group 2's model did not demonstrate any key idea. All four students who were interviewed expressed the first and second key ideas, and all groups except for Group 2 had this idea manifested in their model. To manifest the first two key ideas in the model students had to have a representation of transfer from reactants to products, as well as a representation of concentration and temperature variables that affect the rate of reaction. The following excerpt of an interview with a student from Group 3 shows the first two key ideas, namely an explanation at the microscopic level describing how an increase in the particles' kinetic energy affects the rate of reaction. Student from Group 3: "And then with the temperature, it causes the particles to move faster. If the reaction is caused by collisions of the particles, then if they're moving faster, there'll be a greater chance that they collide and that the reaction will go faster." The third scientific key idea was mentioned by students from Groups 1, 3, and 4. For example, a student from Group 1 said during an interview: "Yes. So, it's decreasing at a decreasing rate. At first, there are a lot of particles in there reacting with each other and then over time it just gets less and less. But they're still reacting with each other, it just takes more time for them all to react." However, this idea was not manifested in any of their models. To include the third idea students had to create a feedback loop in their model that would result in an exponential decay behavior of the variables that represent reactants or absorbance in the model.

Discussion

In this paper, we have explored how students' progress in each of four different modeling practices and found that there is a discrepancy between the students' progression in defining the boundaries of the system, hence defining key variables, and their ability to properly construct the relationship between the variables. The first one trends upwards as the unit progresses and the second one fluctuates.

We believe the curricular approach is partially responsible for this result. There was a greater emphasis on exposing students to key variables, which supports the *define the boundaries* practice, and can be seen in the increasing scores across groups related to this modeling practice. However, the measure of the *design and construct* practice did not show a corresponding overall increase, but rather showed fluctuating success in this area. This supports what Ergazaki et al. (2007) noted in their research, namely that defining the relationship between model components is the most demanding and time-consuming practice students engage in while modeling, and, therefore, requires the attentiveness of modeling facilitators. To better support students in all model building practices, explicit support regarding each practice should be embedded in the curriculum.

A close examination of the fluctuating pattern reveals that students who initiated more simulations were more likely to end up at a higher score than students who relied on teacher-initiated simulations. This finding points to the importance of supporting students in developing agency to progress in their model creation. The findings show that students who are more self-driven are likely to progress in their model creation. As such, supporting students with additional scaffolds to more effectively build, test, revise and evaluate models is needed.

We also noticed that when students were confronted with experimental data that did not align with their model, they gave explanations during the interviews that ranged from trying to adjust their model to fit the evidence (desired approach) to a reluctance to accept the experimental data due to the perception that the model itself represents absolute truth. Similar to Cheng and Lin (2015) and Schwartz et al. (2009), the findings highlight the importance of proper teacher support on the nature and purpose of a model and the interplay between the model and obtained experimental data.

We found that constructing the initial model was very challenging for students. The general strategy students used when they started modeling was to include any variable that came to mind (e.g., time, chemical reaction) and to set relationships between the different variables. Students may resort to this strategy, which requires minimal reflection, to ease the cognitive load of developing a computational model. This means that emphasis should be given to the initial model creation and, in particular, that scaffolds are necessary to address each practice separately to not overload the students as they create their initial model. This correlates with findings from previous studies investigating students' computational modeling processes (Fretz et al., 2002; Stratford, Krajcik, & Soloway, 1998). One possible strategy would be to engage students in simple paper-pencil models. That type of model draws less on students' ability to abstract model components into calculable variables and allows for a greater focus on descriptive mechanisms. Making the transition from paper-and-pencil modeling to a computational system could shine light on how a computational model is different and provide an opportunity to naturally transition to talking about CT and ST practices more explicitly as they support various computational modeling practices.

We believe that the findings presented in this paper provide a foundation for exploring further how teachers can support students in ST and CT through modeling. We characterized some of the challenges students face while engaging in model building, testing, evaluating, and revising, specifically looking through the lens of CT and ST practices. We also suggested some applications and teaching strategies that can be applied in the classroom. However, a better understanding of the interplay between CT, ST, and modeling will allow for the development of curriculum, assessment, and teacher support scaffolds that improve students' engagement, understanding, and problem-solving skills.

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