Analyzing Students' Synergistic Learning Processes in Physics and CT by Collaborative Discourse Analysis

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Abstract: The introduction of computational modeling into science curricula has been shown to benefit students' learning, however the synergistic learning processes that contribute to these benefits are not fully understood. We study students' synergistic learning of physics and computational thinking (CT) through their actions and collaborative discourse as they develop computational models in a visual block-structured environment. We adopt a case study approach to analyze students synergistic learning processes related to stopping conditions, initialization, and debugging episodes. Our findings show a pattern of evolving sophistication in synergistic reasoning for model-building activities.

Introduction

Computation is at the forefront of 21st century education (Wing, 2006). Technological advancements are resulting in the introduction of a variety of computational tools and practices into Science, Technology, Engineering, and Mathematics (STEM) curricula through computational modeling, simulation, data analysis and visualization. Working in technology-enhanced environments also presents opportunities for collaborative learning and problem-solving. We aim to integrate computational thinking (CT) concepts and practices into STEM curricula (Sengupta, et al., 2013) so that learning of STEM and CT can be mutually supportive and help to develop important STEM practices like model-based reasoning, explanation, and argumentation. Computational modeling serves as an effective vehicle for science learning in K-12 (e.g. Basu, et al., 2016; diSessa, 2001; Wilensky & Reisman, 2006). Designed learning environments can support this mutually supportive integration (Basu, et al., 2013; Hutchins, et al., 2018), and such environments have helped students achieve significant learning gains in both STEM and CT concepts and practices (Basu, et al., 2017; Sengupta, et al., 2013). But the mechanisms and processes students employ to develop and apply synergistic learning skills are not well understood.

In this paper, we take on the challenge of understanding and unpacking students' synergistic learning processes while they develop computational models of scientific phenomena using a block-based programming language. Typically, computational modeling involves an iterative process of conceptualization, algorithmic design, implementation as a program, and testing and refining the program to generate a correct model. Students activities related to these processes can be analyzed using log data collected from computer-based learning environments. However, students' underlying reasoning mechanisms when invoking and applying these processes, the difficulties they face, and how they overcome them are hard to unpack from their logged activities. To better understand these mechanisms, we ran a pilot study with students who worked in groups of two or three on model building and problem-solving tasks in physics. We used a screen recording system that simultaneously captured students' interactive dialog as they worked on the system, and then performed a qualitative case study that combined analyses of log data and the interactions among the students to understand students' reasoning processes in synergistic learning of physics and CT concepts.

Collaborative learning and problem-solving

Roschelle and Teasley (1995) defined collaboration as "a coordinated, synchronous activity that is a result of a continuous attempt to construct and maintain a shared conception of a problem." Further research has shown the importance of developing shared understanding among the group members for successful task completion (Larkin, 2006). In addition, interaction skills of making and encouraging contributions of ideas, monitoring of progress, and providing constructive feedback through argumentation and explanation are essential components of collaborative learning (Garrison & Akyol, 2013; Grau & Whitebread, 2012). In the context of our work, this translates to students developing and utilizing their shared understanding of domain and CT concepts to co-construct their physics models, analyze and understand the behaviors generated by simulating their models, and where necessary, apply debugging processes to make refinements to and improve their models.

Working in close proximity and sharing a computer screen, provides students opportunities to explicitly discuss the model construction process, and develop arguments and explanations that support or challenge model constructs they propose or are proposed by their partners (Sins, et al., 2005). Therefore, students' interactive discourse provides opportunities for studying and understanding the reasoning processes they employ for synergistic learning during their computational model building activities. We briefly review discourse frameworks that have been developed for analyzing collaborative discourse in STEM domains.

Collaboration discourse frameworks

The ICAP framework (Chi & Wylie, 2014) defines four different modes of engagement when considering learning behaviors: Interactive, Constructive, Active, and Passive. A learner who is engaging passively receives information but does not respond. An actively engaged learner receives information and manipulates it in some way. A learner who is receiving information, manipulating it and then constructing something with that knowledge is considered to be constructive. Finally, if two constructive learners are conversing about constructs they have generated from information, they are considered to be interactive.

