Understanding Students' Model Building Strategies through Discourse Analysis

Caitlin Snyder[1], Nicole Hutchins[1], Gautam Biswas[1] and Shuchi Grover[2]

[1] Vanderbilt University, Nashville TN 37235, USA
[2] Looking Glass Ventures

Abstract. The benefits of computational model building in STEM domains are well documented yet the synergistic learning processes that lead to the effective learning gains are not fully understood. In this paper, we analyze the discussions between students working collaboratively to build computational models to solve physics problems. From this collaborative discourse, we identify strategies that impact their model building and learning processes.

Keywords: Computational modeling, collaborative discourse

1 Introduction

Technology-enhanced environments can be productive vehicles for engaging students in computational model building and problem solving, a process shown to be effective for learning K-12 science concepts (e.g. [2, 6, 18]). This mutually supportive approach to STEM and CT learning has produced synergistic learning environments [3, 17, 9, 13]where students express domain concepts and laws in a computational form, and then interpret the behaviors generated by these computational constructs to refine their knowledge of the domain. The necessity to combine, represent, interpret, and analyze the two simultaneously in a mutually supportive way is what we call *synergistic learning*. While we have theorized the advantages of synergistic learning [13], and assessments have demonstrated students' learning gains attributed to these environments [1, 2], how they develop and apply these synergistic learning processes to their learning and modeling tasks are not fully understood.

For this research, students learn by building, simulating, testing, and refining their models in C2STEM [9]. We analyze collaborative discourse as students work in small groups to develop a shared understanding of a phenomena by jointly constructing models [11]. While working on their model building tasks on a shared screen, students have the opportunity to discuss, explain, argue about and evaluate their models [14]. In this paper we use students' collaborative problem-solving dialogues along with information on how they progress in their model building to identify students' STEM and CT learning processes, while also gaining some insight into their group dynamics. Specifically, we perform an exploratory analysis to identify dialogue characteristics and model building moves that may be indicative of strategies they use in their computational modeling tasks.

2 Background

Computational modeling of scientific processes provides an effective framework for learning scientific concepts and practices through computational representations and simulation models, as well as CT practices like those evaluated in [17]. Reciprocally, the concepts and practices emphasized in CT are better contextualized and, therefore, easier to understand and learn when they are situated in domain specific model building, analysis, and problem-solving tasks [4, 13]. Such environments that facilitate synergistic learning have proven to be effective in increasing learning gains in the STEM and CT domains [1, 2, 9]. Our work extends these approaches using a block-based computational modeling environment, C2STEM, equipped with tools aimed at scaffolding the learning of STEM and CT. These tools include a domain-specific modeling language (DSML) with physics constructs to help students create dynamic (simulation) models in Physics and control-structure blocks to initialize needed variables (Green Flag) and to program the dynamic behavior changes of each object (the Simulation Step block), aimed at evaluating the step-by-step update of the model via animations and data tools.

We analyze collaborative student dialogue with a learning and social framework to better understand successful and unsuccessful learning processes building on related work [8,10]. Dialogue is characterized by the domain (Physics or CT) of focus during knowledge construction. Discussion are further characterized by a combination of the ICAP framework [5] and the framework proposed by Weinberger & Fischer [16]. The ICAP framework designates four different modes of learning: Interactive, Constructive, Active and Passive. The Passive mode is characterized by a learner receiving information without visible response, whereas an Active learner responds by manipulating the learned knowledge. Constructive learners add one more step by manipulating the information to construct something new. Interactive learners discuss and construct knowledge with a fellow learner. We incorporate the five different social modes in argumentative knowledge construction from Weinberger & Fischer's framework with the ICAP learner modes to interpret the types of dialogues. The social modes are defined as conflict-oriented consensus building, integration-oriented consensus building, quick consensus building, elicitation, and externalization. The three consensus building modes occur when there is a discussion between learners. Elicitation can lead to a consensus building or a learner may answer their own question. Externalization is a primarily singular mode where one learner is vocalizing what they are doing while the other learner(s) in their group are quiet. We combine these two frameworks by mapping the learning modes to the social modes [15].

3 Methods

We conducted a study with 26 high school sophomore students using C2STEM. The students spent one day a week for 2 months completing a CT training module, 3 kinematics modules: 1D and 2D motion including gravity, and 1 force module. Our curriculum included three types of tasks: instructional, model building, and challenge [9].

