The Relationship between Accuracy and Attributes in Students' Causal Diagrams, Total links, Temporal Flow, and Node Positions

Woon Jee Lee
Florida State University
2626 East Park Avenue
Tallahassee FL 32301
wl08c@fsu.edu

Allan Jeong
Florida State University
Stone Building 3205E
Tallahassee FL 32306-4453
ajeong@fsu.edu
(850) 644-8784

Descriptors: causal diagram, map accuracy

Abstract

This case study examined three structural attributes observed in students' causal maps (total links, temporal flow, horizontal location of outcomes nodes) and their relationship to the accuracy of students' maps (number of correct root causes, number of root cause links) to determine the attributes that should be emphasized during map construction. The findings from regression analyses suggest that increasing temporal flow can substantially increase accuracy in number of correctly identified root causes, and placing limits on the total number of causal links can increase the number of correctly identified root cause links. Implications of these findings on how to manipulate the causal mapping task and tools and directions for future research are discussed.

Introduction

Causal maps, a network of nodes and links that define the causal relationships between nodes, can be used in science education as a tool to teach and assess learners' systemic understanding of complex problems and phenomena (Ruiz-Primo & Shavelson, 1996). Given that causal maps in theory represent learner's cognitive structures, their complex reasoning, and conceptual development (Jonassen, 2008), causal maps can be and have been used to elicit, articulate, refine, assess, and improve understanding, analysis, and the identification of the causes and causal mechanism underlying complex problems. Improvements in students' understanding have been observed particularly when students work both individually and collaboratively to construct their own maps as opposed to simply presenting students the instructor or expert maps (Nesbit & Adesope, 2006). Maps can be used to support collaborative learning when students compare their maps to identify, trigger, and focus group discussions around key differences in viewpoints and understanding (Jeong, 2009 & 2010a).

A growing number of studies on causal maps and other types of maps (e.g., concept maps) have formulated various metrics to measure the accuracy *and* structural attributes of students' maps (parsimony, temporal flow, total links, connectedness) – particularly attributes believed to be correlated to map accuracy and attributes that can be potentially used to generate guidelines or constraints to help students create more accurate maps (Scavarda et al., 2004; Ifenthaler, Masduki & Seel, 2009; Jeong, 2009; Plate, 2010). Studies have been conducted to determine how different constraints imposed on the map construction process affect student's maps and learning – constraints like imposing hierarchical order by allowing students to move and re-position nodes (Ruiz-Primo et al., 1997; Wilson,

1994), providing terms for nodes (Barenholz & Tamir, 1992), providing labels for links (McClure & Bell, 1990), and allowing more than one link between nodes (Fisher, 1990).

In addition, studies have been conducted to develop software tools to automate and reliably measure both the accuracy and the structural attributes of maps. Software programs like HIMATT (Ifenthaler, 2008) and jMAP (Jeong, 2010b) are being used to address issues of rater reliability and validity by using software to automate measurements that can be used to test the correlation between different structural attributes and accuracy of students' maps (Ifenthaler, Madsuk & Seel, 2009), and to measure how maps change over time and how observed changes over time contribute to convergence in shared understanding between learners (Jeong, 2010a).

However, students' maps can vary widely in accuracy when maps are compared to expert maps (Ruiz-Primo & Shavelson, 1996; Scavarda et al., 2004). The critical question here is whether the variance in accuracy is a reflection of students' lack of knowledge and understanding of the topic under study, or is it more a reflection of student's lack of understanding and skills with drawing causal maps? Based on their review of the empirical research, Ruiz-Primo & Shavelson (1996) concluded that maps (including the assessment rubrics) 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. In other words, researchers must examine how differences in causal mapping skills and processes lead to differences in map accuracy between students with equal knowledge and understanding of the concepts/problems they are trying to articulate with causal maps. Ruiz-Primo et al. (1997) also found in their study that requiring students to hierarchically structure their maps did not produce any gains in the match between students' and experts' maps. However, Ruiz-Primo at al. conceded that they had difficulties in developing a clear operational definition and measure of hierarchical structure. As a result, more studies are needed to developing and articulating measures of hierarchical structure and how such measures ultimately reflect students' level of learning and understanding.

