CHAPTER 11

VISUALIZING THE PROCESSES OF CHANGE IN LEARNER BELIEFS

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ABSTRACT

Current approaches to understanding the processes of change in learners' beliefs about complex concepts are incomplete and inadequate. The use of concept maps, for example, fails to capture the strength of the links between causal factors and outcomes, the extent to which the links are supported by evidence (or the extent to which the learners cross-examine, test, and evaluate the merits of presented evidence). Specifically, current approaches are inadequate for describing the way link strengths are affected by evidentiary support (or specific processes used to cross examine and test evidence), the patterns in which link strengths change over time, how these patterns of change ultimately affect learners' beliefs, and to what extent each change observed in an individual's belief structure converges toward a target model

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and/or the collective beliefs of a group of learners. To address these issues, this paper presents a preliminary set of software tools and techniques used to visualize the processes of change in learners' beliefs by combining the methods of flexible belief networks and sequential analysis. Pilot data was collected and analyzed with the presented tools and technique to illustrate their application, their limitations, and to identify areas for future study and development.

INTRODUCTION

"I know" is just "I believe" with delusions of grandeur.

Each one of us holds many different beliefs about the world. We can conceive of these beliefs as a network of concepts (nodes) and their relationships (links). Some beliefs may be more accurate than others—depending on the quality of the underlying evidence; and some beliefs may be more or less firmly held—depending on the strength of the links. As educators, we would like to be able to make valid inferences about what a person knows and believes. But beliefs are not fixed and unchanging. Instead, beliefs (like mental models): (a) are incomplete and constantly evolving; (b) may contain errors, misconceptions, and contradictions; (c) may provide simplified explanations of complex phenomena; and (d) often contain implicit measures of uncertainty about their validity that allow them to used even if incorrect (e.g., Ifenthaler & Seel, 2005; Seel, 2003). So beliefs can change, but not randomly—there are typically triggering events that provide the impetus for change. In this paper, we describe our preliminary solutions to modeling evolving (or dynamic) belief networks, and also to identifying the basis for change.

Concept maps are being increasingly used to examine and assess learners' understanding of complex domains and their progress towards increased understanding (e.g., Spector & Koszalka, 2004). Many of the current studies on concept maps focus on well-defined problems (Freeman & Urbaczewski, 2001; Ruiz-Primo, 2004; Ruiz-Primo & Shavelson 1996), and are restricted to a closed format where concepts are provided by the evaluator (Zele, 2004). This closed format, while making it easy to score, provides little insight into the actual process of learning, or more specifically, the cognitive processes underlying the changes learners' make to their concept maps.

To examine the underlying processes of concept mapping, researchers can provide learners with the opportunity to annotate nodes and links in their concept maps (Alpert, 2003). Such annotations can potentially help learners produce more accurate maps (Spector, Dennen, & Koszalka, 2005). Including particular forms of annotation with students' concept maps (e.g. inserting into nodes direct hyperlinks to online discussion threads produced by the students) enables researchers to access, study, and determine some of the cognitive processes (at the granular level) that underlie, trigger, and explain changes (both good and bad) in learners' mental models.

Given the overwhelming complexity and quantity of data that can be produced from close examination of both the concept maps and learners' cognitive processes at the granular level, new software tools and methods are needed to produce visual representations that can *simultaneously* reveal: (a) global patterns emerging in the maps and the cognitive processes, events, and/or conditions that trigger changes in the maps; (b) the extent to which the changing patterns are progressing toward a target model; and (c) detailed and precise information on *what* and *where* changes are occurring within the maps.

Some of the assumptions underlying the research described in this paper include the following:

- Very few of the numerous studies on assessing mental models actually examine the *strength* of links in learners' causal maps. Instead, they tend to focus on the number and nature of the concepts and links in the maps (to see an example of a study that did examine link strengths, see Zapata-Rivera, 2003).
- There is a need for tools that can efficiently and visually convey information about *changes* in students' mental models and the progression toward expert models (or a collective group model) at a more granular as opposed to general level.
- If we can determine precisely where and when changes occur in students' models, we will also need tools to analyze and determine the cognitive processes that *trigger* the observed changes (e.g., the evidence presented and cross-examined by the students on which the strengths of the links are established).

