

The Sequential Analysis, Modeling and Visualization of Collaborative Causal Mapping Processes and Effects on Causal Understanding

Allan Jeong, Woon Jee Lee, Florida State University
Email: ajeong@fsu.edu, woonjee@gmail.com

Abstract: This paper describes a case study that illustrates how particular techniques and two developed software applications can be used to sequentially analyze, model, and visualize the processes and discourse student produce while working collaboratively in pairs to construct a causal diagram. The analysis was conducted at various levels in order to model students' map construction processes, the map construction processes in conjunction with students' discourse, and processes observed within each group versus across all groups. Transitional state diagrams produced from the sequential analysis of each group's behaviors revealed unique sequential patterns in the processes used between the three groups. These observed processes provide potential explanations for the observed differences in the accuracy of the maps between the groups. The implications of the findings and directions for further refinements to the techniques and software tools are identified and discussed in further detail.

One of the essential skills in solving complex problems is the ability to identify, articulate, and understand causal relationships between variables and/or events within a complex system. One way to accomplish this task is to construct a causal map. A causal map is a two-dimensional network of nodes and links that conveys the hierarchical and cause-effect relationships between events or variables within a complex system. Causal maps for example can be used to identify which variables exert direct/indirect effects on an outcome variable, which variables are to be viewed as root causes, and how the effects of variables on a given outcome are mediated by other variables. They can serve as a useful tool for scaffolding learning (Cho & Jonassen, 2002), especially so when students work collaboratively to construct a causal map (Nesbit & Adesope, 2006). Furthermore, causal maps can be used to assess students' causal understanding and systems thinking skills (Jeong & Shin, 2013; McClure & Bell, 1990).

Although various procedures have been developed to provide guidance on how to construct causal maps (Jonassen & Ionas, 2008; Bryson et al., 2004; Scavarda et al., 2006; Clarkson & Hodgkinson, 2005; Decision Systems Inc., 2012), there is little empirical research that have modeled the processes students use and that have identified the specific processes that create more accurate maps (Jeong & Lee, 2012). Based on a review of the empirical research and frequent reports on the high amount of variance in quality often observed across students causal maps, Ruiz-Primo & Shavelson (1996) concluded that maps should not be used in the classroom for large-scale assessments until students' facility, prior knowledge/skills with using maps, and associated training techniques are thoroughly examined. The point is that we do not yet know at this time to what extent students' causal maps (when used as an assessment tool) are measures of their causal understanding or measures of their causal mapping skills/processes. Furthermore, few studies have examined how peer interaction are integral to the processes students use when working collaboratively to construct causal maps, and how these processes affect map accuracy and/or causal understanding.

The purpose of this case study was develop, test, and illustrate a set of techniques and software tools that were developed and used to sequentially analyze, model, and precisely visualize students' map construction processes across multiple levels – map construction behaviors only, the interplay between map construction behaviors and student discourse, and the map construction processes within group versus across all groups. To illustrate our approach, this case study examined the following questions:

1. What sequential patterns exist in students' map drawing processes?
2. What sequential patterns exist between map drawing behaviors and students' dialog when working collaboratively on a shared causal map?
3. Which patterns help to explain observed differences in the accuracy of students' maps?

Method

Procedures. The participants were six graduate students (all female with ages ranging from 22 to 38) enrolled in a computer multimedia development course at a large university in the southeast region of U.S. in fall 2011. Students completed a 15-minute practice session on how to use the jMAP software (Jeong, 2012) to create causal maps and received from the instructor an introduction to causal maps with example applications. The students were paired up with another student, presented with a copy of the jMAP software with 15 pre-specified

events (Figure 1), and collaboratively constructed a causal map to identify chains of events and critical events that explains how and why a given multimedia tutorial (presented in a hypothetical scenario) was producing inferior learning. To correctly link the 15 given events into the correct hierarchical sequence/structure, students had to apply their knowledge of multimedia e-learning principles studied in the course. Each group was recorded on video camera.