The framework proposed by Weinberger & Fischer (2006) to analyze knowledge construction in a collaborative learning environment includes five categories of social modes: externalization, elicitation, quick consensus building, integration-oriented consensus building and conflict-oriented consensus building. Externalization is defined by a learner articulating their thoughts. Elicitation refers to the idea of using the other group partners as resources, this can be seen when a learner questions other group members. Quick consensus building is the act of accepting the contributions of another learner in order to continue progress. Integration-oriented consensus building occurs when one learner's understanding about a concept is changed based on another learner's reasoning. Conflict-oriented consensus building refers to the idea of different learners' perspectives contradicting each other, which leads to the debate and modification of conflicting ideas.

In our work, we superimpose Weinberger & Fischer's categories of social modes in knowledge construction on the ICAP framework to develop our coding scheme. This combination results in a more encompassing framework that considers a learner's social modes along with their mode of engagement on the collaboration task. A collaborative interaction is categorized by the highest level of engagement reached by one or more learners in the group combined with the type of social mode associated with the group. All three types of consensus building modes are only present when the collaboration is considered *interactive* because the group can only reach a consensus when both learners participate in model building. *Constructive externalization* or *elicitation* is categorized by a single student (the lead) is participating in model building and is narrating their actions and thought processes while the other students engage passively by following along silently, or actively, by verbally agreeing. During *constructive elicitation*, the lead student questions the other students in the course of building the model and receives little to no response. If questioning by two or more students is substantial and leads to responses that indicate the students are acting constructively, the collaboration is considered to be *interactive elicitation*. If neither student is participating in the model building but are reading aloud resources or instructions, the collaboration is categorized as *active externalization*. Finally, when none of the students are actively working on the model or saying anything they are in a *passive state*.

Framing our research

Learning physics by building computational models

We use C2STEM, a learning-by-modeling environment that incorporates a physics domain-specific modeling language (DSML) into a block-based programming environment to promote learning of domain-specific and CT concepts and practices through computational modeling and problem-solving exercises. C2STEM uses Netsblox (Broll, et al., 2017), an extension of Snap! (http://snap.berkeley.edu/). The use of a physics DSML aims to help students focus on physics concepts, while also helping students to write self-documenting code. In addition, we scaffold the model-building process by explicitly providing a simulation framework, where students can initialize variables and the use blocks to update the variables at each time step to capture dynamic behaviors.

Figure 1 illustrates a computational model that simulates the dropping of a package from a drone hovering at a specified height above a target. This requires students to think of the impact of gravity on the package's velocity and position with time that increments in steps of Δt when the simulation is run. The student also has to model a stopping condition, using a *conditional* construct to model the object's motion stopping when it hits the ground. Students can use graphing and tabulation tools shown as icons at the bottom of the stage.

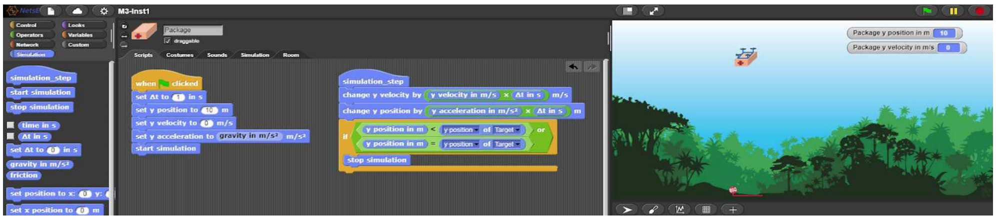

Figure 1. Example final computational model for package drop.

Synergistic learning

The notion of synergistic learning is predicated on the idea that the simultaneous learning of two domains in an integrated context can lead to better learning of concepts and practices in both domains than when the domains are learned separately. Previous work has shown that integration may initially increase the conceptual burden for students, but students are quickly able to overcome these difficulties and learn both domains better (Basu, et al., 2013; 2016). Our previous studies with C2STEM have shown that learning by building computational models of kinematics phenomena helps students gain a deeper understanding of the underlying kinematics concepts, while also helping them gain a better understanding of CT constructs, such as variable initialization, conditional, and loops (Hutchins, et al., 2018). Besides, a number of practices, such as abstraction, decomposition, and debugging transcend both domains (Sengupta, et al., 2013). However, to our knowledge, limited work has focused on identifying the synergistic STEM+CT processes that lead to these learning benefits.