The goal of the research described in this paper is to help resolve problems associated with handling and interpreting the complexity and quantity of causal map and process data. Before we present our new methodology and tools that we have developed for addressing these issues, we first overview two disparate approaches that were merged within this project. The first approach represents the ideas and methodologies related to flexible belief networks (or FBNs, see Shute & Zapata-Rivera, 2008), which take concept (or causal) maps to the next level in terms of explicating and incorporating (a) strength of beliefs (i.e., causal links among concepts), as well as (b) the underlying evidence into the maps. The second represents an approach and tool developed by Jeong (2004, 2015a) called the discussion

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analysis tool (DAT) for sequentially analyzing patterns in event sequences (such as threaded discussions). From these events, DAT generates transitional state diagrams that enable the user to map, identify, and analyze patterns that are observed in social and human-computer interactions, processes, and/or other complex, dynamic procedural tasks.

Flexible Belief Networks

Our approach to representing a learner's (or group of learners') current set of beliefs about a topic is to overlay Bayesian networks (Pearl, 1988) on concept maps. This permits us to model and question the degree to which relationships among concepts/nodes hold as well as the *strength* of the relationships. In addition, prior probabilities can be used to represent preconceived beliefs. A probabilistic network provides us with a richer set of modeling tools that we can use to represent the degree to which people ascribe to a particular belief pattern.

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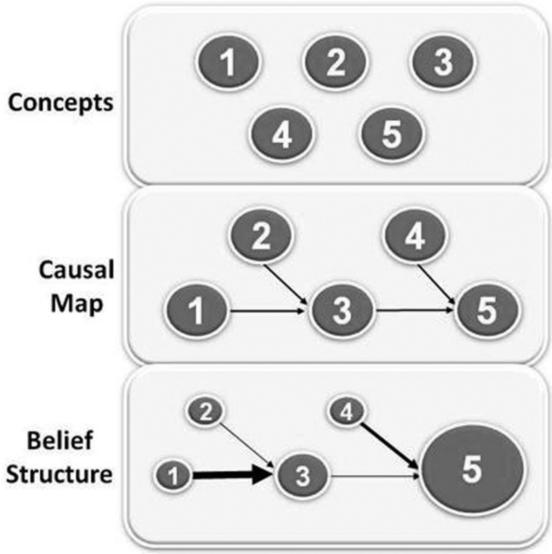
Accomplishing this goal involves incorporating an assessment layer on top of the concept maps to flesh out the maps more fully. This would result in a collection of evidence from students in terms of their evolving mental models as indicated by their relationship to the strength and relevance of associations, directionality of the stated relations, and the specified type or nature of the relationship. The result is a set of flexible belief networks (or FBNs) (for more, see Shute & Zapata-Rivera, 2008). In this chapter, we have decided to work with causal maps instead of working with general concept maps in order to reduce complexity.

Figure 11.1 illustrates a simplified example of the progression from concepts to concept (causal) maps to belief nets when Bayesian networks are overlaid to specify structure, node size, and links (i.e., type, directionality, and strength of association). Evidence is attached to each node relationship which either supports or counters a given claim.

The *size* of the node in the belief structure indicates a given node's marginal probability (e.g., p(node 1 = True) = 0.1—a tiny node with a low probability of being true). *Links* illustrate the perceived relationships among the nodes in terms of *type, direction,* and *strength*. *Type* refers to the probabilistic or deterministic representation—defining the nature of the relationship (in this case,—causes). The s*trength* of the relationship is shown by the thickness of the link, and the *direction* indicates that the relationship has an origin and a destination. The belief structure in Figure 11.1 models the beliefs of a person (or group of people) that, for example: (a) nodes 1 and 3 exist, (b) the current probabilities of node 1 and node 3 are fairly low (0.1 and 0.3 respectively), and (c) there is a positive and strong relationship between nodes 1 and node 3 (represented by a thick line). So,



Source: Adapted from Shute and Zapata-Rivera (2008).

Figure 11.1. Progression from concepts to causal map to belief structure.

if the low probability of node 1 turned out to be true, then the effect on node 3 would be strong.

When comparing two belief nets (e.g., the same student at different points in time; a student with an expert), they may contain the same concepts, but the size of the respective nodes, the directionality of relations, and the strength of the links may be very different. Because we have chosen to use Bayesian networks to represent belief structures, this enables us to examine not only (a) the structure of the map, but also (b) the content (nodes and links), as well as (c) the underlying evidence that exists per structure (and per node). That is, as part of creating a current belief structure, the student arranges concepts and establishes links, and he or she includes specific evidence (sources) per claim (i.e., arguments and relevant documentation in support of, or in opposition to a given claim). This will become important later when we discuss the task used in our pilot study. Figure 11.2 shows a generic belief network with its supporting evidence attached.

