Assessing Change in Learner's Causal Understanding Using Sequential Analysis and Causal Maps

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Abstract: New methods are needed to assess how group discourse triggers changes in causal maps and to measure and visualize across time how changes in causal maps of individuals or the collective group progress toward the group or target map. The software tool, jMAP, was developed to enable learners to individually produce causal maps, download and aggregate the maps across learners. It aggregates learners' maps to reveal similarities between individual/group maps, the percentage of maps sharing particular causal links, average causal strength assigned to specific links, and degree of match between maps of the collective group and target/expert diagram. jMAP produces data to create transitional state diagrams for visualizing how causal maps change over time and the effects of specific dialogic processes. This paper presents findings from two case studies to illustrate how jMAP can be used to support the assessment of causal understanding, and identifies areas for future research.

Introduction

Each one of us holds different beliefs and theories about the world. Learners' theories can be conceived, articulated, and assessed more efficiently in the form of causal maps - networks of events (nodes) and causal relationships (links) between events – than in the form of linearly written text. Some causal maps may be more accurate than others—depending on the presence and/or absence of supporting evidence; and some maps and the causal links within the maps may be more or less firmly held—depending on both the strength of the supporting evidence and the strength of specific causal relationships. Furthermore, causal maps are not fixed and unchanging. Instead, they are incomplete and constantly evolving; may contain errors, misconceptions, and contradictions; may provide simplified explanations of complex phenomena; and may often contain implicit measures of uncertainty about their validity (Seel, 2003). As a result, causal maps can change, but usually not randomly. That is, we presume that events trigger and provide the impetus for change. Causal maps and other similar forms of visual representations are being increasingly used to help assess learners' understanding of complex domains and/or learners' progress towards increased understanding (Spector & Koszalka, 2004; Nesbit & Adesope, 2006). However, the methods and software tools to measure how learner's maps change over time (Ifenthaler & Seel, 2005; Doyle & Radzicki, 2007) and how specific events (e.g., pedagogical discourse) trigger changes in learners' causal maps (Shute, Jeong, & Zapata-Rivera, in press) have not yet been adequately addressed.

To address some of these methodological challenges, Ifenthaler and Seel (2005) used transitional probabilities to determine how likely learner's maps (when examined at as a whole) changed in structural similarity across eight different time periods. Raters were given a specially designed questionnaire to determine if a learner's map at one point differed in structure from the learner's map produced from the most previous point in time. The study found that maps were most likely to change in structure at the early stages of the map construction process with the likelihood of changes dropping from one version to the next. However, Ifenthaler (2008) found that changes in scores on seven of nine measures of structural quality (e.g., total number of links, level of connectedness, average number of incoming and outgoing vertices per node) had no correlation to the degree to which the learners' maps matched the expert map. Not surprisingly, the one aspect of the learners' maps that did correlate to learning was the number of links shared between the learner's map and the expert map. These findings altogether suggest that measures used to gauge changes at the global level (where the unit of analysis is the map as a whole) and measures that are not scored in relation to a target map (e.g., expert or collective group map) may have little or no value as an assessment tool.

One alternative approach is to measure changes at a more micro-level using the node-link-node as the unit of analysis and unit of comparison between learners' and target maps. At this level, we can examine how likely links between specific nodes are to change from one state to another (e.g., strong vs. moderate vs. weak vs. no causal *impact*; or high vs. moderate vs. low *probability/confidence*) as maps change over time. We also see to what extent the observed changes in the values of each causal link converge towards the target causal link values present in the target map. For example, we expect that the causal link values for links representing learner's misconceptions (e.g., erroneous links *not* observed in the target map) or learners' shallow understandings (e.g., links between two nodes not directly related and/or better explained by inserting a mediating node) will converge towards a value of 0 (no causal link) over time, following a close examination and critical discussion of the causal relationships. At the same time, the expectation is that the causal link values of the links *not* observed in a learner's map (but present in the target map) will progress from a value of 0 to the value observed in the target map. Using the node-link-node as the unit of analysis enables a precise examination of how and to what extent observed changes in targeted links help and/or inhibit learners from achieving the target learning outcomes (e.g., deeper and more accurate understanding). Furthermore, this approach enables us to examine how specific interventions/events (e.g., depth of argumentation, the production of supporting evidence) affect the direction and magnitude of changes across links that are missing or links that are valid or invalid.

