Exploring Synergistic Learning Processes Through Collaborative Learner-to-Learner Questioning

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Abstract: While the benefits of computational model building in STEM domains are well documented, students' synergistic learning process are not well known. Questioning, both a STEM and CT practice, provides an opportunity for better understanding synergistic learning processes. In this short paper, we look at student's naturally occurring collaborative questions in the context of three synergistic learning processes: initialization, conditional behavior changes and debugging.

Introduction

Curricula should support and instill a commitment to an authentic pursuit of knowledge. Driven by the needs of the 21st century workforce, this pursuit of knowledge requires the development of problem-solving practices that engage students with technological resources and tools to approach new problems on their own. Curricular standards in STEM (NGSS) and computer science (https://k12cs.org/) emphasize the role of asking questions as a key practice targeting this 21st century need. The teaching of science through computational modeling may support this objective. Computational modeling requires the systematic integration of science and computational thinking (CT) concepts and practices - we term this integration as *synergistic learning* that simultaneously enhances STEM and CT learning opportunities. Computational modeling engages students in authentic science practices and critical thinking processes as they plan, develop, test, and debug models of scientific phenomena. Previous work by researchers has shown that computational model building is an effective strategy for K-12 science learning (Basu, et al., 2016; Wilensky & Reisman, 2006). While the benefits and significant learning gains of these computational modeling environments are well documented (Basu, et al, 2016; Sengupta, et al., 2013), it is not fully understood how students are interweaving the concepts and practices from both domains as they learn. Evaluating student questioning during computational modeling could provide insight into the synergistic process of applying STEM and CT knowledge to develop and test models.

In this paper, we focus on the overlapping STEM and CS practice of asking questions in order to derive a way to more fully understand and evaluate synergistic learning processes during computational modeling. Students worked in groups to develop computational models of scientific phenomena in a block-based synergistic learning environment. Their collaborative interactions provide us with rich dialogue that can be used to interpret the context or purpose of their activities that log-data analysis does not provide. We perform an exploratory analysis of the context and type of naturally occurring learner-to-learner questions during model building and problem solving to gain greater insight into the characteristics of synergistic learning processes through the STEM and CT practice of asking questions.

Background

The practice of asking questions is essential for success in both STEM and CT domains. The nature of such questions can be classified by a multitude of things including who is asking the question, who the question is directed to, text-based questions vs knowledge-based questions (Scardamalia & Bereiter, 1992), psychological mechanisms (Graesser, et al. 1992), the process of conceptual change (Watts, et al., 1997; Mishra & Iyer, 2015) and basic vs wonderment questions (Chin & Brown 2002). While looking at student questions provide insight into their learning processes, it is difficult to get a large sample size due to learner's posing questions in their mind but not verbalizing them or asking the question to a friend, rather than the whole class (Dillon, 1998). Collaborative problem solving provides a unique opportunity to collect and study naturally occurring learner posed questions. Successful collaboration requires a variety of skills including the contribution of ideas, monitoring progress and providing constructive feedback (Garrison & Akyol, 2013; Grau & Whitebread, 2012). All of these necessary skills provide ample motivation for students to pose questions.

This paper looks at learner-to-learner questions as they work in a synergistic learning environment. Although these environments have been shown to be effective, learning CT and STEM concepts can be difficult for learners (Román-González, et al. 2017). Learning introductory programming, even with easier block-based languages (Grover & Basu 2017), can be difficult. Integrating conceptual STEM learning can compound these challenges (Basu, et al. 2016; Chi, 2005). While students find the behavior of objects in the computational model intuitive, the combination of objects with other types of physical phenomena can result in learning challenges (Chi, 2005; Wilensky & Resnick 1999). Other challenges include difficulties transferring their STEM knowledge to CT constructs such as computational parameters and behaviors, and an inability to identify significant objects and relations (Basu, et al., 2016). Additional scaffolding must be implemented to support a lower introductory threshold to facilitate computational model building in STEM domains (Sengupta, et al., 2013; Weintrop, et al., 2016).

