The Influence of Students' Transformative and Non-Transformative Contributions on Their Problem Solving in Collaborative Inquiry Learning

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Abstract: The effectiveness of collaborative inquiry learning in simulation-based learning environments for STEM education has been well-documented. At the same time, research indicates that some students struggle with articulating relevant concepts, making their reasoning explicit and regulating their learning—skills that are necessary for effective collaboration. In this study, using qualitative and quantitative analysis as well as data mining techniques, we investigated what promotes meaningful interaction between students when conducting collaborative inquiry. One hundred and fifty-six students from five high schools and colleges in the United States worked in groups of three to solve electronics tasks with increasing complexity in a virtual environment called Teaching Teamwork. The results showed that when the groups successfully solved the tasks, they showed statistically significant higher proposition generation, regulation and sustaining mutual understanding; when they did not solve the tasks, they showed significantly higher orientation, interpretation and conclusion. Explanations for these results and research recommendations are provided.

Introduction

There is a well-documented body of research that shows the effectiveness of using computer networks for collaborative learning on STEM education (see Jeong, Hmelo-Silver, Jo, & Shin, 2016, for review). In computer-supported collaborative inquiry learning (CSCiL), two or more learners collaborate via the computer, typically in a simulation-based learning environment, to solve problems (e.g., electrical engineering topic as is used in the present study) and co-construct knowledge (e.g., understanding the relation between the values of voltage and resistance). This process entails searching for information, hypothesis formulation, experimentation, interpretation, articulation and sharing ideas for collaborating partners to build upon (Stahl, Koschmann, & Suthers, 2006). Research on collaborative inquiry learning has consistently shown that most students struggle to regulate their learning, articulate relevant concepts in order to actively make sense of the subject matter (e.g., through hypothesis generation and data interpretation) and make their reasoning explicit (de Jong & van Lazonder & Rouet, 2008; Raes et al., 2012; Popov et al., 2017). The core of the present research therefore is concerned with the question of how to effectively promote the kind of meaningful interaction between students when conducting inquiry tasks that allow them to reap the benefits of collaboration.

According to Gijlers and de Jong (2009), when conducting typical collaborative inquiry tasks, students are engaged in transformative learning activities (those that are directly related to knowledge construction) and regulative activities (those that are necessary to coordinate and sustain mutual understanding at all times). Transformative learning processes include: *orientation, hypothesis generation, experimentation, and conclusion*. Regulative learning processes include: *sustaining mutual understanding, planning and monitoring* (Gijlers & de Jong, 2009; de Jong, 2006). Each learning process has specific objectives and requires specific types of collaboration, activities where information is transferred from one participant to another, to be effective. Coordination of such collaborative activities and appropriate distribution of group efforts and resources are of critical importance to the group problem solving (Rummel & Spada, 2005). Furthermore, learning is particularly likely to occur when the collaborating students engage in meaning-making processes by formulating hypotheses about certain phenomenon and connect these hypotheses to prior knowledge, or form new insights based on their experiences in the learning environment (Gijlers & de Jong, 2009).

Building on previous research, this study investigated to what extent students' engagement in transformative and non-transformative learning processes predicts groups' learning outcomes within a simulation-based collaborative inquiry learning environment. By examining which process characteristics positively influence groups' learning outcomes, it may be possible to help teachers encourage specific types of student activities to improve students' learning gains.