For example, Shute, Jeong & Zapata-Rivera (in press) conducted a study to examine the processes of collaborative theory construction in an online graduate course on instructional technology. In this study, each student used jMAP to individually construct a causal diagram (at the beginning, middle, *and* end of the semester) that explains the complex events and conditions (including intermediate events and their causal relationships) that determine when the use of media technology increases learning and achievement. In the causal maps, students assigned a strength value to each causal link (1 = weak, 2 = moderate, 3 = strong impact) based on personal experiences and empirical literature examined in the course. In addition, students were instructed to specify with each causal link added to the causal diagram the quality of evidence they possessed and/or compiled to justify the plausibility of each given link (0 = no evidence, 1 = weak evidence, 2 = moderate evidence, 3 = strong evidence). In this case study, the experimenters coded all the maps by hand and causal links into adjacency matrices because the early versions of jMAP did not perform this function. Once coded, jMAP was used to tabulate the sequential changes in causal links observed in each student's causal diagrams produced *prior* to and *subsequent* to collaborative work (identifying factors; collecting, annotating, and sharing supporting evidence; cross-examining the evidence; interpreting the evidence; consensus making).

The Discussion Analysis Tool (Jeong, 2005) was then used to sequentially analyze the data to produce the transitional state diagram presented below. The state diagram in Figure 1, for example, shows that 50% of all causal links that were assigned a strength value of one remained the same between the first and second, and between the second and third causal diagrams, when *no* evidence was presented nor discussed in the online group discussions to establish the plausibility and the strength of the link. In contrast, the state diagram on the right shows that when evidence was presented with the causal links, these same links with strength value of one were much more likely to remain the same (86% instead of 50%). Overall, this preliminary study illustrates how the jMAP environment – when combined with sequential analysis – can produce a potentially powerful method to studying the *processes* of theory construction and the factors and conditions that both support and inhibit the process.

This presentation will demonstrate the software tool called jMAP that can be used to identify differences between learners' causal maps, initiate collaborative argumentation to produce justifications for proposed causal links, and produces changes in learners' causal maps that better reflect/represent complex phenomena. Similar to the Cognizer program (Nakayama and Liao, 2005), jMAP enable each learner to produce a causal map with numerically weighted links (Figure 2) thus reducing unwanted biases and influences of other learners (Doyle & Radzicki, 2007). jMAP can then be used to: 1) automatically code diagrams into adjacency matrices; 2) upload, download, and aggregate multiple matrices so that the maps of an individual, the collective group, and/or expert (in any paired combination) can be graphically superimposed to determine for example the degree to which a learner's diagram matches that of the expert or the collective group at a given point in time; 3) view the superimposed maps across different time periods to both visualize and quantitatively assess how learners' causal diagrams change over time and the extent to which the changes are converging towards the maps of the expert or the collective group; and 4) sequentially analyze and visualize how particular learners' causal diagrams and causal understanding of complex phenomena change over time under different instructional processes, events, or conditions (Jeong, 2008).

jMAP also enable researchers and teachers to: (a) graphically superimpose an *individual* learner's map over the expert/target map to visually identify and highlight changes occurring over time in the causal maps of an individual or group of learners; (b) determine the extent to which the observed changes progress toward a target or collective model; (c) determine precisely where, when, and to what extent changes occur in the causal links within the causal maps; and most importantly; and (d) identify and measure how and to what extent specific events (e.g., viewing consensus data, discussing evidence, engaging in specific and critical discourse patterns) trigger changes in the causal links between various states (e.g., strong, moderate, weak, and no causal link) as demonstrated in Figure 3.