In this paper, we identify some of the synergistic learning processes that we have observed in previous studies, and develop a framework for analyzing and understanding students' reasoning processes as they work through synergistic learning episodes during their model building tasks. In particular, we focus on the synergistic modeling practices of initialization, debugging, and conditional behavior changes. In our modeling framework, the initialization process can be identified by the addition, editing, and/or deletion of physics-DSML set blocks under the "*When Green Flag Clicked*" block (see Figure 1). Not only is variable initialization a key CT practice (Grover & Pea, 2013), students' selection of physics variables to initialize in the context of a particular task offers insight into their conceptual understanding of the motion processes being modeled. Debugging, a key CT skill (Grover & Pea, 2018), is related to analyzing model behaviors, identifying sources of error in the models, and then correcting the identified errors in physics modeling. In C2STEM, the debugging process is a truly synergistic process, as students must diagnose whether errors in their models result from incorrect representation (modeling) of physics concepts (e.g., an incorrect use of velocity in computing a look-ahead distance (specific point at which object slows down to stop) or an incorrect specification of the CT (or programming) constructs (e.g., writing the Boolean condition expression that initiates the slowing down behavior). Finally, we include the use of conditional expressions to indicate changes in motion behavior (e.g., slow down to avoid a collision). In all of these situations, the nature of the modeling tasks requires students to go back and forth between applying and checking their physics concepts and practices and their CT (or programming) concepts and practices to succeed in their model-building and model-checking tasks. We hypothesize that back and forth transition of concepts and practices across domains provides students with synergistic learning opportunities leading to better model building, and eventually better learning in both domains.

Study description and data analysis methods

The qualitative research method presented in this paper is guided by the question: *What characteristics of synergistic learning and reasoning processes can we derive from students' collaborative discourse as they work on computational modeling tasks?* The primary data source used to answer this question was screen-capture video (using OBS™ software) that recorded students' actions in C2STEM, along with webcam video and audio, of two students ('S1' & 'S2') engaging in collaborative model building.

Our team conducted a two-month-long study that included 26 advanced sophomores assigned by our research team to work in groups of 2 or 3 on a kinematics and dynamics curriculum in C2STEM. The research team met with participants one school-day a week over a two-month period. Students completed one 45-minute CT training unit and four physics modules: three in Kinematics: 1D motion (with acceleration), 2D motion with constant velocity, and 2D motion with gravitational forces, and one in mechanics, i.e., an introductory unit on 1D Force. All students worked collaboratively, either in pairs or triads.

We used the rubric outlined in Table 1 to define and assess key learning objectives in physics and CT from the models that students constructed. The assessment results help us determine how successful students were in different aspects of model building and how their performance could be explained by their proficiency in synergistic learning and reasoning processes.

Table 1: Rubric for evaluating students Models

Expressing physics relations in a computational model (physics component):	**Point(s)**
Program expresses correct relations among and units for needed Physics variables.	2
Program reflects the effect of [velocity/acceleration] on [position/velocity] each time step.	1
Program resulted in an accurate calculation of given task submission question.	1
Using programming concepts to model physics phenomena (CT component)	**Point(s)**
Program makes the distinction between actions that need to happen once during initialization and actions that need to be repeated in the simulation step	1
Program correctly determines which actions always happen or happen under certain conditions	1
Program updates the variable corresponding to the package's velocity: (1) under the correct conditions (e.g. correct conditional logic), and (2) in the correct fashion (e.g. each simulation step)	2
All code in the program is reachable and can be executed; No duplicate code	1

For analysis, we extracted and coded students' discourse mechanisms from the OBS video and voice recordings, capturing sequences of actions that that closely related to learning objectives in the two domains (see rubric), while also recording the challenges they faced, and how they overcame them. Two coders coded the above episodes. Inter-rater reliability was checked by calculating Cohen's kappa value which resulted in excellent agreement (k = 0.94) for collaborative discourse and good agreement (k = 0.71) for synergistic coding. For each task, we noted key actions and conversations that highlighted synergistic learning episodes and parsed these episodes to determine if the students' focus was on the physics or the CT aspect of their model.