Peer collaboration as a source of support in the inquiry learning process

Inquiry tasks are highly challenging for students if they are not sufficiently supported (Makitalo-Siegl, Kohnle, & Fischer, 2011; de Jong & van Joolingen, 1998). Relevant sources of support are typically teachers, small group scripts (i.e. scaffolding that guides students on what to do, what roles to play, what sequences of activities to perform during a learning task), a knowledgeable expert (Mäkitalo-Siegl et al., 2011) or peers (Okada & Simon, 1997). In this study, we focused on peer support by exploring how students find support in working with other peers through collaborative learning, i.e., peer scaffolding. Okada and Simon (1997) found that students who worked in dyads were found to outperform students who worked alone on a molecular biology inquiry learning task, because dyads were able to formulate more alternative scenarios. Piaget's (1926) ideas about sociocognitive conflicts and Vygotsky's (1978) "zone of proximal development" help explain why scaffolding (either provided by peers, teachers or other instructional sources) can be effective in addressing students' individual cognitive abilities. A good scaffold can link a student's current understanding to the learning context. For example, with peer scaffolding, a student may be good at explaining how chemical reactions relate to energy, yet have limited understanding how to interact with dynamic visualizations (Gerrard et al., 2009). The partner student may have expertise in constructing models, yet struggle to design consequential experiments. Each collaborative or knowledge integration unit will enable students to take advantage of the peer expertise.

Based on the Piagetian approach of socio-cognitive conflict, the efficacy of collaborative learning effort is thought to be influenced by the extent to which students can identify and discuss conflicts in their knowledge and beliefs (De Lisi & Goldbeck, 1999). For instance, participatory simulations create a kind of collaborative learning in which every student's experience and contributions build towards a collective understanding of the whole system. This process encourages students to make their thinking visible by explaining their reasoning to their collaborative partners. It is assumed that students working in groups reach a shared understanding through the negotiation of meaning, which requires students to ask questions, have discussions, explain their thoughts and ideas, and support their viewpoints with additional information (De Lisi & Goldbeck, 1999). Previous research supports that learning is likely to happen when the collaborating students build on each other's reasoning by critiquing, challenging and synthesizing opinions, because this form of discourse triggers cognitive activities that stimulate knowledge construction (Andriessen, Baker, Suthers, 2003).

This study explores a series of collaborative (non-)transformative learning processes: orientation, hypothesis generation, experimentation, conclusion drawing, regulation, and sustaining mutual understanding (see Table 1). During orientation, students elicit ideas so that they become aware of their views of the situation, add new ideas to fill in missing information to make sense of the topic and strategize about how to approach/solve a problem at hand. During hypothesis generation, students typically form a statement or a set of statements concerning the relations regarding the values, variables and relation between them in order to solve the task. Previous research studies have particularly examined hypothesis generation process and ways to support this process. This process is important because it triggers students' activation of their prior knowledge that they try to connect to the variables presented in a problem to explain phenomena. During experimentation, students design, test, run experiments and make sense of the outcomes; this occurs very quickly in computer assisted simulation-based learning environments. When drawing conclusions, students review their propositions/hypotheses based on the experimentation data/experiences (Gijlers & de Jong, 2009). During regulation, students manage time allocated to complete the tasks and discuss the big procedures of solving tasks and so forth. Another important aspect of collaborative learning is the ability of group members to sustain mutual understanding throughout the whole process. Several aspects of online communication (e.g., reduced social presence, lack of nonverbal and social cues) might further hinder mutual understanding between collaborative partners, especially when they do not know each other and are collaborating for the first time.

Research questions

1. How do the transformative/non-transformative learning processes look like in more and less successful groups in a collaborative inquiry learning environment?
2. How do groups' transformative/non-transformative processes influence their group problem solving results in a collaborative inquiry learning environment?

Method

Setting

The platform supporting this study was Concord Consortium – an online collaborative inquiry learning environment that includes a database of interactive STEM activities. The participants involved in a series of activities in the electronics domain, which were designed to help them understand and apply Ohm's Law by exploring the relationship between resistance and voltage in series circuits. As shown in Figure 1, the virtual electronics environment includes a series circuit with supply voltage E, external resistance R, R1, R2 and R3 (at the bottom of Figure 1); the initial conditions and the goal (at the upper left of Figure 1); a digital multimeter (DMM) with a black and a red probes that can be used to measure the voltage, current, or resistance of the resistor as controlled by a student (at the middle left of Figure 1); a calculator which will appear if clicked ‘calculator; and a chat window that allows group members to talk about their goal, discuss how to solve their task, monitor their progress and so forth.

