Examining how prior knowledge impacts students' discussions and knowledge construction during computational model building

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Abstract

Student discussions have been shown to be beneficial to student learning (Chi & Wylie, 2014), however the impact of prior knowledge on these discussions is not fully understood. In this research, we analyze students' synchronous spoken discussions to study how prior knowledge impacted group discussions and knowledge construction while constructing computational models of 1D and 2D motion. We present a method for evaluating the impact of prior knowledge on student discussions and individual work. We illustrate this method through a case study analysis of two groups with students across a spectrum of prior knowledge. Our exploratory findings suggest that students with low prior knowledge greatly benefit from group discussions followed by individual model construction.

1. Introduction

Student-to-student interactions during learning scenarios have been shown to be beneficial to student learning (Chi & Wylie, 2014). The benefits of student interactions during learning include communication skills (Dallimore, Hertenstein, and Piatt, 2008) as well as critical thinking skills (Garside, 1996). During student interactions, students externalize their current understanding, shaped by their prior knowledge and it is internalized by the other group members to form a base of shared knowledge (Beers et al., 2005). While prior knowledge has been regarded as a critical factor in student learning (e.g., Tobias, 1994), limited research has examined the impact of prior knowledge on group discussions. In this work, we attempt to extend the research on student discussions by performing an exploratory analysis of how students' prior knowledge may affect group discussions and the impact of these synchronous, spoken discussions.

We adopt a constructivist approach that requires students to construct their knowledge at the same time they are trying to solve a problem, specifically building a computational model of a science phenomenon. The symbiotic relationship of STEM (Science, Technology, Engineering, and Mathematics) and computational thinking (CT; Grover & Pea, 2018) and the learning benefits when students actively construct and generate learning outputs (Chi & Wylie, 2014), support computational model building as an effective vehicle for learning. Our approach combines the learning of STEM and CT concepts and practices through learning-by-modeling. Students learn by building, simulating, testing and refining their own computational models using a block-structured programming environment, instead of exploring existing models. This approach has been shown to be effective in supporting students' knowledge of STEM and CT concepts (Basu et al., 2017; Basu et al., 2016b; Hutchins et al., 2018). However, research has identified student difficulties such as problems translating their STEM knowledge to CT constructs (e.g., Basu et al., 2016a), compounding challenges with introductory programming concepts (Basu et al., 2016; Chi, 2005) and an inability to identify relevant objects in the simulation and specify how these physical phenomena interact (Basu et al., 2016a). Such difficulties may be mitigated by allowing students to work on the models collaboratively or by giving students the opportunity to discuss their individual models in groups like we do in this work. The opportunity to discuss their model construction in groups gives students a chance to construct knowledge as a group and address possible misconceptions.Through discussion students come to a shared knowledge state (Beers et al., 2005) from which they can negotiate, ask questions and provide constructive feedback in order to construct knowledge as they discuss their construction processes of computational models.

In this paper, we examine videos of students' online discussions of computational models in order to gain insights into how students' prior knowledge impacted their discussions and knowledge construction by analyzing three final constructed models over four sessions. This study was conducted entirely over Zoom, because the pandemic prevented us from having in class meetings with students. Students, their instructors, and all of the researchers conducted the instruction and discussions remotely using Zoom. We present an approach for evaluating the impact of prior knowledge in multiple domains on discussions and individual work. We illustrate the impact of our approach through an exploratory analysis of two groups.

2. Study Description

Our work utilizes the Collaborative, Computational STEM (C2STEM) learning environment (as seen in the task images in Table 1). C2STEM is a visual, block-based coding environment developed on top of Netsblox (Broll et al., 2017), an extension of Snap! (http://snap.berkeley.edu/), that leverages a domain-specific modeling language (DSML) to support students' construction of scientific computational models (Hutchins et al., 2020).