Discussion Analysis Tool

Similar to the approach used with FBNs to represent and analyze links and nodes in causal maps, sequential analysis (Bakeman & Gottman, 1997) has been used to model and analyze *sequential links* between behavioral

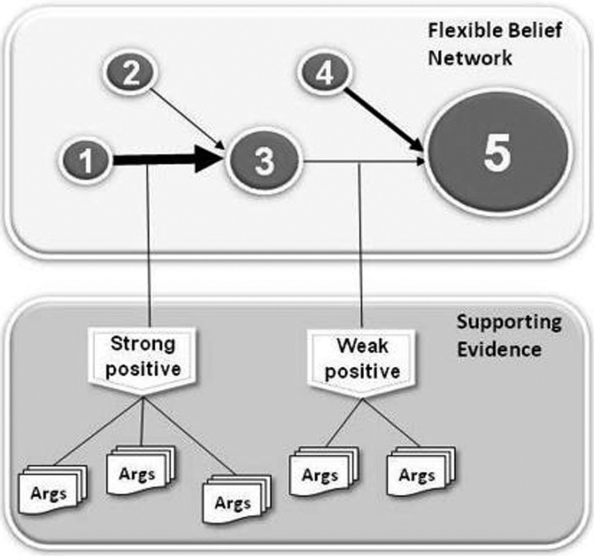


Figure 11.2. Supporting evidence underlying an example FBN.

events to determine how likely one given event is followed by another given event. Jeong (2015a) developed DAT to compute the transitional probabilities between dialog moves observed in online debates. For example, DAT produces a transitional probability matrix to report the percentage of replies to stated arguments (ARG) that are challenges (BUT) versus explanations (EXPL) versus supporting evidence (EVID); and the percentage of replies to challenges that are counter-challenges versus explanations versus supporting evidence (see Figure 11.3). DAT also produces a corresponding *z*-score matrix to identify and automatically highlight transitional probabilities that are significantly higher/lower than expected probabilities to determine which behavioral sequences can be considered a pattern in a group's behaviors.

To visually and more efficiently convey the complex data revealed in the transitional probability matrix, DAT converts the observed probabilities into transitional state diagrams (see Figure 11.4). Potential differences in behavior patterns between experimental groups—such as groups with students that are high vs. low in intellectual openness (Jeong, 2007)—can be easily discerned by juxtaposing state diagrams and observing the differences in the thickness of the links between events (signifying the strength of the transitional probabilities between given events). Once specific patterns and differences are identified between particular events, DAT automates

	+ARG	+BUT	+EXPL	+EVID	-ARG	-BUT	-EXPL	-EVID	Replies	No Replies	Givens	Reply Rate	% replies	% givens
+ARG	.02	.03	.25	.17	.00	.49	.00	.04	213	21	127	.83	.25	.10
+BUT	.00	.10	.05	.10	.00	.66	.06	.03	135	162	289	.44	.16	.23
+EXPL	.00	.02	.08	.15	.00	.67	.06	.02	52	64	112	.43	.06	.09
+EVID	.00	.00	.10	.13	.00	.71	.00	.06	31	50	84	.40	.04	.07
-ARG	.00	.48	.03	.02	.00	.02	.26	.19	174	21	124	.83	.20	.10
-BUT	.00	.61	.11	.02	.00	.08	.08	.09	157	185	328	.44	.18	.26
-EXPL	.00	.56	.13	.00	.00	.04	.17	.10	52	56	102	.45	.06	.08
-EVID	.00	.62	.05	.03	.00	.00	.15	.15	39	49	81	.40	.05	.06
	4	254	99	69	0	269	84	74	853	608	1247	.53		

Example: 48% of replies to opposing arguments (-ARG) were challenges (+BUT)

Figure 11.3. Transitional probability matrix produced by DAT.

the process of tabulating raw scores to reveal, for example, how many challenges are elicited by *each* argument, or how many explanations are elicited by *each* challenge. These raw scores can then be used to test for differences in the mean number of challenges elicited per argument and the mean number of explanations elicited per challenge between two or more experimental groups using two-way analysis of variance.

Purpose of the Study

The goal of the research described in this paper was to develop a set of tools and methods to produce *dynamic visual diagrams* that can be used to assess the following:

1. Changes in the strengths of links (i.e., no link, weak, moderate, and strong) between nodes in students' causal models while students: a) discuss the issues online; and b) insert into their causal maps direct hyperlinks to the relevant discussion thread(s) that address the perceived strengths of a given link between given nodes in the causal maps.
2. The extent to which these changes in link strengths—in the models of each student and groups of students—are progressing toward an expert model.