The students worked in groups of three on separate computers. They were all in the same room, but team members were kept separate from one another and were not allowed to communicate other than by the computer-supported chat window. Before working on the tasks, the students watched an introduction video and were informed that each of them only controlled part of the circuit and they had to work together as a group to solve the tasks.

The electronics domain was divided into four tasks with increasing complexity. The reason for increasing complexity gradually rather than requiring students to work on full complexity at the beginning is to avoid overwhelming them (Carroll & Carrithers, 1984). Students were free to start at any level and to move back and forth of different levels. However, in practice, students usually started with Level A, and then moved to Level B and other more complex tasks. Often, they did not move to the next task until they solved the current one. In Level 1, both E and R values are given, R equals R1, R2 and R3, and the goal voltage across R1, R2, and R3 equals; in Level 2, both E and R values are given, R does not equal zero, and the goal voltage values across R1, R2 and R3 are different; in Level 3, E is unknown, R is given and does not equal zero, the goal voltage values across R1, R2 and R3 are different; and in Level 4, both E and R values are unknown and the goal voltage across R1, R2 and R3 are different.

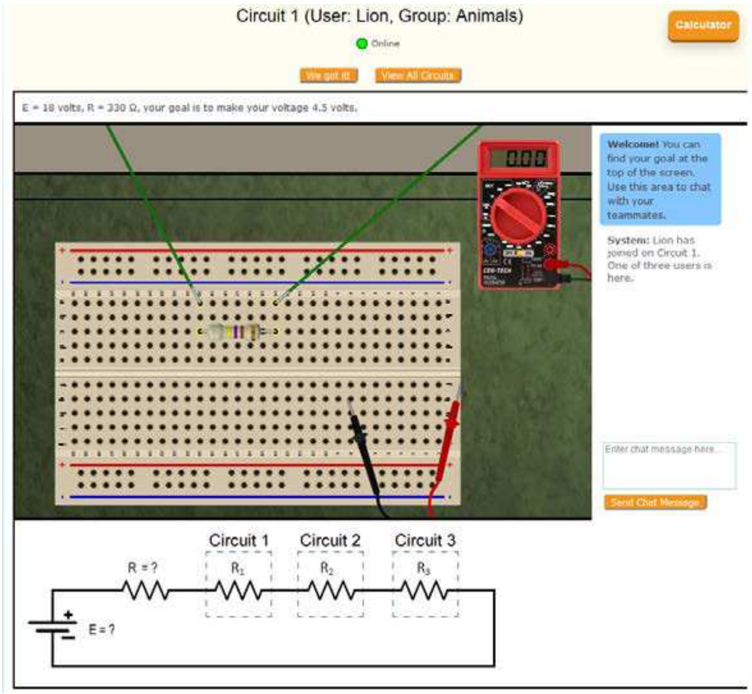

Figure 1. Screenshot of a simulation of Level 1 task.

Participants and procedures

156 students from five different high schools and colleges in the United States participated in this study, and they worked in 52 groups. The teachers did not assign the students to any groups ahead of time. Students from the same class were given a class code so that they could join in the same class space. When they did their teamwork, they could select to join in any team as long as there were fewer than three students in the team. Therefore, the grouping process was random. Each student was assigned a fake name, and the students did not

know who their team members were in the teamwork process unless they discussed this issue in the chat window.

Before students participated in the Teaching Teamwork, they read an introduction on the design of the tasks, how to get started, how to use the online chat window and on-screen calculator, and how to submit results. Students were also provided with an introduction video to help them get familiar with how the system works and how to operate the tools.