Given all of the above, new research is needed to: a) identify tendencies and potential weaknesses in the way students construct causal maps with minimal or no prior instruction on causal mapping; and b) determine to what extent each noted weakness affects the accuracy of students' maps while controlling for students' level of knowledge and understanding of the concepts/problems they are trying to articulate via causal maps. A clear understanding of the weaknesses and their effects will provide the foundation on which to identify the most appropriate guidelines, constraints, and interventions for improving the map construction process and quality/accuracy of students' causal maps.

Using the case study method, this study examined the accuracy of students' maps based on the ratio of correctly/incorrectly identified *root causes*. This study also examined accuracy in terms of total number of correctly identified *root links* (links stemming from root causes) to gauge how well students understand the causal chains, mechanisms, and mediating factors underlying cause-effect relationships between root causes and outcomes. These measures were tested for their correlations with three attributes: total number of causal links (*total links*), ratio of right/left pointing links (*temporal flow*), and distance of outcome node from left edge of screen (*location* of the node representing the final effect/outcome).

The purpose of the study were to determine to what extent do these three attributes (number of links, temporal flow, and location of outcome node) are correlated with (and possibly contributes to) level of accuracy. The findings can then be used to identify which attributes to emphasize to students by imposing specific constraints within the causal mapping software interface (e.g., limit total number of links, each newly created link points by default from left to right, position by default final outcome nodes at right most portion of screen) – constraints that can be implemented in future versions of our mapping software called jMAP (Jeong, 2010b), specifically developed and used for this case study. To address these discussions, this case study examined two research questions:

1. Which structural attributes (total links, temporal flow, outcome node location) are correlated with accuracy?

2. What is the relative magnitude of each attribute's impact on accuracy?

Method

Participants

Nineteen graduate students (8 male, 11 female) enrolled in a Masters level online course on computer-supported collaborative learning at a large southeastern university participated in this study. The participants ranged from 22 to 55 years in age, and the majority of the participants were enrolled in a Master's level program in instructional systems/design.

Procedures

The course examined factors that influence collaborative learning and instructional strategies associated with each factor. In week 2 of the course, students used a Wiki webpage to share and construct a running list of factors believed to influence the level of learning or performance achieved in group assignments. Students classified and merged the proposed factors, discussed the merits of each factor, and submitted votes on the factors believed to exert the largest influence on the outcomes of a group assignment. The votes were used to select a final list of 14 factors that students individually organized into causal diagrams.

In week 3, students were presented six example diagrams to illustrate the characteristics and functions of causal diagrams. Students were then provided a MS Excel-based software program called jMAP (pre-loaded by the instructor with nodes for each of the 14 selected factors) to construct their first causal map (see Figure 1). The purpose of each student's map was to graphically explain their understanding of how the selected factors influence learning in collaborative settings. Using the tools in jMAP, students connected the factors with causal links by: (a) creating each link with varying densities to reflect the perceived strength of the link (1 = weak, 2 = moderate, 3 =