We studied 22 high school students who worked on three C2STEM modules that covered 1D motion and 2D motion with gravitational forces over a five week period. The modeling assignments can be seen in Table 1. Students had 10-15 minutes of instruction and 15-20 minutes of group discussion every week, with the exception of week 3 that consisted of a full 30 minutes of instruction. Instruction occurred online, over Zoom, and group discussions took place online in individual group breakout rooms. Students were instructed to work on their models individually for homework but discussed ideas or started the model as a group. The group discussions all had a group supervisor in the Zoom breakout room the entire time for questions and comments.

3. Analysis

The research presented in this paper is guided by the following questions: *How does students' prior knowledge affect group discussions and the impact of such discussions? How do students' group discussions impact their computational modeling?* To answer these questions, we analyzed three data sources: (1) students' pretest scores, (2) group discussions and (3) students' final models. We graded the students' pretest and final model scores according to rubrics (see an example of the truck task rubric in Table 2). We present a method to analyze the content of students' discussions through coding transcribed utterances according to physics and CT concepts, seen in Table 3, with a secondary code that identifies the correctness of the utterance, as seen in Table 4. Two coders coded the utterances with almost perfect agreement ($\kappa = 0.83$). With these codes, we calculated the normalized difference between correct (COR) and incorrect (INC) utterances for all the physics and CT concepts, i.e., $(COR - INC)/\,(COR + INC)$. Thus, the difference range is {-1, 1} with a score of -1 indicating all incorrect utterances in a given category and 1 indicating all correct utterances. An *NA* indicates that there were no utterances for a given category.

We illustrate the use of this coding method through a case study analysis of two groups with three and four students each. We examine their individual pretest and model scores, their group discussion characteristics and dialogue segments. We selected the groups for case study analysis to have a representative mixture of prior knowledge, measured through a pretest, in both STEM and CT. The physics portion of the test had a total score of 17 points, and the students averaged 12.5 points ($\sigma = 2.35$). The CT portion of the test had a total score of 16 points, and the students averaged 9.25 points ($\sigma = 2.81$). We categorized students as high or low prior knowledge based on whether their physics and CT scores were above or below the two averages, respectively. In addition to the prior knowledge distinction representation, the two groups selected for analysis each had the same group supervisor, thus mitigating the effect different supervisor styles may have on the students' discussions and model construction.

4.1 Group Results

Table 5 shows the pretest scores of each group and their prior knowledge designation.

Group 1

G1 has four students, two with high prior knowledge in both CT and physics and two with low prior knowledge in both domains. As seen in Table 6, the majority of utterances on most days are by the high prior knowledge students, S1 and S2. D4 is the exception where S4 says more than S2 (0.28 to 0.17, respectively). With the exception of D2, the normalized difference of correct and incorrect utterances is higher with CT utterances in comparison to physics utterances. This implies that the students in G1 may be more knowledgeable in their discussion of CT concepts.

Group 2

G2 has three students, one for each configuration of CT and physics prior knowledge, with the exception of a student with high CT, high physics prior knowledge. As seen in Table 7, S5 and S6 contribute to the conversation much more than S7, with the exception of D5. S6's participation was mixed but on days D1 and D4 they contributed more to the discussion (proportions of 0.44

and 0.48 respectively) as opposed to days D2 and D5 where their contributions were much less (proportions of 0.17 and 0.07 respectively). On the days where S6 contributes less to the discussion (D2 and D5), the group makes more incorrect than correct utterances as a whole, as seen by the negative total normalized differences.

4.2 Individual Student Results

Table 8 shows the normalized difference between correct and incorrect utterances over the entire four days. This includes the normalized difference over all the utterances as well as the physics and CT utterances. Table 9 shows their model scores broken down into scores for the CT and Physics components.