Student task performance in physics and CT

Our qualitative case study analyzed the model-building activities and the accompanying dialogue of two students who worked together on a laptop. We chose this group because they were the only pair in our study (all other students worked in triads), therefore, exchanges between them were easier to code. Besides this group was quite expressive, so we derived a lot of rich information from their dialog. Typically, one of them controlled the mouse and the keyboard, but the other student was always very attentive, and often initiated interactive dialog to discuss aspects of the modeling and debugging tasks. Their model scores (Figure 2) were assessed using the rubric described above on four model building tasks from each curriculum unit: 1D Motion, 2D Constant Velocity, 2D Motion with Gravity, Forces. As demonstrated, the group initially struggled in CT (3 out of 5), but improved to a perfect CT score by the final unit, even though the CT constructs and practices were more difficult. In physics, the group started off well, scoring a 3 out of 4 on the first two modeling tasks, improving to 4 out of 4 on the final modeling tasks. It is important to note that for both 1D motion and 2D constant velocity, the group did not receive a point for "program resulted in an accurate calculation of given task submission question," because this rubric item requires appropriate use of CT constructs. As such, further analysis of the modeling process is needed to understand issues related to transitions between physics and CT applications in the modeling process in order to understand the cause for their error.

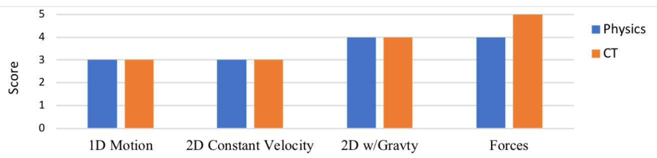

Figure 2. Group 1 model building scores.

Case studies

Utilizing our synergistic learning framework) we have extracted segments of work and accompanying dialog that correspond to episodes of initialization, formulating conditional logic/stopping conditions, and debugging. The segments are presented in the order in which they occurred to study the students' progression in their model building skills and synergistic learning skills (Figure 2).

Segment 1: Conditional logic and stopping conditions

Episode 1 below describes a conversation and activity segments for a dyad (students S1 and S2) working on the 1D Motion module. In this task, students model the motion of a truck that speeds up from rest to a given maximum speed (defined by a speed limit), maintain that speed and slow down and stop at a stop sign. This requires the students to calculate a lookahead distance from a stop sign. These two segments demonstrate their application of synergistic learning processes (their back and forth reasoning between the physics and CT concepts) to model the motion changes of the truck. We use the characterizations developed from the two collaborative frameworks to analyze and interpret the dialog constructs.

Table 2: Episode 1 (use of conditionals)

Student's Words and Actions	Physics and CT	Collaboration
S1: "15 m/s. So it needs to hit 15 m/s and then stop accelerating. So... If statements. If statements is the easiest way to do this." **S2:** "I thought you would do a when block. **S1:** Why would you do a when block?" **S2:** "when the speed reaches..." **S1:** "Well, that's the thing because this starts a sequence, we need to put it inside the simulation step so that it will constantly repeat."	**CT focused:** S1 and S2 agree on the physics concept but disagree on how to model it computationally, i.e., what CT construct(s) to use. S1 and S2 attempt to develop a shared understanding of different conditional operators	**Interactive conflict-oriented consensus building:** S2 challenges S1's reasoning about a CT construct. S2 suggests a different idea and S1 pushes S2 to verbalize his reasoning.
S2: "Oh, I see." **S1:** "Right so if x velocity is greater than or equal to 15 then just change the x position by velocity. Else, change x velocity by acceleration."	**Physics focused:** Since S2 seems to agree, S1 brings the conversation back in context of physics. Using the language of the conditional block, S1 describes the relationships between position, velocity and acceleration.	**Interactive quick-consensus building:** S2 seems to agree with S1's reasoning but as seen in the continuation of the conversation, he is not fully convinced.
S2: "And you're telling me that's the easiest way?" **S1:** "That's the easiest way to do it because otherwise we have to do this and that's not a loop."	**CT focused**: S2 turns the conversation back to CT and challenges S1 again on the choice of conditional structure.	**Interactive conflict-oriented consensus building:** S2 challenges S1 again on the choice of conditional structure. After showing S2 on the screen, S1 and S2 develop a common understanding of the physics and CT concepts to use in their model.
S2: "I would think like just like if velocity equals … like if velocity equals 15 m/s set acceleration to 0 m/s…"	**Physics focused:** S2 attempts to support his reasoning by bringing in the relationship between velocity and acceleration.	
S1: "We could do that but that would be… eh... I just I don't like the way that sounds cause yeah but yeah I know what you're saying." **S1:** "Ok so basically if velocity is equal…is greater than or equal to whatever. then change. then both of these…else just the bottom part. Ok." **S2:** "Oh I see why you put that there." **S1:** "Exactly"	**CT focused:** S1 shows S2 on the model how his idea would work	

In this segment, the dyad was having trouble converting their physics understanding into the computational constructs because they were unsure about the conditional constructs. Their consensus-building collaborative dialog demonstrates how they applied explanations, and argumentation to develop a shared understanding of the model building task (e.g., why select the "if" block and not a "when" block). However, their explanations are not deep, therefore, their justification for their model building steps is shallow. For example, S1 verbalizes his actions to develop a consensus and shared understanding with his partner, but the explanation "just doesn't like the way that sounds" implies an incomplete understanding of CT. In contrast, the physics knowledge is strong (including a correct calculation of the lookahead distance), and this is reflected in their task performance score.