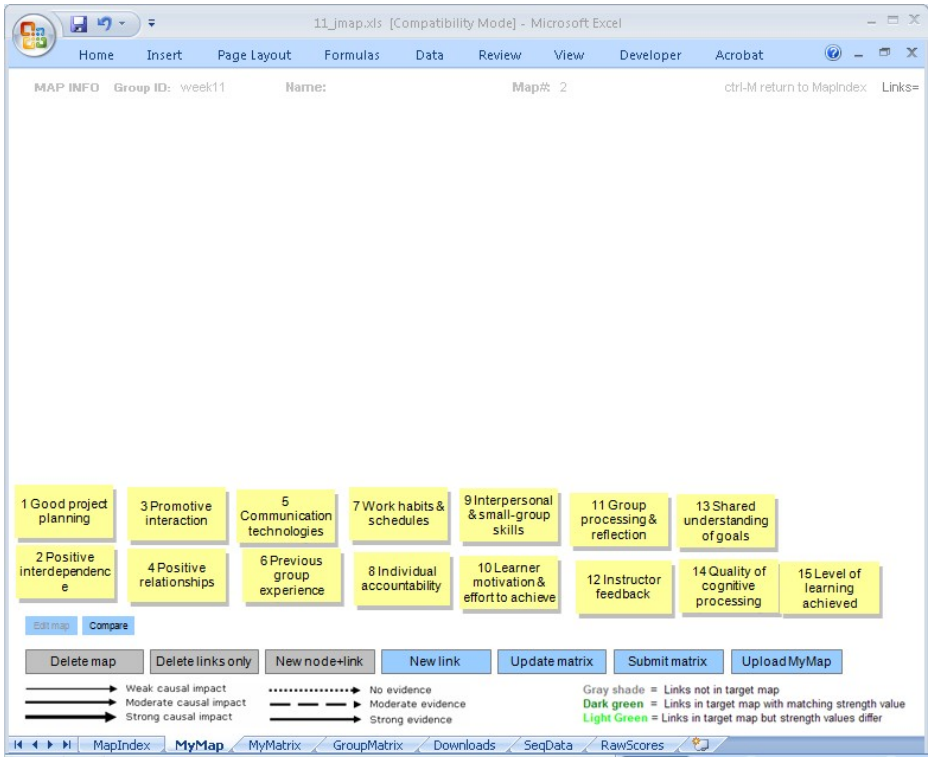

Figure 1. jMAP template preloaded with 14 factors and outcomes.

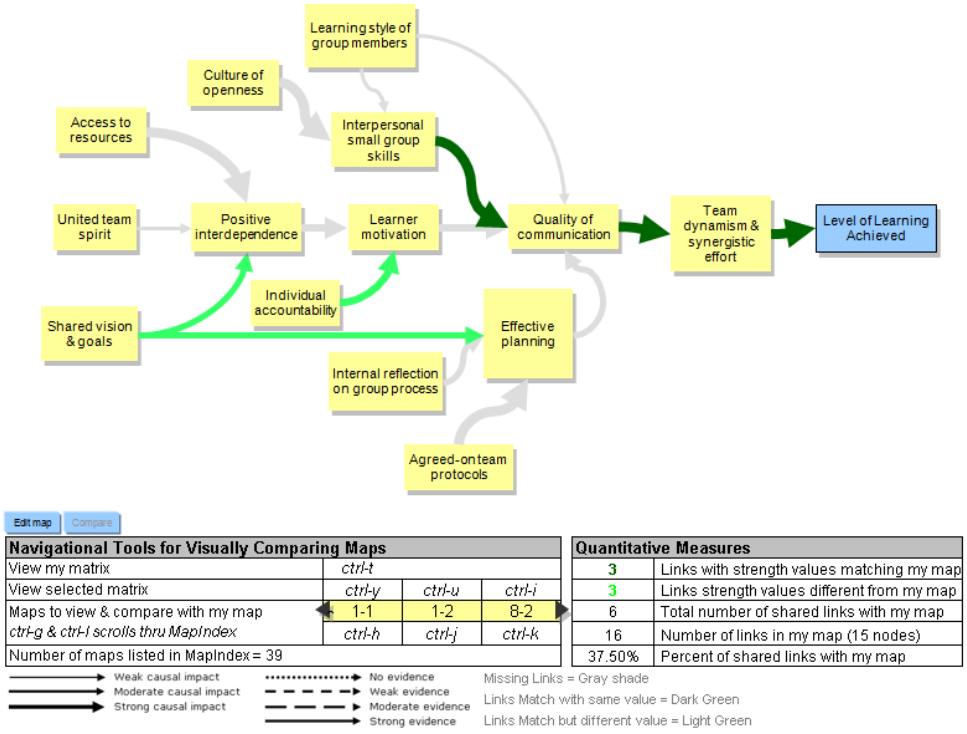

Figure 2. Student 8's map is superimposed over the instructors' map to reveal green and gray links that indentify those in the instructor' map that are presenting and missing in the student's map.

strong); and (b) selecting different types of links to reveal the level of evidentiary support (from past personal experiences) for the link. The course instructor also used jMAP to construct an expert map that was used in this study to assess the accuracy of students' maps (see Figure 2). Students were permitted to omit any factors that he/she did not believe to directly or indirectly influence the learning outcome. Personal diagrams were completed and electronically uploaded within a one-week period to receive class participation points (class participation accounted for 25% of the course grade). The diagrams were also used to complete a written assignment describing one's personal theory of collaborative learning (due week 4, and accounting for 10% of course grade).