Question analysis framework

The framework used in our analysis is based on Pedrosa de Jesus, et al.'s grouping into two types of questions: confirmation and transformation (2003). This categorization is based on naturally occurring questions that happen between learners and are not facilitated by the teacher. **Confirmation questions** clarify information, deal with logistics, seek reassurance about an idea and attempt to find the location of system specific objects. These confirmation questions usually only require a shallow understanding of concepts. Some examples of such confirmation questions are the following: "*Where is the if block*?", "*So the velocity is 4, right*?", "*What is the speed limit supposed to be*?", "*What are you trying to figure out*?". **Transformation** questions challenge previous actions or statements, pose higher level concept ideas and guide the modeling process. These questions require a higher level of understanding than confirmation questions. Some examples of transformation questions are the following: "*Are you sure it's not supposed to be an if else*?", "*If we change velocity to 0 and leave acceleration as what it is, will the truck move*?", "*Okay so how long did the truck take to go from the start to the stop sign*?".

In previous work, we identified three essential synergistic learning processes: initialization, debugging and conditional behavior changes (Hutchins, et al., 2018; Snyder, et al., 2019). Variable initialization is a key CT practice (Grover & Pea, 2018), and it also provides an insight into a student's conceptual understanding of the motion processes being modeled. Debugging, another key CT skill (Grover & Pea, 2018) requires students to analyze the model's behavior, identify the error in the model and then correcting the error. Debugging requires students to identify if the error is due to an incorrect representation (modeling) of physics concepts or an incorrect specification of the CT (or programming) constructs. Conditional behavior changes require students to use conditional expressions to represent changes in motion behavior using their physics concepts to identify when and in what context the change in behavior should happen, along with using appropriate CT constructs to represent it.

Study description and data analysis methods

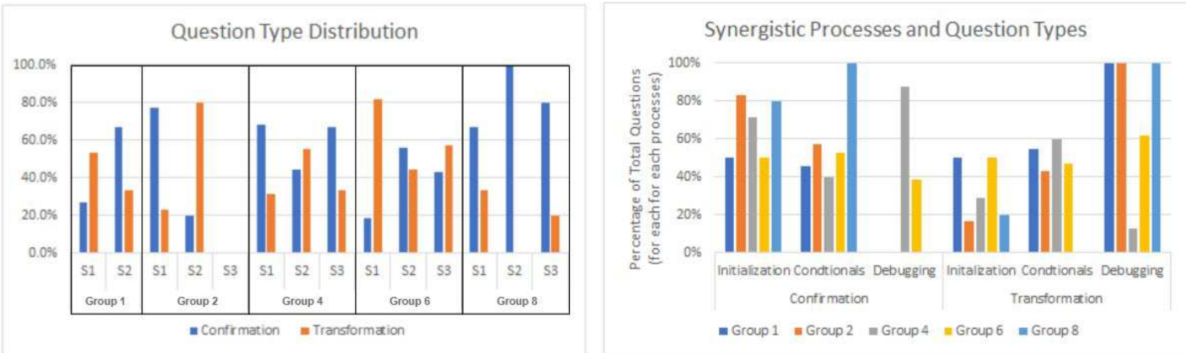
The research method presented in this paper is guided by the research questions: *What characteristics of synergistic learning and reasoning processes can we derive from learner-to-learner questions as they work on computational modeling tasks? What characteristics of students' questioning can be we derive as they work in a synergistic learning environment?* We conducted a study where 26 high school sophomore students worked in the C2STEM environment in groups to complete kinematics and dynamics computational modeling tasks. The students spent one day a week for 2 months completing a CT training module, 3 kinematics modules, and 1 forces module. Kinematics modules include: 1D motion (constant velocity and constant acceleration), 2D motion with constant velocity, and 2D motion with gravity. Student learning and model building was supported by three types of tasks: (1) instructional, (2) model building, and (3) an overarching challenge (Hutchins, et al. 2018). 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. Model scores were computed utilizing a predefined rubric divided into physics and CT constructs for all modeling tasks.