Predicting transformative and non-transformative discussion

In order to understand group discourse while doing their teamwork activities, we adapted a coding scheme (as shown in Table 1) from Gijlers and de Jong (2009) to analyze what kinds of transformative/non-transformative utterances influence collaborative inquiry learning. Group discourse was categorized into transformative and non-transformative utterances. Transformative utterances closely relate to knowledge construction, and are further divided into orientation, proposition generation, experimentation, and interpretation and conclusion. The non-transformative utterances relate to technical features and time/group/task management, such as regulation and sustaining mutual understanding.

Most previous research on communication in small group learning is based on manually coding small samples of messages (e.g., Kwon, Liu, & Johnson, 2014; Lee, O'Donnell, & Rogat, 2015). These qualitative and content analysis techniques are impractical, at least difficult, for thousands of lines of log data in our context. Previous research has demonstrated that it is possible to automate the analysis of conversations in CSCL (Mu, Stegmann, Mayfield, Rosé, & Fischer, 2012; Rosé et al., 2008). Therefore, in this study, machine learning models were built to automatically identify the transformative and non-transformative messages in the small group collaboration. Machine learning models apply statistical procedures to map a set of input features to output targeted categories (Wang, Krut, & Levine, 2012). In our data, the inputs were various kinds of features and the outputs were categorical values representing the category of transformative and non-transformative discussion an utterance belongs to.

This machine learning model construction involves three steps: first, two human coders manually code a random sample of 25% messages to identify which category of transformative and non-transformative discussion each message represents. Their judgements are considered as the ground truth data. Second, all these manually coded messages are represented by a set of linguistic features as input into machine learning algorithms. Third, various algorithms are tested with different combinations of feature sets, and then evaluated for their performance based on 10-fold cross validation. After the machine learning model is constructed, this model will be applied to the rest of the dataset so that every message in all groups can be classified into transformative or non-transformative category.

For the first step in creating a machine learning model, 25% of the chatting messages were randomly sampled from the entire dataset. Two senior researchers with extensive background in CSCL coded them independently. The sample of the coding is demonstrated as Table 1. The initial agreement between the two researchers was 76.8%; the remaining disagreements were discussed and resolved. Second, three types of textual features were used to capture the different language strategies employed by students when engaging in collaboration: 1) rule-based structural features discovered by the coders that capture the key elements of high-order concept propositions. These features are based on the researchers' qualitative insights as what words or number combinations are more likely belong to which kinds of transformative or non-transformative categories; 2) functional and linguistic relevant words (e.g. emotion and cognition words) from the Linguistic Inquiry and Word Count (LIWC) program (Pennebaker et al., 2015); and 3) topical features based on Latent Dirichlet Allocation (LDA) topic modeling to create specialized small group collaboration related dictionaries (as shown in Table 2). Then each LDA topic feature computes the frequency of words in an utterance matching its corresponding topic dictionary. Third, to optimize the performance of the machine learning model, four different kinds of classic algorithms were used: Naïve Bayes, Logistic Regression, Support Vector Machines (SVM), and Decision Tree. Details of these algorithms can refer to Kotsiantis, Zaharakis, and Pintelas (2007). All these algorithms were evaluated based on 10-fold cross validation to show the robustness of the prediction performance.

Results

By using various algorithms and features, the machine learning models were built and their performance is shown in Table 3. The performance of the machine learning model was measured by precision measure, a classical metric to evaluate the supervised models. Through comparing various algorithms and different features sets, the results showed that the decision tree with structural features had the best performance, reaching 79.8% predictive power.