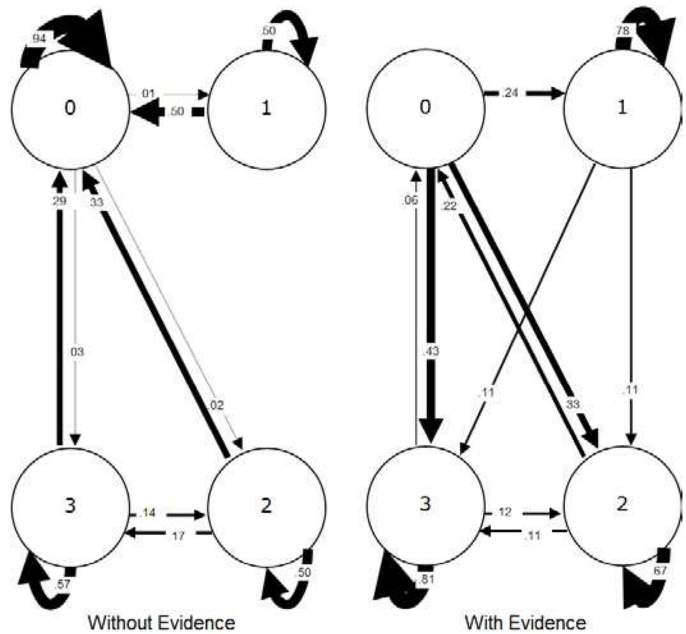


Figure 1. Transitional state diagrams revealing the direction and likelihood of changes in causal strengths when links are presented without vs. with supporting evidence

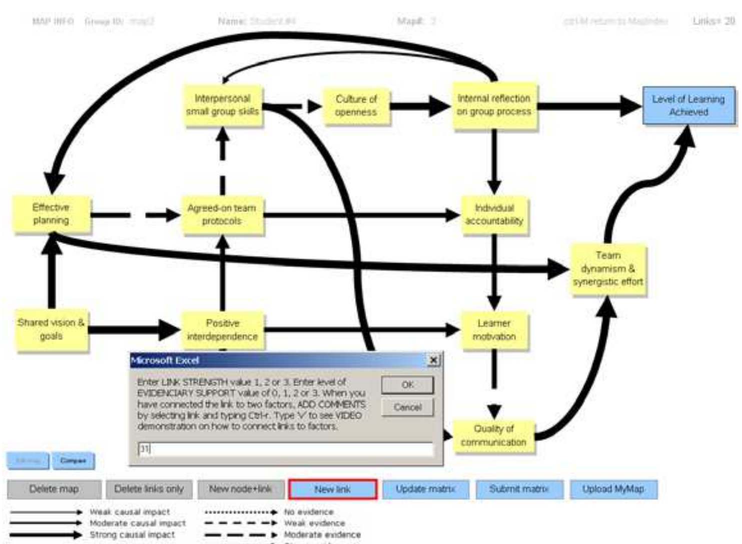
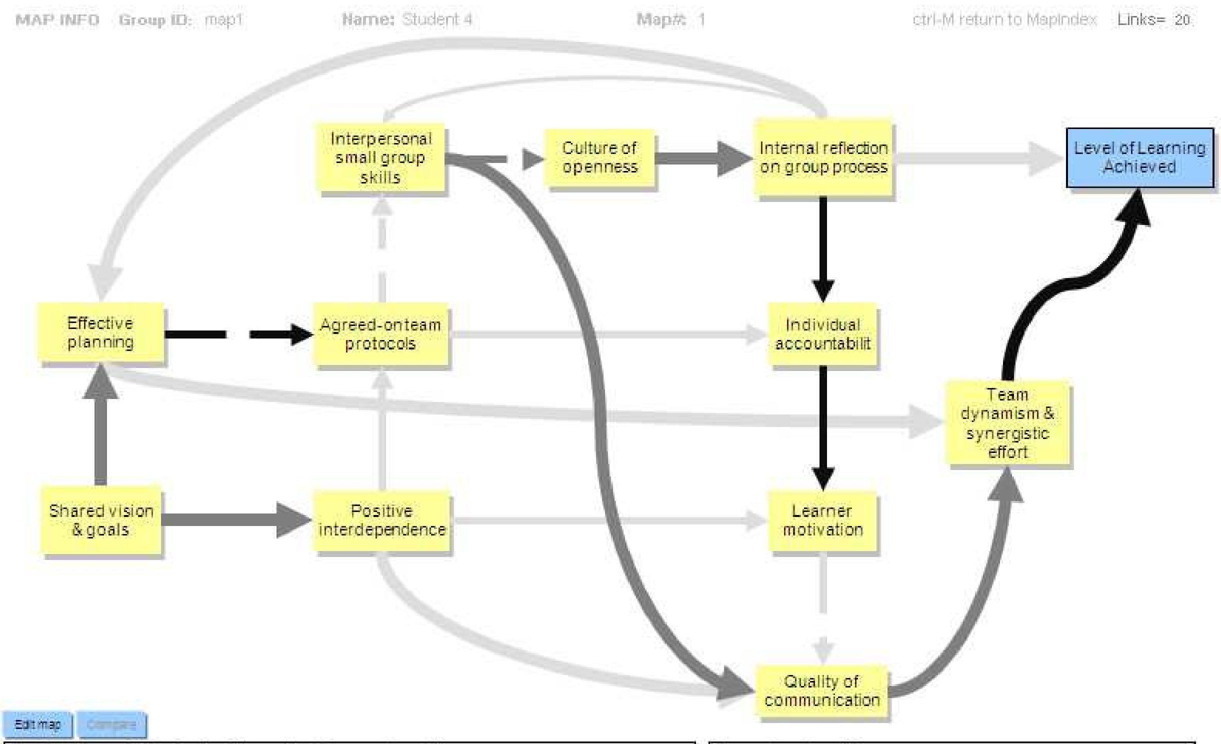