Once all the students submitted their first causal map, the instructor used jMAP to download and aggregate all diagrams (n = 17) to produce and share with students a matrix conveying the percentage of diagrams that possessed each causal link. For example, the matrix in Figure 3 shows that the causal link between 'Individual Accountability' and 'Learner Motivation' was observed in 47% of students' diagrams. The links highlighted in yellow in the matrix above (on the right) identifies the common links observed in 20% or more of the students' diagrams (note: this criterion was specified by the instructor when aggregating diagrams in jMAP). Presented in the left matrix are the mean strength values of only those links observed in 20% or more of the diagrams. The highlighted values reveal links that are present or absent in the expert's map (i.e., dark green = links and strength values match, light green = links match, but strength values do not, gray = missing target links).

In week 9, students were presented the matrix revealing the percentage of diagrams (map 1) that possessed each link. Students posted messages in online threaded discussions to explain the rationale per link. Each posted explanation was labeled by students with the tag 'EXPL' in message subject headings. Postings that questioned or challenged explanations were tagged with 'BUT.' Postings that provided additional support were tagged with 'SUPPORT.' In weeks 9 and 10, students searched and reported quantitative findings from empirical research in a Wiki to determine the instructional impact of each factor.

Finally, in week 10, students reviewed the discussions from week 9. Within each discussion thread for each examined link, students posted messages to report whether they rejected or accepted the link (along with explanations). At the end of week 10, students revised and submitted their causal maps (map 2) based on their analysis of the arguments presented in class discussions.

Measurement

The number of total links was measured by counting all links in each student's diagram. Temporal flow was computed by dividing the number of right pointing links to the number of left pointing links. Links that were perfectly aligned in a vertical position (pointing straight up or straight down) were not included in the computation. Position of outcome node was based on the number of pixels separating the left edge of the screen to the left edge of the outcome node. By using the matrices automatically generated by jMAP (see Figure 4) to identify the causal root links and root cause nodes shared between each student's map and the instructor's map, the ratio of correct/incorrect root nodes and the number of correct root links were computed.

Analysis

The study applied the linear regression via SPSS 17.0. The diagrams produced *before* and *after* discussions were analyzed by using two regression models:

Model 1: Ratio of correct root $\text{causes}_i = \beta_0 + \beta_1(\text{number of total link}_i) + \beta_2(\text{ratio of temp flow}_i) + \beta_3(\text{outcome node location})$

Model 2: Number of correct root $\text{links}_i = \beta_0 + \beta_1(\text{number of total link}_i) + \beta_2(\text{ratio of temp flow}_i) + \beta_3(\text{outcome node location})$

Student Maps: 1-1 2-1 3-1 4-1 5-1 6-1 7-1 8-1 10-1 11-1 12-1 13-1 14-1 15-1 16-1 17-1 18-1

n = 17 (mean scores rounded to zero decimals)

Selection criteria: 20% or more of maps with given links

Mean Link Values

	Shared vision & goals	United team spirit	Effective planning	Learning style of group mer	Access to resources	Culture of openness	Agreed-on team protocols	Internal reflection on group	Learner motivation	Individual accountability	Interpersonal small group s	Positive interdependence	Quality of communication	Team dynamism & synergis	Level of Learning Achieved
Shared vision & goals			2									2			
United team spirit														2	
Effective planning					2		2								
Learning style of group members															
Access to resources			2												
Culture of openness								2					3		
Agreed-on team protocols	2														
Internal reflection on group process										2		2			
Learner motivation															3
Individual accountability									2						
Interpersonal small group skills						1							2		
Positive interdependence														2	2
Quality of communication														2	2
Team dynamism & synergistic effort												2			3
Level of Learning Achieved															

Percent of Maps with Given Links (n = 17)