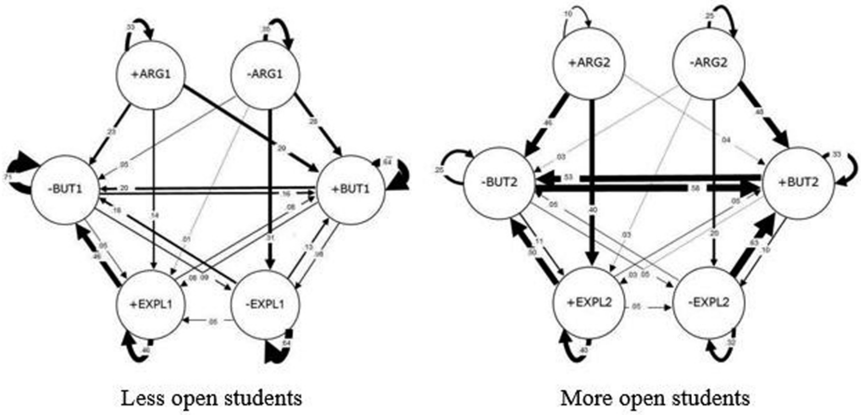


Figure 11.4. Transitional state diagrams of response patterns produced by less (on the left) versus more (on the right) intellectually open students.

3. The impact of particular patterns of discourse produced during the presentation and cross-examination of arguments and supporting evidence (e.g., observed transitional probabilities between patterns of argument-rebuttal, rebuttal-evidence, or evidence-rebuttal) on the strengths, or changes in the strengths of links observed in students' mental models (FBNs). In other words, (a) What kinds of patterns are observed with the students' evolving maps? (b) What kinds of patterns can be observed using discourse analysis? (c) How do the patterns found in (a) relate to those found in (b)?

Goals 1 and 2 above support the process of measuring change in students' mental models, and goal 3 supports the process of identifying factors and measuring their impact on the changes in students' mental models. Given these goals, this is primarily a concept paper on methodology. At the same time, and to a certain extent, we will illustrate the application of our proposed methods on data from an empirical pilot study, but only for illustrative purposes.

METHOD

Participants

Twelve graduate students in the instructional systems program at FSU participated in a weeklong, online discussion on the topic: *Technologies* *and Media in Distance Education*. Students were assigned a set of relevant readings and were required to post at least six contributions to the discussion forum across the one week period. Furthermore, they were asked to produce three concept maps representing their current beliefs of the functional/causal relationships among a set of 10 variables related to the topic. Because several of the students failed to complete one or more of the maps, their data were excluded from the analysis. In total, eight students completed all three maps which will be used for illustrating our proposed tools and methodology.

Procedure

The learning objectives for this one-week section of the course are that students should be able to understand and describe the conceptual differences between *media, technology,* and *instructional methods*; and state criteria for making decisions about the selection and use of delivery systems. To support the goals, reading assignments and study questions were provided. The reading assignments were carefully selected to show two opposing views on the issue: (a) media makes no difference on learning (e.g., Clark, 1983), and (b) media does make a difference (e.g., Kozma, 1991). The readings also enabled students to extract some of the arguments, counter-arguments, explanations, and supporting/opposing evidence for use during the weeklong debate. Study questions were designed to help students prepare their arguments for the debate activity.

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Schedule

The weeklong events involved students reading their assigned papers, debating the issue of the effects of media on learning, and drawing three causal maps of their evolving understandings. Figure 5 shows the scheduled events.

As seen in Figure 11.5, the maps (i.e., M1, M2, and M3) were scheduled to be completed at three specific times during the week: (a) before reading and discussions began (for a baseline representation), (b) in the middle of the week's discussion, and (c) at the end. Next, students debated three days on one side of the issue (Position A), and the remaining three days on the opposite side (Position B). The initial position was assigned to each student prior to the debate and students switched positions mid-week (Thursday evening). The issue they debated (either in support of, or opposed to) was the following:—*One's choice of media (text, graphics, audio, and video) significantly increases student learning*. Switching positions was intended to ensure

DAY	Mon.	Tues.	Wed.	Thur.	Fri.	Sat.	Sun.
MAP	M1			M2			M3
ACTIVITY		Reading and debating from Position A			Reading and debating from Position B		
POSTING		≥ 3 postings, where at least 2 have supporting evidence			≥ 3 postings, where at least 2 have supporting evidence		

Figure 11.5. Daily events across the week for the students in the online course.

that everyone had the opportunity to actively explore both sides of the argument. We hypothesized that at the end of the week, having argued both sides of the issue, students' mental models (and hence belief networks) would be more balanced compared with their earlier map efforts.