Figure 2. Drawing a causal map with jMAP using weighted links to specify strength of each causal relationship and dotted links to specify level of confidence or evidenciary support



Navigational Tools for Visually Comparing Maps			
View my matrix	*ctrl-t*		
View selected matrix	*ctrl-y*	*ctrl-u*	*ctrl-i*
Maps to view & compare with my map	g1	1-1	2-1
ctrl-g & ctrl-l scrolls thru MapIndex	*ctrl-h*	*ctrl-j*	*ctrl-k*
Number of maps listed in MapIndex = 17			

Quantitative Measures	
4	Links with strength values matching my map
6	Links strength values different from my map
10	Total number of shared links with my map
20	Number of links in my map (15 nodes)
50.00%	Percent of shared links with my map

Figure 3. Visually comparing student 4's first map with the aggregated group map (g1) with darker links revealing matching causal strength values, lighter links revealing shared links (differing in values), and light gray links revealing missing links.

The following case study illustrates how jMAP can be used to assess how differences in the quality of learner's argumentation affect changes in learner's causal diagrams. Furthermore, this paper will also demonstrate how jMAP can be used to compare causal maps between learners, identify differences between learners' maps and initial/current consensus on map links, and to initiate and structure learners' discussions in ways that might help to improve their causal maps. The case study presented in this paper presentation addressed the following research questions:

1. *What are the effects of consensus observed in initial maps on the level of consensus in subsequent maps?* When learners use jMAP to determine which causal links are shared most among everyone's initial maps, are the most commonly shared links more likely to remain in learners' subsequent maps than the less commonly shared links?

2. *What is the relationship between initial levels of consensus and level of argumentation?* Do learners engage in more argumentation when a causal link is more or less commonly shared between learners? In other words, do higher or lower levels of initial consensus trigger higher levels of argumentation?

3. *What are the effects of argumentation levels on consensus in subsequent maps?* Do high levels of argumentation lead to higher or lower levels of consensus in maps produced subsequent to group discussions/debates?

Method

Participants

Nineteen graduate students (8 male, 11 female) enrolled in an 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 success in collaborative learning and instructional strategies associated with each factor. In week 2, learners 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 voted 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 learners individually organized into causal maps.

In week 3, students were presented six example maps to illustrate the desired characteristics and functions of causal maps (e.g., temporal alignment, parsimony). Students were provided the jMAP program (pre-loaded by the instructor with nodes for each of the 14 selected factors) to construct their first causal diagram (map 1). Map 1 allowed students to graphically explain their understanding of how the selected factors influence learning in collaborative settings. Using the tools in jMAP, learners 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 = strong); and (b) selecting different types of links to reveal the level of evidentiary support (from past personal experiences) for the link. Personal maps 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 maps 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).

Using jMAP, the instructor *aggregated* all the initial maps (n = 17) submitted by students into a group matrix. The group matrix was shared with students to convey to the students the percentage of maps that possessed each causal link. The links enclosed in boxes in the right side of the figure are *common links* observed in 20% or more of the learners' maps. For example, the causal link between 'Individual Accountability' and 'Learner Motivation' was observed in 47% of learners' maps. To select this 20% cut-off criterion, the instructor ran multiple aggregations of the learner maps at different cut-off criterion until the instructor felt that a sufficient number of links were present for group discussion and to discriminate between links that were more versus less shared between learners. A corresponding group matrix was also produced in jMAP to report the mean strength values of the links observed in 20% or more of the maps. The values were highlighted by jMAP to reveal which links were present in the expert's map but missing in the group map (i.e., dark shaded cells with values = links shared and strength values match, lightly shaded with values = links shared with non-matching values, lightly shared boxes with no values = missing target links).