	Shared vision & goals	United team spirit	Effective planning	Learning style of group members	Access to resources	Culture of openness	Agreed-on team protocols	Internal reflection on group process	Learner motivation	Individual accountability	Interpersonal small group skills	Positive interdependence	Quality of communication	Team dynamism & synergistic effo	Level of Learning Achieved
Shared vision & goals		18	24				6		12		6	24	18	12	12
United team spirit	6					6		6	12	6		12	6	29	12
Effective planning	6	6		12	24		47	6		12		12	6	18	12
Learning style of group members		6	12			6	6	6	12	12	18	12	6	12	6
Access to resources			35	6					18	6	6	6			12
Culture of openness	12	18		12	6		6	24	12	12	6	18	24	6	12
Agreed-on team protocols	29	12	6	6		12		18		12	6	12	12		12
Internal reflection on group process		6	12	6					6	24	6	24	12	6	18
Learner motivation	6	6		12		12	6	6		18	6	6	12	12	29
Individual accountability	12	6		6		18		6	47			12	6	6	12
Interpersonal small group skills	12	6	6			29	12			12		6	35	12	6
Positive interdependence	6	24	24				6		12	6			18	24	29
Quality of communication	12	6	18	6	6	6	18	12		12	12	6		24	35
Team dynamism & synergistic effort	12	24	6				12				6	24			47
Level of Learning Achieved															

Figure 3 Matrix displaying percentage of students' maps with each causal link and mean impact values assigned to causal links observed in 20% or more of the students' maps

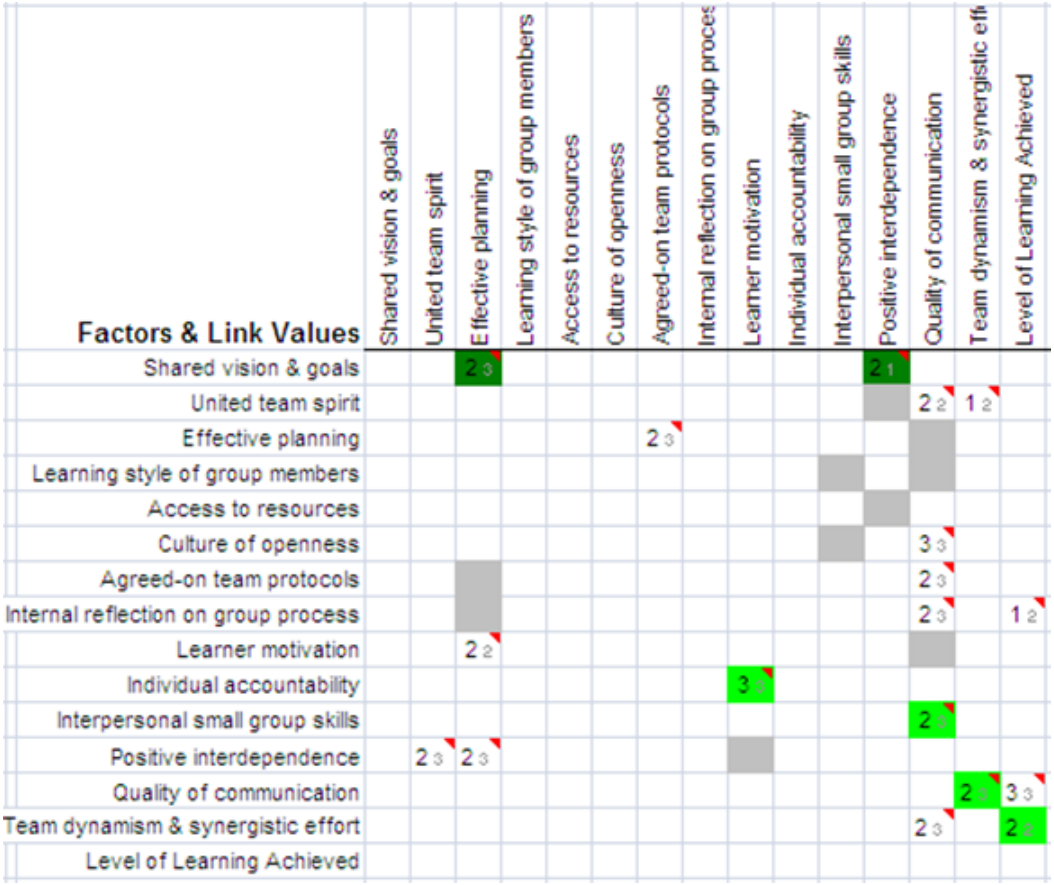

Figure 4. Matrix representation of student 8's causal map (causes listed by row, effects listed by column with green cells representing causal links correctly identified and blank columns indentifying root causes. Student explanations for causal links are stored in comments that can be accessed by placing the mouse over the red triangles.