The accuracy of each group's map was assessed in comparison to the instructor's map. In figure 2 is the instructor's map in jMAP viewed in relation to each group's map (dark green links = correct link with correct causal direction; light green = correct link with incorrect causal direction; gray = missed link; green halo = correctly identified root cause). Map accuracy was based on the total number of dark green links, nodes with green halos, and number of 1, 2nd, and 3rd order links that stem directly from a correctly identified root cause.

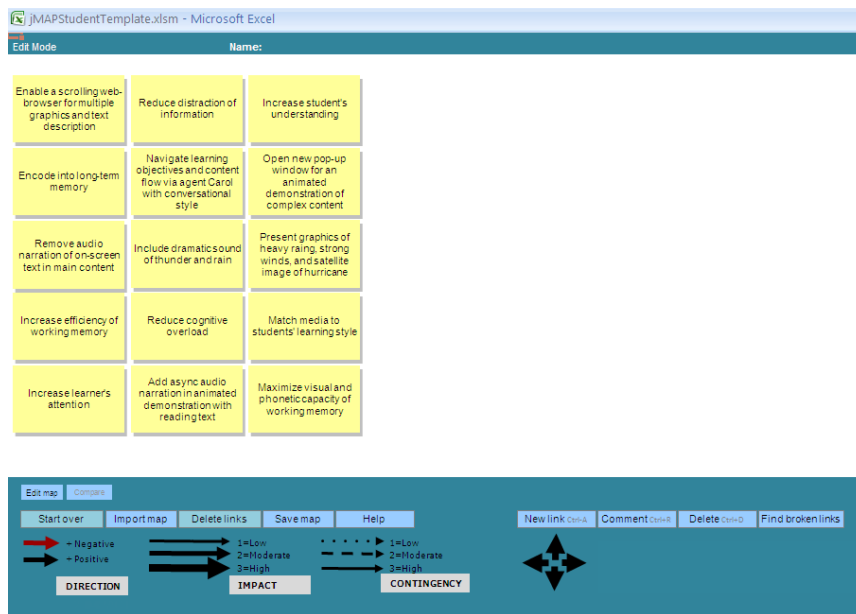
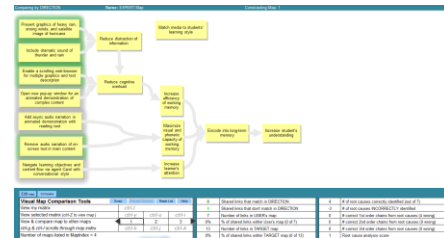
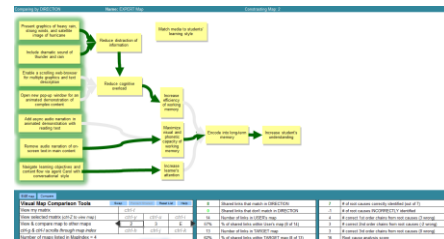
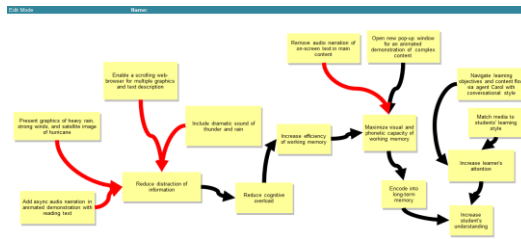


Figure 1. A screen capture of the initial causal map presented to students in jMAP.

Group 1
Low
accuracy



Group 2
High
accuracy



Group 3
Medium
accuracy

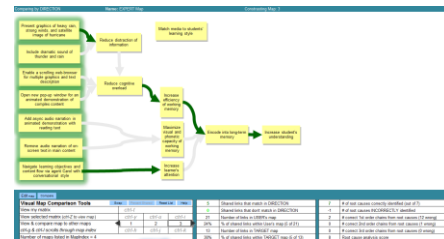
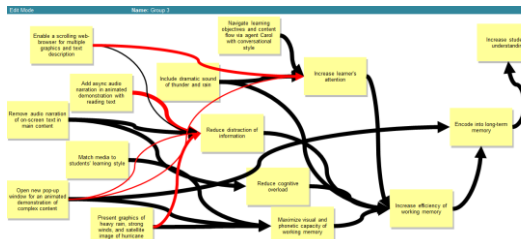


Figure 2. The maps of each group and the instructor's map viewed in relation to the group's map.