<u>High Physics, High CT Prior Knowledge: S1, S2</u>

Although S1 is categorized as having high prior knowledge in both physics and CT, S1 is one of the three students that made more incorrect than correct physics utterances over the course of the four days as seen in the normalized difference of -0.33. S1 has difficulty understanding the relationship between velocity and acceleration during the truck task and introduced an error by setting velocity to the 15 m/s speed limit, explaining to the group that it goes from *"zero to 15 like really quickly*". They required help to recognize that they must update velocity using the mathematical formula representing the relationship between velocity, acceleration and time (derived from Newton's first and second laws) in order to get a steadily increasing velocity. While they struggled with physics, S1 made more correct CT statements (0.14 difference value). This is notable, given that S1's physics pretest (76%) was higher than their CT pretest (69%). When looking at the final model scores, we see that S1 had higher CT scores except for the Drone 2 package task. S2, in contrast, only made correct physics utterances and mostly correct CT utterances. Despite a strong initial performance on the first two tasks, with scores of 1.00 and 0.98, respectively, S2 also struggled on the Drone 2 package task. Similar to S1, S2's CT score was worse than the physics score for this task.

<u>Low Physics, Low CT Prior Knowledge: S3, S4, S5</u>

When S3 did contribute to the conversation, none of the utterances about either physics or CT were correct statements, as seen by the -1 normalized difference in both categories. However, S3 improved in their model construction as seen by the initial score of 0.65 and the final score of 0.76. Although S3's contributions were rare and often incorrect, S3 often questioned the other group members saying, during the truck task, "*Why do you guys think velocity changed, but the acceleration didn't? Like it stayed constant through the whole thing. Although the velocity kept increasing*". S2 and S4 answer S3, explaining that they "*set the exact value for acceleration*", and thus it stayed constant but the velocity was updated each time step and resulted in the velocity value being "*adding on and adding on and then got bigger*". When S3 did contribute, it gave the other group members an opportunity to address misunderstandings and come to a more shared understanding. S4 and S5 were very successful in the final model with scores of 0.90 and 0.92 respectively. They both contributed more to the discussions than S3 and had more correct than incorrect statements.

<u>High Physics, Low CT Prior Knowledge: S6</u>

Similar to S1, a higher physics pretest score (82%) than CT pretest (38%) did not translate to more correct utterances in physics than CT for S6 as seen by the normalized CT difference of 0.42 and physics difference of 0.20. We hypothesize this may be due to the fact S6's lack of knowledge in CT led to more contributions focused on this knowledge gap. However, while they were able to contribute correct CT focused statements to the group, S6 was not able to translate this to their model construction, particularly seen in the CT component of their model scores. An example of this can be seen while the group is discussing how to model the truck cruising at a constant velocity once it hits the speed limit. S6 correctly conceptualizes the conditional statement saying "*If you say x velocity equal 15, I think there may be a block that you could use that will limit [the speed]*" but is not confident in their understanding of how it will impact the simulation saying "*but that might just make it stop moving in general, I'm not really sure.*" S6 then continues and gives a different idea that involves a misconception about how to update variables. A lack of confidence in S6's original correct statements leads to incorrect implementations in their model.

<u>Low Physics, High CT Prior Knowledge: S7</u>
Similar to S3, S7 rarely contributed to the group discussion and made a majority of incorrect statements as seen by the total normalized difference of -0.67. The model scores for the first two tasks reflect the higher CT prior knowledge compared to physics, however, in the last task S7 does particularly well on the physics components of the model. We hypothesize this may be due to their increased participation on the last day.