Segment 2: Initialization

The second episode in our case study involves the 2D constant velocity task focused on the initialization process. In this task, students needed to program a boat to cross a river, stopping at two islands located at different points on the way. The key physics concepts students have to learn are 2-D velocity, and how to compute the resultant velocity, given that the river current. In this episode, students are considering the importance of initializing the heading variable of the boat given the need to change the boat's direction when moving towards a new target.

Table 2: Episode 2

<table>
<tr><th>Student's Words and Actions</th><th>Physics and CT</th><th>Collaboration</th></tr>
<tr><td>S1: "So it's 5 m/s in the x and y. So, we could set a different x velocity and different y velocity. Because it needs to go 15, so we could set the x to 5 and in the same three seconds if we set the y velocity to 2, then it would go 6 forward and 15 to the right."
S2: (agreement sound)</td><td>Physics focused: S1 is verbalizing thought process on the relationship between x and y velocities and the respective distances moved in 3s</td><td rowspan="2">Constructive externalization: S1 externalizing his modeling constructs with S2 following along, occasionally agreeing</td></tr>
<tr><td>S1: "let's move this back and set the heading."
[S1 ADDS "set heading to" block and hardcodes it to the value 291.28. Clicks on the block to change direction of the boat and then removes block from stage.]
S1: "so we need to set position to 0, -10.6"
[S1 ADDS and EDITS set position block]</td><td>CT focused: S1 adds an initialization blocks that supports his verbalization</td></tr>
<tr><td>S2: "How come you threw that block away?"
S1: "What, that block? (pointing) Because we've already set the heading."
S2: "Alright, but when you reset it's..."
S1: "Right."
[S1 ADDS set heading block under GF and hardcodes to 291.28]
S2: jokingly says other student's name
S1: "My wits have taken leave."</td><td rowspan="2">CT focused: S2 challenges S1's removal of one of the blocks — presumably place in the wrong location causing the simulation to reset to an initial value.</td><td>Interactive conflict-oriented consensus building: S2 challenges S1's action of discarding a set block, S1 tries to explain his reasoning and after further prompting by S2, sees the error</td></tr>
<tr><td>S1: "And then, set position, set velocity"
[S1 ADDS set x velocity block under GF]</td><td rowspan="2">Constructive externalization: S1 reverts to narrating actions with S2 following along</td></tr>
<tr><td>S1: "and that's all we need to know, because it won't let us accelerate. It will let us accelerate in 2D air because that is when we start factoring in gravity. So then, start simulation, simulation step."
[S1 ADDS start simulation to GF and simulation step flag]</td><td>Physics focused: S1 concludes that they have completed the physics required for the model</td></tr>
</table>

This segment illustrates a synergistic process where an understanding of the physics variables is needed to accurately model the object behaviors. We analyze how the students collaborate to resolve issues in the link between initialization and the modeling of the updates to capture dynamic behavior. The conflict-oriented consensus building approach allowed both students to consider the initialization process in the context of a complete model. By questioning the deletion, the group went from a predominantly constructive externalizing approach focused on the physics content, to an approach centered on generating consensus in understanding how the computational model should be set up. This conflict-oriented approach also occurred in Segment 1 in which the students also came to a consensus via questioning of the selection of a conditional block, but in this initialization scenario, we are beginning to see better justification as part of their reasoning. Although the improvements are observed in the synergistic discourse, the students' model score on this task was similar to Segment 1.

Segment 3: Debugging
The final episode is an example of synergistic learning during debugging in a 2D gravity drop motion task, where the students modeled the delivery of two packages by a drone moving horizontally, calculating the look-ahead distance needed to release each package in order to safely land each at the desired targets on the ground. It is important to note that the group's score in both Physics and CT improved in this scenario, with the group developing a model that they used to correctly answer the task submission question.