The data sources used in our analysis were screen-capture videos that recorded the student's screens along with the student's webcam video and audio. Due to technical issues, we were unable to fully hear the discourse of four of the groups and removed them from our analysis. For the rest of the groups, we focused our analysis questions that occur naturally as the students work on the 1D motion challenge task. In this module students were instructed to model a truck that speeds up from rest to a maximum speed given by a speed limit, maintain that speed and then slow down to a stop at a stop sign. To be successful in this module students must understand the relationship between acceleration and velocity and be able to calculate a lookahead distance from a stop sign. Models were evaluated utilizing a predefined rubric divided into physics and CT constructs for all modeling tasks. In order to gain insight into the type of question a student asks, we coded questions as confirmation, transformation or incomplete. Inter-rater reliability was checked by calculating Cohen's kappa value which resulted in substantial agreement ($k = 0.80$).

Results

Each group's computational model was scored using a rubric with a max physics score of 4 and a max CT score of 8. The highest performing groups, Group 2 and 4, received physics scores of 3 and 6, respectively, and CT scores of 6 and 5, respectively. The lowest performing group, Group 1, received a physics score of 3 and CT score of 2. Group 6 and Group 8 both received physics scores of 3 and CT scores of 4.

The question type distribution for each student can be seen in Figure 1(a). The group members seemed to fall into roles of either *transformation questioner* or *confirmation questioner*. This is extremely apparent in Groups 1 and 2, as seen by the fact that one group member had a much higher percentage of one of the question types. All of the groups had at least one group member asking transformation and confirmation questions, respectively, except for Group 8. In Group 8, all members asked mostly confirmation questions. While this did not seem to affect the overall scores, this phenomenon is interesting due to the fact that we did not specifically assign students questioning roles or instructed them on different types of questions.



(a) (b)

Figure 1. (a) Question Type Distribution (b) Synergistic Processes and Question Types.

The percentage of total questions for each synergistic process can be seen in Figure 1(b) above. For most of the groups, more of their initialization questions where categorized as confirmation questions. We hypothesize that this is due to the concrete nature of initialization. While determining which variables to initialize and what values to assign to those variables, students are mostly concerned with confirming what the starting conditions are (which are given in the instructions). All except Group 8 had a relatively equal amount of confirmation and transformation questions when looking at conditional behavior changes. Finally, in the highest performing groups, Group 4 and Group 6, all or some of their debugging questions were confirmation questions while the other groups had all transformation debugging questions. While the other two processes had both confirmation and transformation questions, debugging questions were polarized. We had hypothesized that debugging questions were more likely to be transformation questions due to the complex nature of debugging, but this is not the case for Group 4, one of the higher performing groups. Most of the questions asked by Group 4 during the debugging process were clarification questions about what the other person suggested may be the problem such as "What do you mean?" and "What?".

Discussion and future work

Our preliminary results suggest that group members will take on specific roles during model building without being explicitly assigned to them. We believe this may be due to the fact the students pose questions during collaborative problem solving for a variety of reasons including challenging a partner, guiding the group, or clarifying a group member's statement. The roles assumed by group members may be informed by these variations. They may also be informed by the students' prior knowledge. In addition, it may also be related to other roles or tasks that students assign to themselves during their collaborative work in other activities. Future work will include investigating the purpose for student's questions in the context of synergistic learning.

In order to fully understand synergistic learning, we must investigate the underlying learning processes students use. Our results demonstrate that successful initialization processes may require discussion on concrete and basic understanding of domain concepts, as seen by the higher proportion of confirmation questions by the higher performing groups in the initialization context. The relatively equal distribution of confirmation and transformation questions while groups worked on modeling conditional behavior changes may suggest that this synergistic process requires a balance between basic, concrete details and a deeper understanding of high-level concepts. In the synergistic processes of debugging, groups had a higher amount of transformation questions which suggests a need for discussion about high-level concepts. However, the outlier group, which had almost all confirmation questions, points to a need to further explore this idea. Further research is necessary to look more in depth at how the synergy of the two domains is present in student's questions and how different types of questions may be crucial to the learning of different domain concepts.

References

Basu, S., Biswas, G. & Kinnebrew, J.S. (2016). Using multiple representations to simultaneously learn computational thinking and middle school science. *In Thirtieth AAAI conference on Artificial Intelligence* (pp. 3705-3711). Phoenix, Arizona, USA.