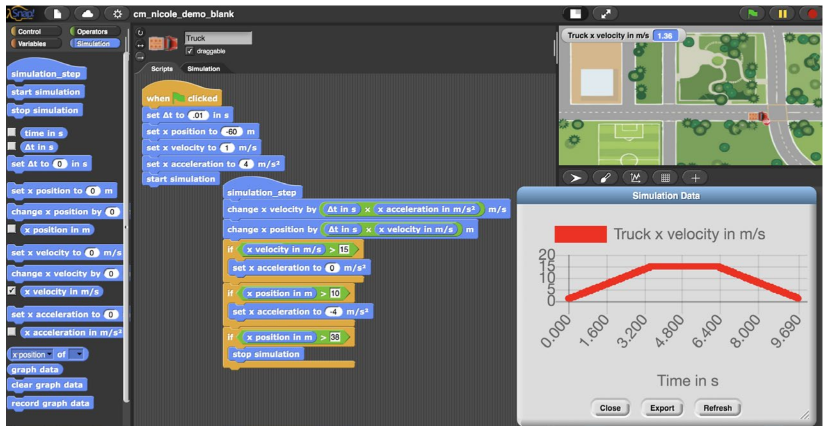
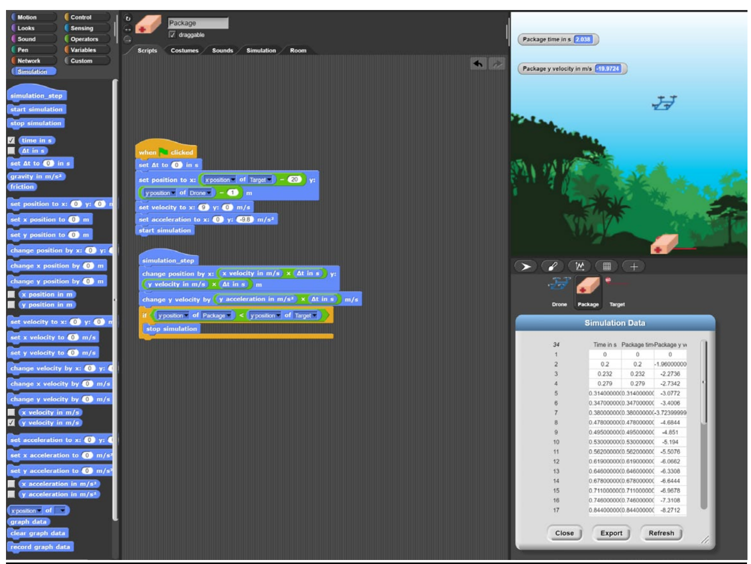
4. Conclusions and Next Steps

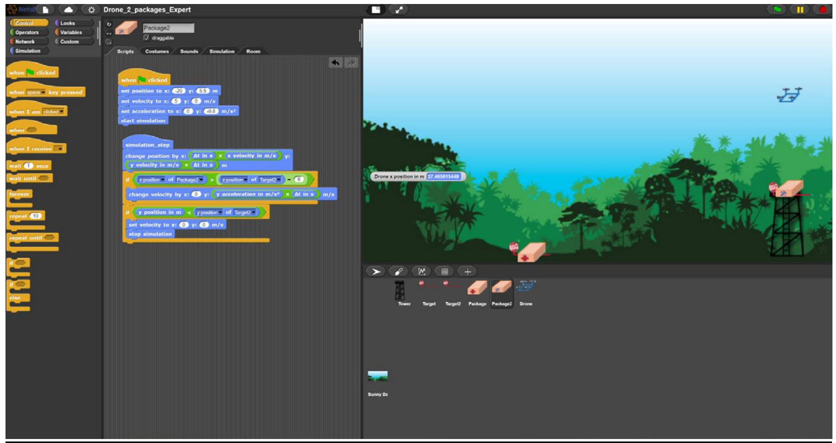
From these exploratory results, we can see that high prior knowledge in a domain does not necessarily translate to correct externalized knowledge as seen in S1 and S7 who made more incorrect than correct statements in the domain that they had high prior knowledge in. Similarly, low prior knowledge did not predict discussion contributions as seen by S6 who more successfully externalized knowledge in their low prior knowledge domain compared to the domain they had high prior knowledge in.