We divided the students into 9 different groups, 8 groups had three students per group, and the ninth was a group of 2 students. Each group was instructed to work together on one computer screen to build their models. There was discussion across groups. These were not discouraged and are reported as part of our analysis.

Our data sources are OBS™ screen-capture videos that recorded the students' screens along with the webcam video and audio and model scores on submitted tasks. We focused our qualitative analysis on the 2D motion with constant velocity challenge task. In this module, students modeled a boat crossing a flowing river while stopping at two different islands along the way. Model scores were computed utilizing a pre-defined rubric divided into use of physics and CT constructs in order to evaluate proficiency in each domain separately.

4 Results

Using the collaborative dialogue framework described above for qualitative analysis, we identified 5 predominate problem-solving strategies. Table 1 provides transcript evidence to support our identification of problem-solving approaches. We saw increased performances by groups 2, 4 and 5 over time. Interestingly, Group 2 seemed to have the strongest CT skills from the onset of the curriculum. This group showed gains in Physics (75% to 87.5%) and CT (75% to 90%) performance,. Group 5 started with a high performance in Physics (100%) and maintained that with a 100% on the 2D motion challenge (there was a slight dip in score when they started with 2D motion). We hypothesize this indicates some prior knowledge in Physics. Group 5 did show increases in CT over time (from a 62.5% to 90%). Group 7's Physics and CT performances dropped (from 75% to 25 and 62.5% to 20%, respectively). Groups 6 and 9 scored lower in CT but maintained their performance in Physics. We conjecture this correlates with the common difficulty of translating Physics knowledge to a computational model [13].

Table 1. Dialogue Examples of Strategies

Strategy	G	Example Quotes
Hardcoding	1, 2	S1: "it goes 5 m/s, but to go 6 meters forward it would be 1.2 seconds. So we need to figure out, we know the distance we know the time we know the change in distance over the change in time now that will give us the velocity. So 15 / 1.2 [calculates it on paper]. 12.5.
Data Tools	4, 5	S10: "So we find x y coordinates and find the slope and then go there and there [referencing the islands] S11: "So where is this. Wait how do we look at the variables" S9: "Display x and y position"
Debugging	5	S12: "just for testing purposes let's make this an if else and put stop simulation in the else so once it gets there it should stop moving"
Trial and Error	6, 8, 9	S22: "just change the velocity to be lower" S23: "okay we will change that" S22: "just trial and error, make it -4"
Replication/ Help	7	Other group: "Here's the thing, your x velocity should be 5" S19: "No I think that since the river is 2 you need to add more to it"

5 Discussion

The only group to receive lower scores in Physics and CT on this task compared to previous tasks utilized a replication problem solving approach, aiming to copy a solution of another group. This was the only group to engage in *constructive externalization*, instead of working together or communicating as a team. This group began with a successful strategy (using the data tools) but were unable to interpret the physics calculations. We conjecture that confidence in knowledge application or abilities to translate gained Physics knowledge to a more challenging computational model may have caused this decline as the group elected to seek help elsewhere.

The two groups that showed constant Physics scores but decreasing CT scores utilized trial and error or replicating code strategies. These strategies avoid switching between physics and CT. In fact, the groups who did trial and error primarily focused on the computational model and did not attempt to utilize physics concepts like the kinematics equations to solve the problem. Alternately, Group 8 utilized a combination of trial and error and the data tools. The combination of one unsuccessful strategy, trial and error, with a successful strategy, data tool use, seems to have resulted in neither a loss nor a gain in knowledge construction in both Physics and CT.

Finally, the groups whose model scores remained constant or increased in physics and CT, based on model scores utilized hardcoding, data tools, and debugging strategies. These strategies show switching of focus between physics and CT understanding. The hard coding of values into the computational model requires some physics knowledge. Utilizing the data tools, students identified initial positions values for use in their physics equations. Debugging strategies required students to interpret their model behaviors using physics constructs and to identify errors in their models. All of these strategies can be considered synergistic learning processes.

6 Conclusion

A systematic approach that combines quantitative and qualitative analysis of collaborative, computational model building strategies provides useful information into how students problem solve to learn Physics and CT simultaneously. Through careful evaluation of instances in which both Physics and CT knowledge are needed to build a computational model, successful strategies can be characterized by the use of synergistic processes. For example, when a group implements a combination of strategies such as debugging (a CT strategy [7]) and data evaluation (a Physics strategy [12] and a CT process [17]), this results in increased scores in both domains. Unsuccessful strategies do not exploit synergy between the domains, and lead to drop in performance. Combination of good and bad strategies produce mixed results.

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