Table 1: The coding scheme of the chatting history during the collaborative inquiry learning process

Contribution type	Category	Description	Example
Transformative (utterances that directly result in knowledge construction)	Orientation	Form an idea of the structure and the complexity of the task at hand by collecting goal-related information, the current values of the resistance or voltage and how these measures meet the individual or group goals.	r = 560 here; ok i need 6.69; i got my v; how many volts do you guys need? its a series circuit
	Proposition generation	Form a statement or a set of statements concerning the relations regarding the values of the resistance or voltage in order to solve the task.	youre gonna need a higher resistance value then; so we can find the current at 6.71mA going thur the resistor, then we can find our r values using ohms law
	Experimentation	Include testing their ideas, and adjusting the resistors by making them lower or higher.	everyone set to 180 - see what that does; let me get 1v hold up; let me readjust; ok let me go a little higher then; R1 at 680 ohms just lowered to 3.8 V; I will switch R1 to 680; can u just change your resistor to 4.7k ohms i jsut wanna see
	Interpretation and conclusion	Review the proposition in light of the experimentation outcomes.	i still need to adjust; well our total v of c1 - c3 is12.24 right; so there is a 3.76 drop across r=560 totals to 16
Non-transformative (utterances relate to technical features, and time/group/task management, etc.)	Regulation	Manage time, group dialogue, the big procedures of solving tasks and so forth.	Lets get move on snow; one sec; where tf is the other person; lets try calculating; get to the goal; dont we need the third pers
	Sustaining mutual understanding	Indicate shared/different understanding among different group members.	Ok; same here; yea; got it; now it does; thats good
	N/A	Information that cannot be coded with the six categories above.	who this; who cares; and I aint trynna do this math tbh;

Table 2: Feature sets

Structural features	LIWC features	LDA topical features
deed (to be) + number, getting + number, number + away, at + number, what is everyone.	*Summary Dimensions* – word count, sentence count, tone *Punctuation marks* – period, comma colon, exclamation, dash, quote etc. *Function words* – pronounce, article, adverb, negate *Other Grammar* – verb, adj, compare, number, quant etc.	anger, sad, family, friend, social, insight, cause, differ, hear, feel, percept, body, affiliation, power, reward, risk, forecast, future, motion, space, time, money, leisure, assent, swear etc.

Table 3: Prediction Performance

Feature sets	Naïve Bayes	Logistic Regression	SVM	Decision Tree
Structural Features	43.0%	72.3%	72.2%	79.8%
LIWC Features	20.2%	35.2%	41.6%	44.1%
Topic Features	38.5%	61.8%	54.4%	52.2%
Structural + LIWC Features	39.1%	69.4%	64.5%	76.0%
LIWC Features + Topic Features	34.6%	61.8%	60.2%	61.9%
Structural + LIWC + Topic Features	42.9%	66.5%	60.2%	72.6%

Table 4: Significant Univariate Effects for Performance

Dependent Variable	Performance	Means	Standard Deviations	F	Pr > F
Orientation	1 (Task solved)	64.9	10.04	9.55	0.003**
	0 (Task unsolved)	73.4	15.33		
Proposition generation	1 (Task solved)	0.78	1.87	5.74	0.018*
	0 (Task unsolved)	0.04	0.27		
Experimentation	1 (Task solved)	13.2	1.25	9.55	0.266
	0 (Task unsolved)	11.18	8.81		
Interpretation and conclusion	1 (Task solved)	1.09	2.21	4.34	0.040*
	0 (Task unsolved)	2.51	5.04		
Regulation	1 (Task solved)	7.44	8.96	4.7	0.032*
	0 (Task unsolved)	4.08	4.61		
Sustaining mutual understanding	1 (Task solved)	12.59	7.68	6.9	0.010**
	0 (Task unsolved)	9.78	6.41		

* < .05, ** < .01, *** <- 0.001

We then applied this built model to the rest of the group chats. Then for each category of the transformational and non-transformational discussions, we calculated the percentage of each category in each task chat. Table 4 shows the descriptive statistics of those transformative and non-transformative discussions over the tasks groups.

A MANOVA analysis in which students' performance on tasks as independent variable and the six codings as dependent variables showed a significant multivariate effect for the six latent variables as a group in relation to performance of different group students in different levels of tasks ($p<0.001$). Univariate ANOVAs (as follow-ups to MANOVA) were conducted in order to check which individual variables (as opposed to all variables together) differ between solved and unsolved tasks. The results indicated that the frequency of proposition generation, regulation and sustaining mutual understanding were significantly higher in the solved tasks than that in the unsolved tasks; the frequency of orientation and interpretation and conclusion were significantly lower in the solved tasks than that in the unsolved tasks; and the difference of experimentation in the solved and unsolved tasks was not significant (as shown in table 4).