Data Analysis. The map drawing behaviors observed in the video recordings were coded into the six categories: PN - Position a node for the first time, RN - Reposition a node, AL- Add a causal link between two nodes, CA - Change the attributes of a causal link, DL- Delete a causal link, CL- Insert a comment to explain a causal link. The inter-reliability between two coders showed very good agreement (Cohen’s Kappa coefficients $k = .926, .893$ and $.889$ for codes assigned to behaviors observed in Group 1, 2, and 3, respectively). A total of seven dialog moves were identified from a close review and analysis of the discussion transcripts (Table 1). The inter-reliability between two coders showed good agreement ($k = .712$ in Group1, $.734$ in Group2, and $.748$ in Group3). Using these seven dialog moves, student conversations were manually classified into six forms of discourse based on specific dialog move sequences (Table 2) to better examine the relationship between specific map construction behaviors and the discourse that took place prior to, after, and/or concurrently with each observed behavior. In the future, multidimensional scaling can be used to classify dialog move sequences with more scientific rigor.

Table 1: Seven codes used to classify dialog moves

Codes	Code Descriptions
EXP	Explain one’s ideas in reference to specific nodes and their causal relationships.
DIR	Provide directions on how to construct the map (e.g., move the node, make the link, etc.) and how to use the mapping tool (e.g., “click the arrow button”)
QUE	Ask questions. The question may require a specific answer, an opinion, or simply a confirmation (e.g., “right?”).
AGR	Agree with partner’s explanation or directions; positive responses to the confirmative questions.
DIS	Disagree with partner’s explanation or direction, plus showing negative responses to the confirmative questions.
STA	Self-talk aloud to verbalize current actions performed on the causal map.
EVI	Provide evidence based on the reading materials. (e.g., it is saying that ...)

Table 2: Six forms of discourse based on observed dialog move sequences

Discourse	Description	Indicators in terms of dialog move sequences
Collaborative	Information and idea sharing	EXP→AGR→AGR
		EXP→AGR→EXP→AGR
		EXP→EXP→EXP→... →AGR
Interrogative	Exchange of questions & answers	QUE→EXP
		QUE→AGR
Argumentative	Conflicting viewpoints	EXP→DIS→EXP
		QUE→DIS
Confirmative	"Right?" and "Yes"	QUE (“Right?”) →AGR (“Yes”)
Explanation	Single explanation	EXP
Agreement	Single expression of agreement	AGR

For each group, the codes for the map behaviors were entered sequentially into a spreadsheet column with each code assigned a sequence number in the adjacent column based on their natural chronology (e.g., first action performed by the group is assigned the sequence number 1). This data was used to model the map drawing processes independent of the discourse that took place during the map construction process. To examine the interplay between the map construction process and discourse, the codes for both the map drawing behaviors and discourse were entered sequentially into another spreadsheet with each code assigned to a sequence number reflecting their chronological order. For behaviors and forms of discourse that occurred simultaneously and/or concurrently, these events were assigned the same sequence number.

Each of the resulting data sets were sequentially analyzed using the Discussion Analysis Tool (DAT) (Jeong, 2012b). DAT produced frequency matrices to compute transitional probabilities for each event pair. To determine which two-event sequences could be deemed to be a behavioral “pattern”, the DAT software computed z-scores for each reported probability. Probabilities that were significantly higher/lower than the expected probability were identified by z-scores that were greater than the critical z-score of 1.64 at $\alpha = .10$ with observed frequencies of no less than five (Bakeman & Gottman, 1997). The DAT software was then used