Results

Correlations between attributes and accuracy

In the student's initial maps (map 1) produced *prior* to discussion, temporal flow was *negatively* correlated to the number of correct root links (r=-.461, p=.047), and outcome node position was *negatively* correlated to the number of correct root links (r=-.465, p=.045). In the maps produced *following* discussion (map 2), temporal flow was *positively* correlated with ratio of correctly/incorrectly root causes (r=.688, p=.003), while total causal links was *negatively* correlated with number of correct causal root links (r=-.523, p=.037).

Relative magnitude of attribute impact

The regression model for the ratio of correct/incorrect root causes following online discussions was found to be statistically significant (F(3,12)=5.025, p=.017). The model explains 44.6 % of the variance (Adjusted R^2=.446) and power was 0.73. In this model, temporal flow was the most highly and positively correlated to the ratio of correct/incorrect root causes (β=.772, p=.004), while total causal links showed relatively stronger negative correlation than the outcome node position.

Regardless of model significance, the regression model for the number of correct root links following online discussion explains 28.1% of the variance (Adjusted R^2=.281). In this model, total causal links was the most highly and negatively correlated to the number of correct root links (β=-.554, p=.028), while temporal flow showed relatively stronger positive correlation than outcome node position.

Table 1 Correlations between variables

Variables	TL	TF	NP	RC	RL
Prior to online discussion					
Total causal links (TL)	1				
Ratio of temporal flow (TF)	.028	1			
Outcome node position (NP)	.334	.254	1		
ratio of correct/incorrect root causes (RC)	-.213	-.432	-.381	1	
number of correct root links (RL)	-.165	-.461*	-.465*	.541*	1
Following online discussion					
Total causal links (TL)	1				
Ratio of temporal flow (TF)	.023	1			
Outcome node position (NP)	.159	.303	1		
ratio of correct/incorrect root causes (RC)	-.261	.688*	.085	1	
number of correct root links (RL)	-.523*	.352	.153	.492	1

*p<.05. **p<.001.

Table 2 The unstandardized and standardized regression coefficients for the variables

Variables	ratio of correct/incorrect root causes			number of correct root links		
	B	SE	β	B	SE	β
Prior to online discussion						
Total causal links	-.448	1.606	-.065	-.015	.037	-.089
Ratio of temporal flow	-.805	.508	-.362	-.020	.012	-.372
Outcome node position	-.040	.037	-.267	-.001	.001	-.341
Following online discussion						
Total causal links	-2.935	2.176	-.263	-.247	.099	-.554*
Ratio of temporal flow	.796	.223	.722**	.014	.010	.321
Outcome node position	-.021	.047	-.092	.001	.002	.143

*p<.05. **p<.001.

Discussion

The findings in this case study (though not conclusive) suggests that asking students to position nodes in temporal sequence might inhibit students' ability to identify the correct root causes when students are producing their *initial* causal maps (before discussion). It is possible that when students re-position one node closer to another node (but farther away from other nodes) based on the consideration of their temporal relationship, the nodes increased distance from *other* nodes (and reduction in visual proximity) may lead students to skip and omit from consideration other possible relationships with a given node. In other words, imposing temporal flow early in the map construction process may inhibit the brainstorming process and consideration of all possible relationships between nodes. As a result, this might push students to prematurely take specific courses of actions that lead to less accurate maps.

However, the findings also suggest that once students are given the opportunity to discuss and compare their maps (and have winnowed down in number the possible cause-effect relationships), imposing temporal sequence may actually help students correctly identify root causes. The results show that an increase in temporal flow by one standard deviation while holding total causal links and outcome node location constant can potentially increase the ratio of correct/incorrect root causes by .722 standard deviations. One possible explanation for this

finding is that the process of positioning nodes in temporal sequence creates new options or opportunities to articulate and refine the causal chains and identify the causes that mediate root causes and outcomes. This finding is somewhat contrary to previous findings where hierarchical structure was found to have no effect on accuracy (Ruiz-Primo, 1997). However, computing temporal flow in each student's map in this particular case study did not pose any methodological problems as it did in the study conducted by Ruiz-Primo at al. The differences in measures between this study and the study by Ruiz-Primo at al. may have contributed to the differences in findings.