Discussion

This study was conducted in an authentic setting and on large scale, which supports its ecological validity. The intellectual merit of this study originates from its contribution to our understanding of the role that both transformative and non-transformative learning processes play in collaborative inquiry learning and how important they are to the success of problem-solving. Specifically, we discovered the extent to which transformative and non-transformative learning processes contribute the group problem solving outcomes. For example, the importance of orientation, as well as interpretation and conclusion, is well recognized in the literature (Gijlers & de Jong, 2009), but we found that if students do not go beyond orientation and focus too much on making conclusions without sufficient experimentation evidence or without discussing about the relationship between variables seriously through proposition/hypothesis generation process, they do not end up solving the task. Also, it should be noted that the groups, which had higher frequency of sustaining mutual understanding contributions, were more likely to solve the task. This finding shows the importance of the social aspect, which plays a large role for the group cohesion, coordination efforts and interactional dynamics of the group in general (Kreijns et al., 2003).

The results showed the importance of understanding topic-related cognitive knowledge, forming it into a statement and conveying it to other group members, managing time, dialogue and problem-solving procedures, and achieving shared understanding between the group members. On the other hand, when the group members focused too much on discussing their goal and reporting their resistor and voltage status but did not really discuss the relationship between resistance and voltage or interpreted and concluded without enough evidence or explanation, they were likely to fail in the collaborative problem solving. Previous studies also showed the difference between high-performing and low-performing groups. For instance, Malmberg, Järvelä, Järvenoja and Panadero (2015) indicated that high-performing groups mainly focused on regulating the cognitive, motivational, and social aspects of their collaboration while low-performing group focused more on external challenges such as the environment and time management. Sinha, Rogat, Adams-Wiggins and Hmelo-Silver (2015)'s study showed that some social, cognitive and metacognitive, as well as emotional indicators, may influence students' engagement in collaborative learning, resulting in improving students' learning performance. Their study indicated that the low engagement group developed vague and incomplete plans; the ideas contributed by the group members were not elaborated, backed up with evidence, or further discussed; their task monitoring was mainly focused on the spelling of components rather than its content; and the words they used indicated a focus on individual thinking and individual activity such as "I think", "I am going to" and "my turn", while the high engagement group used words that refer to the collective (e.g., we).

Furthermore, in this study we built accurate machine learning models to identify the transformative and non-transformative discussion in small group collaborative learning. While previous CSCL studies (e.g., Kwon, Liu, & Johnson, 2014; Lee, O'Donnell, & Rogat, 2015) usually applied qualitative analysis to examine a few group collaborative processes, this research examined a relatively large number of groups and their collaborations. Such larger scale endeavors can provide more generalizability compared with qualitative cases studies. In addition, this study is not a purely quantitative and data mining research. In fact, we started with human qualitative coding and examination of the group collaboration process for the transformative and non-transformative discussion, and then applied machine learning algorithms to capture the human insights for automatic coding. By using diverse set of features through various algorithms, we optimized the performance of the automatic coding process. The extracted features can be easily applied to construct prediction models in other group learning contexts. While the LIWC features can be readily to use in other scenarios, the rule-based features and LDA topic features may need to be adapted for specific context. These two steps usually require little effort. As a whole, this study is a practical exemplar for future research to conduct large-scale CSCL analysis while not losing the human insights.

Collaborative inquiry learning manifests many facets and remains a complicated process, as demonstrated by the results of this study. The findings can inform instructional design choices as wells offer recommendations for teachers in terms of what specific types of student activities need to be fostered and where support is most needed to benefit from CSCiL.

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