Chi, M. T. H. (2005). Common sense conceptions of emergent processes: Why some misconceptions are robust. *Journal of the Learning Sciences*, 14, 161–199.

Chin, C., & Brown, D. (2002). Student-generated questions: A meaningful aspect of learning in science. *International Journal of Science Education*, 24, pp521-549.

Dillon, J.T. (1988). The remedial status of student questioning. Journal of Curriculum Studies, 20, 197–210.

Garrison, D. R., & Akyol, Z. (2013). The Community of Inquiry Theoretical Framework. In *Handbook of distance education*(122-138). Routledge.

Graesser, A.C., Person, N.K. & Huber, J.D. (1992). Mechanisms that generate questions. In T. Lauer, E. Peacock, & A. C. Graesser (Eds.), *Questions and information systems* (167–187). Hillsdale, NJ: Erlbaum.

Grau, V., & Whitebread, D. (2012). Self and social regulation of learning during collaborative activities in the classroom: The interplay of individual and group cognition. *Learning and Instruction*, *22*(6), (401-412).

Grover, S., & Basu, S. (2017). Measuring student learning in introductory block-based programming: Examining misconceptions of loops, variables, and Boolean logic. *In Proceedings of the 2017 ACM SIGCSE Technical Symposium on Computer Science Education* (267-272). ACM.

Grover, S., & Pea, R. (2018). Computational Thinking: A competency whose time has come. In Sentance, S., Carsten, S., & Barendsen, E. (Eds*). Computer Science Education: Perspectives on teaching and learning*, (19-38). Bloomsbury.

Hutchins, N., Biswas, G., Maroti, M., Ledezci, A., & Broll, B. (2018). A Design-Based Approach to a Classroom-Centered OELE. *In International Conference on Artificial Intelligence in Education* (155-159).

Mishra, S., & Iyer, S. (2015). An exploration of problem posing-based activities as an assessment tool and as an instructional strategy. *Research and practice in technology enhanced learning*, 10(1), 5.

NGSS Lead States. (2013). Next Generation Science Standards: For states, by states. Washington, DC: *The National Academies Press.*

Pedrosa de Jesus, H., Teixeira-Dias, J., & Watts, M. (2003). Questions of chemistry. In *International Journal of Science Education* Vol. 25, 1015–1034.

Román-González, M., Pérez-González, J.-C., Jiménez-Fernández, C. (2017) "Which cognitive abilities underlie computational thinking? Criterion validity of the Computational Thinking Test", *Computers in Human Behavior* Vol. 72, 678-691.

Scardamalia, M., & Bereiter, C. (1992). Text-Based and Knowledge-Based Questioning by Children. *Cognition and Instruction*, 9(3), 177-199.

Sengupta, P., Kinnebrew, J. S., Basu, S., Biswas, G., & Clark, D. (2013). Integrating computational thinking with K-12 science education using agent-based computation: A theoretical framework. *Education and Information Technologies*, *18*(2), 351-380.

Snyder, C., Hutchins, N., Biswas, G., Emara, M., Grover, S., Conlin, L. (2019). Analyzing Students' Synergistic Learning Processes in Physics and CT by Collaborative Discourse Analysis. *In Proceedings of the International Conference on Computer Supported Collaborative Learning*, Lyon, France, (360-367).

Watts, M., Alsop, S., Gould, G., & Walsh, A. (1997). Prompting teachers' constructive reflection: Pupils' questions as critical incidents. *International Journal of Science Education,* 19(9), 1025-1037.

Weintrop, D., Beheshti, E., Horn, M., Orton, K., Jona, K., Trouille, L., & Wilensky, U. (2016). Defining computational thinking for mathematics and science classrooms. Journal of Science Education and Technology, 25(1), 127-147.

Wilensky, U., & Reisman, K. (2006). Thinking like a wolf, a sheep, or a firefly: Learning biology through constructing and testing computational theories—an embodied modeling approach. *Cognition and instruction*, *24*(2), 171-209.

Wilensky, U., & Resnick, M. (1999). Thinking in Levels: A Dynamic Systems Perspective to Making Sense of the World. *Journal of Science Education and Technology*, 8(1).

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