The other main finding in this study suggests that if a limit is imposed on the number of causal link within a map to promote parsimony (or if students are encouraged to reduce the number of causal links in their maps), students are better able to correctly identify root cause links. This finding was consistent with the negative correlation found between total links and ratio of correct/incorrect root causes. A plausible explanation for this finding is that the students that tended to insert excessive numbers of links into their maps may have been the students that: (a) tended to link all nodes that are causally related regardless of whether they are directly or indirect related; and (b) are not able to identify the correct causal chains and mechanisms underlying the complex phenomenon/problem.

Future Research & Development

The findings in this study are not conclusive. Nevertheless, the preliminary findings provide ideas as to what and when to impose specific types of tasks and/or software constraints on the causal mapping process. Some directions for further research are the following: a) control for individual differences in knowledge and understanding of the concept/problem under study in order to fully determine the effects of students' knowledge and skills with causal maps on map accuracy; b) increase size of sample and data corpus; c) set the default location of the outcome node at the center of the screen rather than to the right portion of the screen in order to fully assess the effects of initial node location; d) measure final node location relative to the right edge of the screen (rather than left edge) if temporal flow if left to right rather than right to left; e) integrate these rules/constraints into jMAP to conduct a controlled experimental study to test and determine the effects of limiting number of links, manipulating the option to create links that can point in any or in only one direction, and intentionally varying the default location of outcome nodes; f) consider how the effects of each constraint vary when examining causal maps across different domains or topics that are or are not naturally temporal in nature; and g) test other metrics for assessing the accuracy of students' maps in relation to an expert map or in relation to a map representing that of the collective group.

References

Barenholz, H., & Tamir, P. (1992). A comprehensive use of concept mapping in design instruction and assessment. *Research in Science & Technological Education*, *10*, 37-52.

Dick, W., Carey, L & Carey, J. (2009). *The systematic design of instruction*, Allyn & Bacon.

Fisher, K. (1990). Semantic networking: The new kid on the block. *Journal of Research in Science Teaching*, *27*, 1001-1018.

Ifenthaler, D. (2008). Relational, structural, and semantic analysis of graphical representations and concept maps. *Educational Technology Research and Development*, *58*(1), 81-97.

Ifenthaler, D., Masduki, I. & Seel, N.M. (2009). The mystery of cognitive structure and how we can detect it: tracking the development of cognitive structures over time. *Instructional Science*. doi: 10.1007/s11251-009-9097-6.

Jeong, A. (2009). Superimposing individual and group causal maps to trigger critical discourse and change in learners' causal models. Paper presented at the American Educational Research Association conference, San Diego, CA.

Jeong, A. (2010a). Assessing change in learner's causal understanding: using sequential analysis and causal maps. In Shute, V., & Becker B. (Eds.), Innovative Assessment for the 21st Century: Supporting Educational Needs. New York, NY: Springer-Verlag.

Jeong. A. (2010b). jMAP Retrieved July 14 2010 http://cscl.wikispaces.com/jmap.

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. O. (2006). Learning with concept and knowledge maps: A meta-analysis. Review of Educational Research, 76(3), 413–448.

Nicoll, G. (2001). A three-tier system for assessing concept map links: a methodological study. *International Journal of Science Education*, 23(8): 863-875.

Plate, R. (2010). Assessing individuals' understanding of nonlinear causal structures in complex systems. *System Dynamics Review*, *26*(1): 19-33.

Ruiz-Primo, M. & Shavelson, R. (1996). Problems and issues in the use of concept maps in science assessment. *Journal of Research in Science Teaching*, *33*(6), 569-600.

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.

Assessment Interpretations: An Experiment Testing the Assumption Of Hierarchical Concept Maps in Science

Scavarda, A. J., T. Bouzdine-Chameeva, et al. (2004). A review of the causal mapping practice and research literature. Second World Conference on POM and 15th Annual POM Conference, Cancun, Mexico.

Wilson, J. (1994). Network representations of knowledge about chemical equilibrium: Variations with achievement. *Journal of Research in Science Teaching. 31*, 1133-1147.