to generate transitional state diagrams (Figure 3) to visually convey the observed probabilities so that similarities and differences in behavioral patterns between groups can be easily identified. In the state diagrams, the thickness of the arrows in the diagrams is in direct proportion to the observed transitional probabilities. The black and gray arrows identify probabilities that are and are not significantly greater than expected. The first and second numerical value displayed in each node identifies the number of times the given action was performed and the number of events that followed the given action. The size of the glow emanating from each node conveys the number of times the given action was performed. Note that the state diagrams in figure 3 and 4 do *not* reveal the transitional probabilities found to be significantly *lower* than expected (showing action sequences that a particular group may have the tendency to avoid). If necessary, these probabilities can be identified with gray arrows drawn with sparsely dotted lines (e.g., - - - >).

What is important to note is that the relative position of each node in a state diagram is identical in all state diagrams for other groups. As a result, the similarities and differences in sequential patterns between the groups are immediately apparent, making the patterns easier to identify and easier to interpret. If the location of any given node were to vary from one state diagram to another, the differences and similarities become very difficult to discern (the same kind of difficulty one experiences when trying to compare the causal maps produced by different groups as illustrated at the top half of figure 2). However, holding the node positions is a fixed location in the state diagrams also presents some disadvantages. The nodes must be positioned in a circular alignment so that all possible transitions between nodes can be clearly displayed in the state diagram. When the number of nodes exceeds six (as in Figure 4), there is insufficient space to clearly display all observed transitions because the arrows cross over and partially obstruct one another. As a result, a state diagram with more than 6 nodes shows only those transitions found to be significantly higher than the expected probability (diagrams with black arrows only with gray arrows omitted).

Results

Mapping processes used by students across all groups. To identify sequential patterns in the map construction process exhibited by students across all three groups, the sequential data from each group was appended into one spreadsheet column and entered into the DAT software to produce the left state diagram in Figure 3. This state diagram revealed six sequential patterns to suggest two general procedures. In one procedure, students moved a node into position, then attached a link to either point to or from the node, changed the link attribute (positive or negative in causal relationship), then inserted a comment into the link to explain the causal relationship, and either revised the existing comment or inserted a new comment to another previously added causal link. In the second procedure, students deleted a link from the causal map (which was performed relatively infrequently), then repositioned a node just prior to inserting a link to point either from or to that node. Once the link was added, they progressed through the same sequence of actions by changing the link attribute, and inserting one or more comments to explain one or more causal relationships. In the future, data will be collected (using the same procedures presented in this case study) to generate a state diagram that identifies the processes used by the instructor and other experts. This can then be compared to the findings revealed in Figure 3 to reveal potential differences (if any exists) and possible deficiencies in student's mapping processes and the processes to scaffold and facilitate in future causal mapping software systems.

Mapping processes associated with map accuracy. The state diagram in Figure 4 revealed some unique patterns between groups (with only 1 of the 10 total patterns observed in all three groups). Despite the absence of an expert process model in this case study, the unique patterns revealed in Figure 4 provide plausible explanations as to why differences in map accuracy were found between the groups. For example, the low performing group, which produced the least accurate map among the three groups, exhibited a four-step linear process of positioning node, inserting causal link, changing link attributes, and inserting comments on link. The medium performing group, which produced the second most accurate map, used more of a stepwise process in which multiple nodes were placed into position first before links were added to the nodes. In contrast, the high performing group, which produced the most accurate map among the three groups, exhibited a three-step linear but iterative process of positioning nodes, adding links, and specifying link attributes (spending no time adding comments into the links to explain the causal relationship). A close review of the video showed in fact that this group work progressively backwards from nodes that had the most direct to the least direct effect on the outcome variable. Although the sample size was not sufficient to make these findings conclusive, the findings serve to illustrate how the techniques and tools described in this study can be used in the future to analyze larger data sets. This is now possible given that the latest version of the jMAP tool automatically logs up to 26 unique and more precise actions that can be performed on a causal map at any time (Jeong, in press).