Table 3: Episode 3

Student's Words and Actions	Physics and CT	Collaboration
S1: "Did we miscalculate? Did we miscalculate? Does it need to be like 9 meters or something? Let's try 9 meters just to be sure. I have a sneaky, sneaky suspicion."	**Physics focused**: S1 is pointing out that the physics calculations put into the model may be incorrect.	**Interactive integration-oriented consensus building**: S1 and S2 work together to find the error in their model, and they conclude that it is likely a time miscalculation
[**S1** edits subtraction in if via hardcode]. **S1: "**Let's try this again." [**S1** presses play] **S1:** "Drop…" **S2:** "It's not.." **S1:** "Yeah, that's not right." **S2:** "Wait, I want to see it" [**S2** takes control of mouse]	**CT focused:** S1 and S2 are using the model to determine why the package is not ending up in the correct place	
S1: (inaudible) "Did we miscalculate the time?" **S2:** "We might have" **S1:** "We might have miscalculated the time. Let's go back and look at the time equation. We could do this one, too, couldn't we?" **S2:** (agreement sound)	**Physics focused**: After their model does not work as expected, S1 and S2 go back to determining where they made an error in modeling the physics relations.	

This segment illustrates how the students use the animation of the object's motion to realize they have made an error, and then work together to find its source. The discussion is mostly physics-focused, but it does require them to analyze how the sequence of blocks they have used to build the model relates to the behavior they are observing. Their suspicion is that they did not model the release time of the object correctly. The episode does show some switching between a physics and CT focus in their conversations. This was also observed in the earlier episodes, but this one demonstrates a level of maturity in that they are not arguing over what construct to use, but are trying to related behavior back to model structure, which implies higher level synergistic reasoning.

Discussion

When the S1 and S2 are successful in their modeling tasks, the conversation has the characteristic of integrating both CT and physics reasoning, and adopts a back and forth between the two domains in the model construction task. We believe that this back and forth, i.e., analyzing relevant domain concepts required for modeling and representing them using computational constructs, and going back and forth to establish the correctness of the physics and its computational representation is a key element of synergistic learning and reasoning. A conversation that integrates both CT and physics reasoning does not necessarily imply students will succeed, as seen in Episode 3. The students go back and forth between the physics concepts and the CT construct in their conversation, but run out of time before they come up with the correct form of the model. However, they gain a synergistic understanding that they apply later in their modelling process. The dyad also discusses look-ahead distance calculations in the 1D constant velocity module, but this earlier conversation does not have them switching between physics and CT reasoning. The discussion that can be split into two completely separate conversations; one where students determine the physics calculations separately and then a second discussion about the computational modeling. When comparing the progress made between episode 1 and 3, it is clear that the students are better able to integrate their physics and CT knowledge. Their synergistic learning gains are shown as their modeling score increase in physics and CT from the 1D constant velocity to Forces modules (Figure 2).

Conclusions and future work

One challenge of using video analysis to study synergistic learning is recognizing evidence of synergistic learning in practice. Another challenge in using video analysis to study synergistic learning is knowing where to look, amongst the many hours of video data. We have found evidence of synergistic learning in three specific contexts: when students were (1) using conditional blocks, (2) initializing variables, and (3) debugging code. These findings will help us hone our search for episodes of synergistic learning in future research.

Focusing on one student dyad, we first found evidence of synergistic learning, initially in their inability to reconcile the physics conceptual knowledge with the computational constructs required to construct the computational model. This involved a lot of dialog about whether the physics knowledge was correct, and then whether the computational construct reflected that the physics knowledge had been applied correctly. Studying the students' conversations in this phase provides us with some understanding of their difficulties, which can be in the domain concepts, the computational constructs, or the representation of the domain concepts correctly in the computational form. It is also clear from the students' dialog that such exercises force them to think deeper about both the domain concepts and the computational constructs. Initially, this may increase their difficulties. However, by executing their computational representations, i.e., simulating their model, they have the opportunity to implement debugging processes that may help them understand and overcome their difficulties. It also provides us with opportunities to detect such episodes, and adaptively scaffold students who are unable to overcome their difficulties. In our particular case study, the two students succeeded in working through their difficulties on their own, after some initial stumbles.

Our next steps include expanding our analysis to a broader group of students and extending our analysis to gain insights into collaborative regulation.

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