In week 9, learners were shown the matrix that revealed the percentage of maps (map 1) that possessed each link. Students posted messages in an online threaded discussion forum to explain the rationale and justification for each proposed causal link. Each posted explanation was labeled by learners 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, learners searched for and reported quantitative findings from empirical research into a group Wiki that could be referenced and used later to determine the instructional impact of each factor.

Students received instructions on how to use jMAP to *superimpose* their own map over the aggregated group map (Figure 2) to visually identify similarities and differences between their own maps and the collective conception of the causal relationships between factors and outcomes. For example, figure 2 reveals the similarities and differences between an individual student's first map (student #4) and the group map (g1) generated by the aggregation of all the maps produced by all students at the first time period. The course instructor used jMAP to superimpose his expert map over the group map produced at time period one (g1) and in time period two (g2) by using the control keys (ctrl-h, ctrl-j, ctrl-k) to toggle between maps g1 and g2. By using the navigational tools to toggle between the two group maps, the instructor was able to visually and quantitatively observe the progression of changes averaged across all the students' maps in order to assess the extent to which the observed changes converged towards the expert map. Jeong (2008) presents more detailed information on how to use jMAP to visualize and animate progressive changes in maps created by a select learner (or group of learners) across multiple time periods relative to a target map.

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

Data Analysis

To measure the level of change in learners' maps, link frequencies from each learner's second map (n = 15) were aggregated to determine the percentage of maps that shared each link. Differences in the reported percentages between maps 1 and 2 were computed and presented in a matrix. Overall, the percentages in 19 of the 24 commonly shared links increased by an average of 26%. Four of these shared links changed by an average of -10.75%.

The level of critical discourse produced within each discussion on each link was determined by the number of observed EXPL-BUT, BUT-BUT, BUT-EXPL or SUPPORT, and BUT-SUPPORT exchanges. Challenges to explanations, and explanatory responses to challenges were used as a measure of critical discourse because explanations, when generated in direct response to conflicting viewpoints, have been shown to improve learning (Pressley et al., 1992). Pearson correlations between variables are presented below.

Table 4. Correlations (n = 24) between level of initial agreement, critical discourse, and change percent of learners sharing each causal links

		LevelAgree	CritDisc	%Change	Expl	But	Support	Expl-But	But-Ex/Sup	But-But	Expl-Sup
LevelAgree	*r*	1	.385	-.089	.233	.328	.291	.330	.365	.177	.153
	signif		.063	.679	.272	.118	.168	.115	.079	.409	.476
CritDiscourse	*r*	.385	1	-.152	.339	.921	.120	.867	.921	.494	-.135
	signif	.063		.478	.105	.000	.575	.000	.000	.014	.530
PercentChange	*r*	-.089	-.152	1	-.058	-.173	.313	-.051	-.167	-.219	.386
	signif	.679	.478		.788	.420	.136	.814	.435	.304	.063

Findings

Effects of consensus in initial maps on level of consensus in subsequent maps.

Based on links (n = 24) that were observed in 20% or more of students' maps and discussed by students on the discussion board, the correlation (Table 4) between the percentage of students that shared a causal link in the first map and the average change in the percentage of students that shared the causal links was not significant (r = -.089, p = .679). The opinions of the majority did not appear to influence learners' decisions to include or exclude causal links into their revised maps. This suggests that the use of jMAP to reveal the similarities and differences between students' maps did not foster group think.

Relationship between initial agreement and level of critical discourse.

The correlation (n = 24) between the percentage of students that shared a causal link in the first map and the level of critical discourse that was generated by students to exam the strength of each causal link approached statistical significance (r = .385, p = .063). The students engaged in more critical discussion over the causal links when the causal links were shared by more students rather than less students. This finding suggests that students did not simply accept or give into the status quo. Conversely, the finding also suggests that students exhibited some tendency to engage in *less* critical discussion over the causal links when the casual links were shared by *fewer* students. One possible explanation for this finding may be that the causal links shared by the fewest number of students where those that exhibited the most obvious flaws in logic and as a result, these links did not warrant much debate to omit the causal link from the causal maps.