Students with low prior knowledge in one or both domains benefited the most from the group discussions, as seen by the higher final model scores of S3, S4, S5 and S7. These group discussions supported low prior knowledge students' ability to translate conceptual knowledge to computational form. The benefits of group discussion exist even when the students rarely contribute to the discussion, as seen in S3 and S7. We hypothesize these students, while not actively contributing to the conversation, may be actively listening and are able to gain a shared knowledge understanding that they then use in their individual model building. While low prior knowledge students benefited from this type of structure, the students with high prior knowledge in both domains, S1 and S2, did worse on their final model than their first model. Due to the many variables that may have impacted these students with high prior knowledge, such as a ceiling effect or boredom, further research is necessary to fully understand the impact of group discussion on students with high prior knowledge.

While this analysis is limited in its small sample size, we hope it provides a starting place for analysis of group discussions that focuses on the knowledge externalized by students during their knowledge construction process. In future work, we will expand upon our sample size as well as mapping the specific utterances made in group discussions about STEM and CT concepts to the students' individual model construction processes. In this way, we will be able to better identify characteristics of the discussion and externalized knowledge that had the most impact on students with low prior knowledge. Future work will also investigate how a groups' composition of prior knowledge impacts individual and group knowledge construction.

Table 1: Task Description

Task	Image
Simulate a truck speeding up to a speed limit of 15 m/s, cruising at that speed and then slowing down to a stop at a stop sign	
Simulate a drone dropping a package onto a target	

Simulate a drone dropping two packages onto two individual targets.	

<u>Table 2: Truck Task Rubric</u>

Item	Points
Expressing physics relations in a computational model	
Program initializes x position to the correct starting value	1
Program initializes x velocity to the correct starting value	1
Program initializes x acceleration to the correct starting value	1
Program expresses correct relations among velocity, position and time, and correct units for each	1
Program expresses correct relations among acceleration, velocity, and time, and correct units for each	1
Program expresses correct values for updating acceleration	1
Program accuracy - (1) accelerates to the speed limit, (2) cruises at the speed limit and (3) slows to a stop at the stop sign	3
Using CT concepts to model physics phenomena	
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 initializes variables (except delta t) that are utilized in the updating of the simulation behavior	1
Program initializes delta t for use in modeling desired relationships	1
Program sets initialized variables in the correct fashion	1

Program updates variables with correct function	1
Program updates variables with correct operators/expressions	1
Program updates initialized variables in the correct sequence	1
Program updates / sets initialized variables under the correct conditions - (1) Sets acceleration to 0 when the speed limit is hit and (2) decelerates at a distance far enough from the stop sign to come to a stop	2
No duplicate code	1
Simulation ends based on stopping logic	1

Table 3: Physics and CT concept codes

First Code	**Description**	**Example**
PHY.VEL_ACC	Referencing velocity explicitly or how fast a physical object or sprite is moving in addition to acceleration explicitly or the slowing down or speeding up of a physical object or sprite	*"Why did the velocity change? It just kept increasing."*
PHY.VEL_POS	Referencing velocity explicitly or how fast a physical object or sprite is moving in addition to the position of a physical object or sprite; Not the position of blocks or components in the environment	*"[Velocity] is going to be negative without that code so then it is going to start going backward."*
PHY.EQU	Referencing the physics equations (given as a reference for the students)	*"It says that position change equals velocity times delta t."*
CT.DELTA_T	Referencing delta t explicitly	*"What does delta t need to be?"*
CT.INIT_VAR	Referring to initializing variables explicitly or what variables should start as	*"Once I added the set x velocity block it worked."*
CT.UPD_VAR	Referring to updating variables explicitly, how variables should change	*"Set acceleration to negative 4"*
CT.OPR_EXP	Referring to operator blocks or expressions	*"Use greater than 15 instead of equal to 15."*

CT.COND	Referring to what control structure blocks(if, if-else, repeat, repeat while, etc.) to use or what conditions something should change	*"Update velocity inside the if instead of outside"*
CT.GF_SIM	Referring to the green flag or simulation step structure	*"That should go under the green flag"*