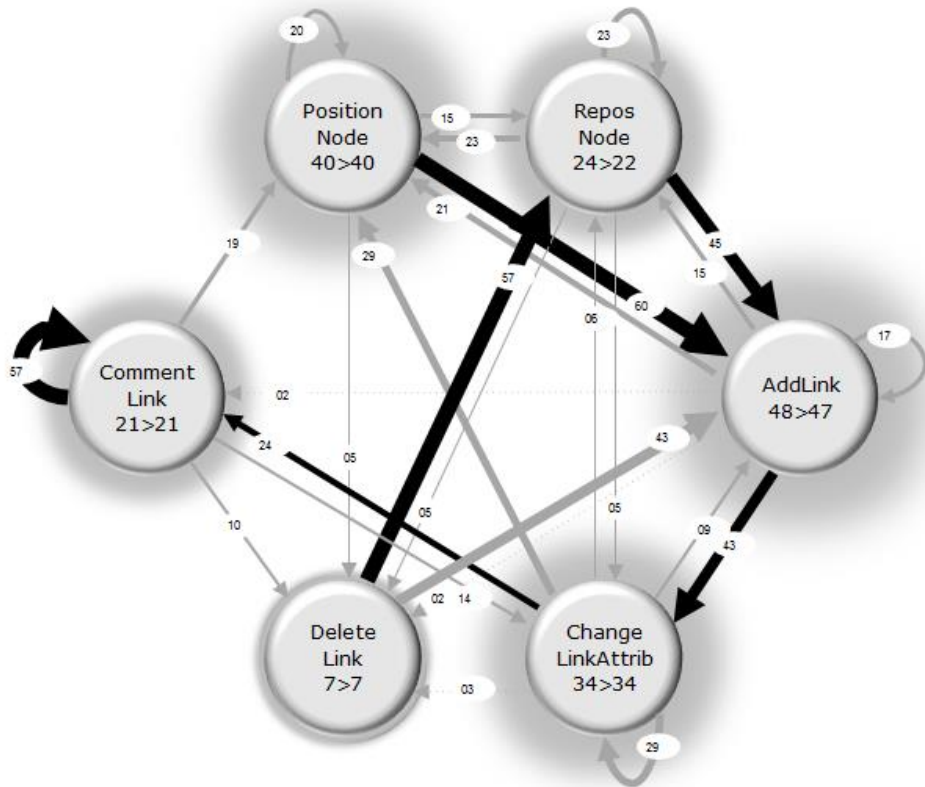


Figure 3. Transitional state diagrams of the map construction process across *all* groups