Effects of argumentation on changes in agreement in subsequent maps

No significant correlation was found between the level of critical discourse over each causal link and the change in the percentage of maps sharing each casual link (r = - .152, p = .478). This finding suggests that the level of critical discourse over each causal link neither increased nor decreased the percentage of students that rejected a causal link.

However, post-hoc analysis on the individual effects of each of the four types of exchanges (all of which were aggregated and used to measure the level of that critical discourse) revealed the frequency of EXPL-SUPP exchanges observed in discussions over each link were moderately and positively correlated (*r* = .386, *p* = .063) with changes in the percentage of students that shared each causal link. Supporting statements that were specifically posted in direct response to other learners' causal explanations (e.g., presenting supporting evidence, simple expression of agreement) were the types of events/exchanges that were most likely to persuade learners to adopt new links into subsequent causal maps. This finding is consistent with the findings from a previous case study in which causal link strength values were more likely to remain the same or increase in value when links were supported with evidence. Worth noting here is that the frequency of supporting statements alone in the discussions over each causal link (without regard to what messages they were posted in response to) revealed a similar correlation but of lesser statistical significance (*r* = .313, *p* = .136). This suggests that message-response exchanges as opposed to simple message frequencies alone could provide more explanatory power when analyzing the effects of critical discourse on causal understanding.

Additional findings

To be included at the time of presentation will be the findings produced from the visual comparison of the transitional state diagrams (like Figure 1) depicting how the causal maps (or more specifically, the strength values of each causal link) changed over time resulting from the high vs. low presence of EXPL-SUPP exchanges observed in the discussions of each causal link.

Implications

The findings in this case study illustrate how jMAP can be used to assess the impact of critical discussions or other instructional events/interventions on learners' causal understanding. When used as a research tool, jMAP provides insights into the processes of learning (e.g., causal understanding) and insights into how specific processes (e.g., EXPL-SUPP) lead to specific learning outcomes/behaviors. At the same time, this case study illustrates how jMAP can help learners work collaboratively to build and refine their causal understanding. Learners can identify similarities and differences in their causal understanding relative to others. Then they can use the differences as the starting point to discuss and explore the causal relationships.

Directions for Future Research & Development

The findings in this case study are not conclusive given the limited sample size. Nevertheless, this study illustrates how jMAP can be used to assess how causal understanding evolves over time and how specific processes of discourse (including processes of scientific inquiry) influences causal understanding. More research is needed to identify the specific discourse processes and interventions that foster critical discourse that can trigger changes in causal links – particularly changes that converge towards the expert and/or group model.

To support future research, online discussion boards could be integrated into jMAP to automatically create discussion threads for each causal link observed in learners' causal maps, to seed discussions with learners' initial explanations, to support message tagging, and to compile and report scores that measure certain qualities observed in the group discussions for any given set of causal links. Such a system could be used by instructors to assess not only the quality of learners' causal maps and understanding, but also the quality of learners' discourse and its impact on their causal understanding. Additional functions can be added to jMAP to recognize nodes that are indirectly linked via mediating nodes to fully account for observed differences between learner and expert maps. Another useful function would be one that can identify and measure to what extent and in what temporal direction changes in causal links propagate subsequent changes in adjacent links – a measure that could be used to determine to what extent learners apply a systematic approach to break down the causal relationships. To examine this issue in more detail, a function can be added to jMAP that captures and logs every action performed in jMAP as learners construct their maps.

In addition, refinements to the jMAP user interface will be necessary to make map construction easier, more intuitive, and less time consuming if systems like jMAP are to be used in school-based applications – particularly for learners at younger ages. Instructions and guidance on how to conceptualize a coherent causal map/model (e.g., temporal flow, parsimony) should be embedded directly into the jMAP interface to assist learners that lack the skills needed to construct a causal map. Other useful functions to add to jMAP include: swap and change the target map so that one can compare different combinations of maps (individual, collective group, expert); show the percentage of students' maps that possess each target link by varying the density of each link to reflect the observed percentages; and select links to include in the aggregate/collective group map based on link frequencies that are significantly higher than the expected frequencies based on a user-selected critical z-score.

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