Table 4: Secondary correctness codes

Secondary Code	Description	Example (VEL_ACC)
INC	Statement that is conceptually incorrect about concept x	*"Set acceleration to a negative number so that it will stow down to the stop sign"*
COR	Statement that is conceptually correct about concept x	*"To get velocity to stay at 15, just set it to 15, you don't need to do anything with acceleration."*
No Secondary Code	Statement about something related to concept x but it is a neutral or unclear statement	*"The velocity block is right there"*

Table 5: Pretest scores

Group	Student	Pre-Phy	Pre-CT	Prior knowledge
G1	S1	76%	69%	High Phy, High CT
	S2	82%	59%	High Phy, High CT
	S3	65%	34%	Low Phy, Low CT
	S4	72%	50%	Low Phy, Low CT
G2	S5	53%	41%	Low Phy, Low CT
	S6	82%	38%	High Phy, Low CT

	S7	71%	81%	Low Phy, High CT

Table 6: Group 1 proportion of total utterances for discussion contributors and normalized difference between correct and incorrect statements

Description	Day 1	Day 2	Day 4	Day 5
Supervisor utterances	0.36	0.22	0.14	0.07
S1 utterances	0.24	0.26	0.41	0.39
S2 utterances	0.23	0.34	0.17	0.41
S3 utterances	0.03	0.06	0.00	0.00
S4 utterances	0.13	0.13	0.28	0.11
Total COR-INC	0.50	0.10	0.43	0.58
PHY COR-INC	*NA*	0.20	0.23	0.33
CT COR-INC	0.50	0.05	0.52	0.60

Table 7: Group 2 proportion of total utterances for discussion contributors and normalized difference between correct and incorrect statements

Description	Day 1	Day 2	Day 4	Day 5
Supervisor utterances	0.21	0.37	0.24	0.26
S5 utterances	0.34	0.46	0.56	0.40
S6 utterances	0.44	0.17	0.48	0.07
S7 utterances	0.00	0.00	0.02	0.28
Total COR-INC	0.38	-0.15	0.58	-0.18
PHY COR-INC	1.00	-0.20	1.00	-1.00
CT COR-INC	0.33	-0.13	0.48	0.06

Table 8: The normalized difference between correct and incorrect utterances over all four days

Group	Student	Prior knowledge	ALL COR-INC	PHY COR-INC	CT COR-INC

G1	S1	High Phy, High CT	0.04	-0.33	0.14
	S2	High Phy, High CT	0.87	1	0.82
	S3	Low Phy, Low CT	-1	-1	-1
	S4	Low Phy, Low CT	0.44	0.50	0.43
G2	S5	Low Phy, Low CT	0.12	0	0.14
	S6	High Phy, Low CT	0.37	0.20	0.42
	S7	Low Phy, High CT	-0.67	-1.00	-0.60

Table 9: Student model scores

Student	**Truck - Total**	**Drone 1 - Total**	**Drone 2 - Total**	**Truck - Phy**	**Drone 1 - Phy**	**Drone 2 - Phy**	**Truck - CT**	**Drone 1 - CT**	**Drone 2 - CT**
S1	0.80	0.85	0.78	0.78	0.70	0.82	0.82	1.00	0.73
S2	1.00	0.98	0.78	1.00	0.95	0.82	1.00	1.00	0.73
S3	0.65	0.58	0.76	0.56	0.45	0.79	0.73	0.70	0.73
S4	0.70	0.80	0.90	0.56	0.60	1.00	0.82	1.00	0.77
S5	0.60	0.50	0.92	0.44	0.35	1.00	0.73	0.65	0.82
S6	0.90	0.65	0.62	0.89	0.70	0.75	0.91	0.60	0.45
S7	0.70	0.68	0.80	0.67	0.55	0.96	0.73	0.80	0.59

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