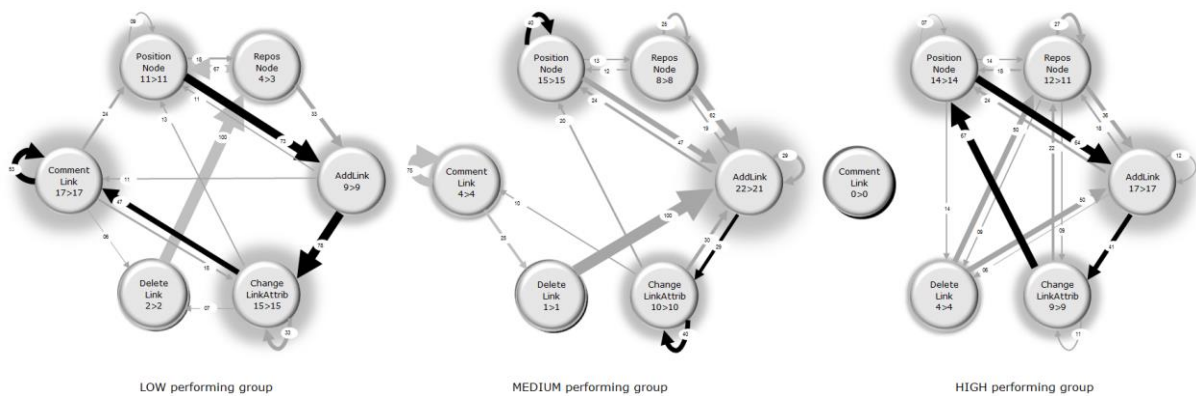


Figure 4. Transitional state diagrams of the map construction processes by group

Map and discourse processed performed by student across all groups. The state diagram in Figure 5 revealed a total of six action sequence patterns between mapping actions (move and/or reposition a node, add and/or delete a node) and forms of discourse. The main patterns or processes revealed in Figure 5 are that: a) the movement of nodes was generally preceded by either confirmative → collaborative or interrogative discourse; and b) the adding and deletion of links were generally preceded by argumentation → agreement → explanation. Once again, future plans are in the works to generate an expert process model to determine to what extent the processes observed in Figure 5 are different to those processes performed by experts (if any exists). Comparing the findings in Figure 5 (or similar findings produced with a larger data set) to the expert model can help to determine how to scaffold the communications between group members to trigger the mapping actions most likely to produce more accurate causal diagrams. The ultimate goal is to help students produce more accurate causal diagrams in order to increase students' ability to explain the causal mechanisms underlying direct and indirect cause effect relationships between variables in complex systems.

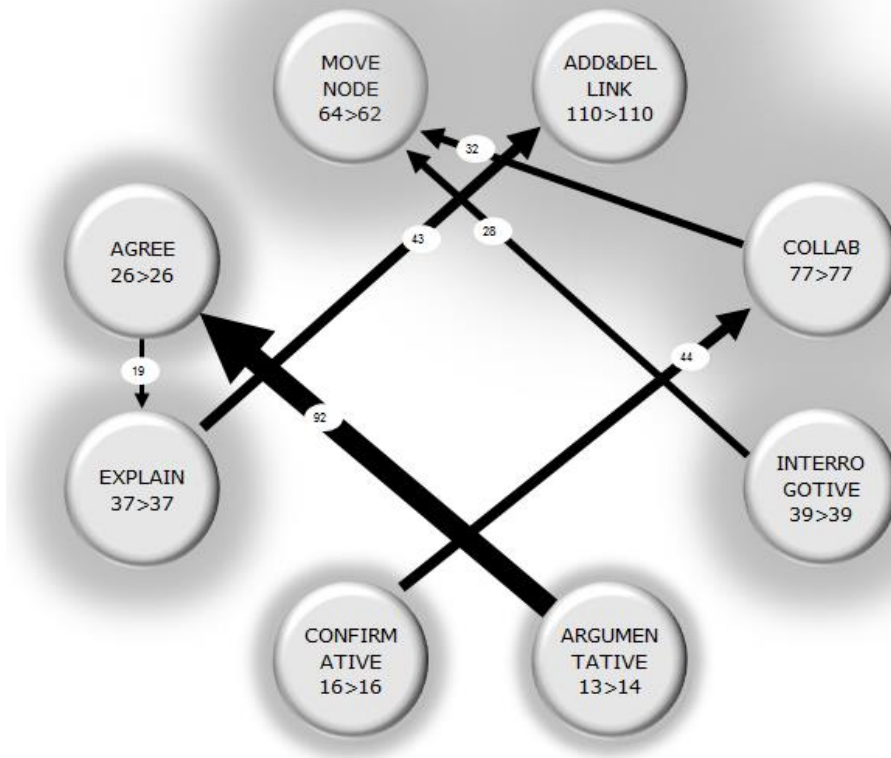


Figure 5. Transitional state diagram of map and discourse processes performed across all groups

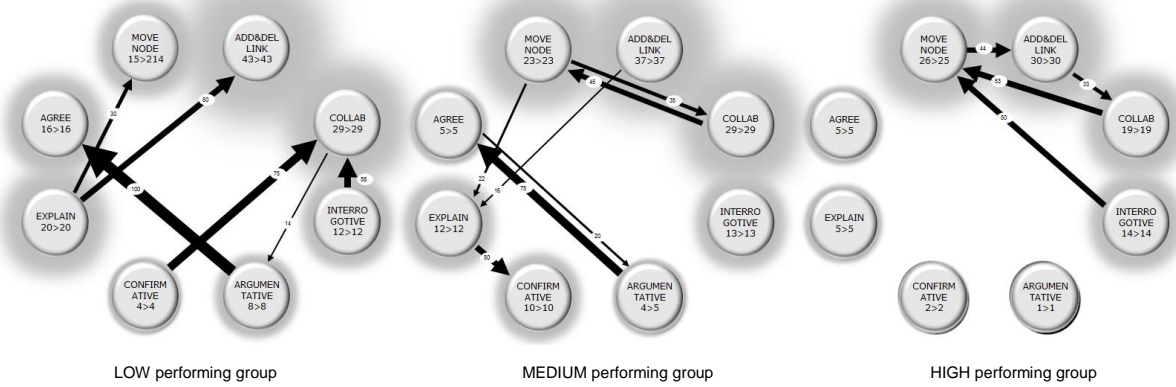


Figure 6. Transitional state diagrams of the map construction *and* discourse processes by group

Mapping and discourse processes associated with map accuracy. The state diagrams in figure 6 reveal a total of 15 unique patterns between mapping actions and discourse. Of these 15 unique patterns, not one of these patterns was observed in all three groups. Among the patterns that were observed in at least two of the groups was the collaborative discourse that took place just before moving a node, and the argumentation that took place just prior to expressing agreement. With respect to map accuracy, here are just some of the findings revealed via a comparative analysis of the three state diagrams in Figure 6. In both the high and medium performing groups (but not in the low performing group), the movement of nodes was preceded by collaborative discourse. These differences suggest that collaborative dialog \rightarrow move node action sequence may have contributed to increases in map accuracy relative to the low performing group. To help explain how the high performing group produced a more accurate causal map than the medium performing group, the state diagrams show that the high performing group moved nodes and linked the nodes just prior to engaging in collaborative discourse. These particular changes to the causal map (moved node with added link) may have been tentative changes used to create a shared visual artifact used to scaffold and facilitate the collaborative discussion and assessment of the proposed actions - similar to the processes described in Cho & Jonassen's (2002) study on the use of argument diagrams for scaffolding group debates. Once the actions were assessed through collaborative discourse, the state diagram shows that the collaborative discourse was then followed by further actions on the placement of the nodes. A close review of the discussion transcripts will be necessary to identify excerpts that illustrate and validate this particular process.

In a similar manner, the process of making tentative changes to the causal map to scaffold further discussion was also observed in the medium performing group, which helps to explain why this group produced a better causal map than the low performing group. The state diagram for the medium group shows that explanative discussion immediately followed the movement of a node and the addition/deletion of a link. The explanative discussion was then immediately followed with confirmative exchanges. In contrast, the low performing group to an extent performed this process in reverse order – explaining (or simply announcing) the act of moving a node or adding/deleting a link, then executing the proposed and/or explained action. A close review of the video revealed that in the low performing group, one of the students controlled and dominated the task, with the dominant student often explaining or simply announcing (as opposed to discussing) her next course of action.

Discussion

Although the sample size in this case study was not sufficient to determine conclusively if the observed patterns are stable or completely unique to the groups across different levels of performance, this study's primary purpose was to illustrate how the described techniques and software tools can be further refined and used in the future to better understand the complex interplay between students' actions and supporting discourse when working collaboratively to construct causal diagrams. While the findings suggest that the processes students perform while constructing causal diagrams can vary widely (which is consistent with Ruiz-Primo & Shavelson's 1997 findings), this study illustrates how a comparative analysis of processes between groups can provide plausible explanations as to why, when, and how some groups produce more accurate maps than others (and/or achieve and exhibit better causal understanding and causal reasoning skills). This approach may be most appropriate when studying complex ill-defined domains where it may be the case that there is no one particular process (or expert model) that produces the best results.

With the ability to automatically log and capture more precise actions performed on a causal diagram within the jMAP software, larger data sets can now be acquired and processed more quickly. But more importantly, the type of data captured in the jMAP logs will enable future studies to examine and model students' causal reasoning processes in far greater detail. For example, the captured log data can now be used to determine when a student is deleting the link $A \rightarrow C$ (when the causal map is currently showing $A \rightarrow C$ and $B \rightarrow$) and inserting a link $A \rightarrow B$ in order to produce the causal chain of events $A \rightarrow B \rightarrow C$ (having realized that B alone is sufficient to cause C and that the effects of A on C is mediated by B). This type of data can help determine to what extent a student is using a backward/deductive vs. forward/inductive approach and depth vs. breadth-first approach (work in progress).

Overall, this paper describes an approach that can be used to conduct further and larger scale studies to identify and validate the key processes that produce higher quality causal diagrams. Once these key processes are identified and tested, the next generation of causal mapping software can be developed to actively monitor, scaffold and standardize the processes (using either a fixed or a dynamic model) to help ensure that the causal maps students produce are accurate measures of their causal understanding rather than a measure of their causal mapping and causal reasoning skills. Such an application can then be used not only as an instructional tool, but also as an alternative and potentially powerful tool for assessing causal understanding in science education on a large-scale basis.

References

- Bakeman, R., & Gottman, J. (1997). *Observing interaction: An introduction to sequential analysis*. Cambridge, UK: Cambridge, University Press.
- Bryson, J. M., Ackerman, F., Eden, C., & Finn, C. B. (2004). *Visible thinking: Unlocking causal mapping for practical business results*. Chichester: John Wiley and Sons.
- Cho, K. L., & Jonassen, D. (2002). The effects of argumentation scaffolds on argumentation and problem solving. *Educational Technology Research & Development, 50*(3), 5-22.
- Clarkson, G. P., & Hodgkinson, G. P. (2005). Introducing Cognizer™: A comprehensive computer package for the elicitation and analysis of cause maps. *Organizational Research Methods, 18*(3), 317-344.
- Decision Systems, Inc. (2003). Root cause analysis using REASON. Last retrieved July 2012 at <http://www.rootcause.com>.
- Jeong, A. (in press). Sequentially analyzing and modeling causal mapping processes that support causal understanding and systems thinking. To appear in Ria Hanewald & Dirk Ifenthaler's (Eds.) *Digital Knowledge Maps in Education: Technology Enhanced Support for Teachers and Learners*, Springer.
- Jeong, A. & Shin, H. (2013). The sequential analysis of causal mapping processes that support causal understanding and systems thinking. Paper to be presented at the 2013 American Educational Research Association conference in San Francisco, CA.
- Jeong, A. & Lee, W.J. (2011). Developing causal understanding with causal maps: The impact of total links, temporal flow, and lateral position of outcome nodes. *Educational Technology Research & Development, 60*(2), 325-340.
- Jeong, A. (2012). *jMAP*. Last retrieved on November, 2012 at <http://myweb.fsu.edu/ajeong/jmap>.
- Jeong, A. (2012b). *Discussion Analysis Tool*. Last retrieved on November, 2012 at <http://myweb.fsu.edu/ajeong/dat>.
- Jonassen, D. H., & Ionas I. G. (2008). Designing effective supports for causal reasoning. *Educational Technology Research and Development, 56*, 287-308.
- McClure, J., & Bell, P. (1990). Effects of an environmental education-related STS approach instruction on cognitive structures of pre-service science teachers. University Park, PA: Pennsylvania State University. (ERIC Document Reproduction Service No. ED 341 582).
- Nesbit, J. C., & Adesope, O. (2006). Learning with concept and knowledge maps: A meta-analysis. *Review of Educational Research, 76*(3), 413-448.
- Ruiz-Primo, M., Shavelson, R., & Schulz, S. (1997). On the validity of concept map-base assessment interpretations: An experiment testing the assumption of hierarchical concept maps in science (CSE Technical Report 455). Los Angeles: University of California.
- Scavarda, A.J., Bouzdine-Chameeva, T., Goldstein, S.M., Hays, J.M., & Hill, A. V. (2006). A methodology for constructing collective causal maps. *Decision Sciences Journal, 37*(2), 263-284.