Creating Belief Nets (M1, M2, M3)

Students downloaded an MS Excel file that was setup to allow users to easily produce their graphical representation (causal map) representing current beliefs on how the choice of media affects learning. There were 10 variables that they needed to map, and 1—learning outcome variable. The variables and their definitions are presented in Table 11.1.

Instructions at the top of the Excel file included the following:

1. Spatially organize the 10 blue-colored nodes. Create and insert arrows between nodes to describe their causal relationships to one another AND to learning outcome.
2. Vary the density of the links between nodes to convey your perception of how much impact one node has on another node.
3. If necessary, insert new factors/nodes into your causal map by clicking on—Create new factor.
4. At anytime during the debate, identify supporting/counter-evidence presented in the debate. Then insert evidence nodes on top of the links and insert into each evidence node direct hyperlinks (right mouse click on node & select Hyperlink) to the referenced messages/evidence posted in the forum (open message in new browser window to get the URL) to justify the perceived level of impact one node has on another node. Change density of link to reflect any changes in your perception of the strengths of a causal link.
5. At anytime during the debate, insert into each factor/node a direct hyperlink to a forum message that describes/discusses the factor.

Table 11.1. Variables Relating to Media and Learning for Use in Mapping Exercises

Variable	Description/Example
Novelty	The instructor is excited and enthusiastic about using, for the first time, new media technology with his/her students.
Instructor Competence	The instructor is highly skilled with developing and implementing media technologies.
Time & $$$	The instructor has sufficient time and money to commit to developing and integrating media into his/her instruction.
Media Fits Content	The form of media (e.g., video) selected by the instructor fits the type of content (e.g., motor skills like dancing) covered in the instruction.
Learning Style	The selected form of media matches the learning styles (e.g., visual, verbal) of the students.
Quality Media	The quality of the media developed by the instructor and used in the instruction is high.
Cognitive Process	Students perform the essential cognitive processes to achieve the desired learning objectives.
Decrease Time	The amount of time students need to achieve the target outcome(s) is decreased.
Cognitive Load	The cognitive load placed on students during the instruction is reduced.
Student Motivation	Students are motivated to learn.
Learning Outcome	Student achieves the target learning outcome.

Students had 30 minutes to complete the map activity on each of the three designated days, and they saved and posted their maps to the forum by the assigned deadlines. The instructor of the course also created a map using the same variables as the students had used. This comprises the expert map used in our pilot study analyses (see Figure 11.6).

Generating a Flexible Bayes Net From the Expert's Causal Map

After establishing the expert's causal map, we created a flexible Bayesian network (see Figure 11.7) that includes prior and conditional probabilities among all of the variables used in the expert model. That is, based on the structure and strength of relations as indicated by the expert's causal map, we generated prior and conditional probabilities for the flexible Bayesian network using a qualitative-inspired method to produce probability values

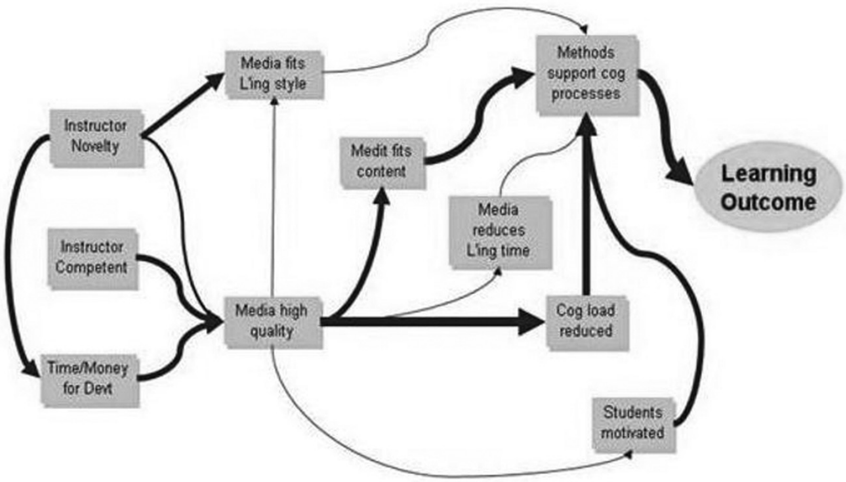

Figure 11.6. Expert map linking 10 media-related variables to learning outcome.

based on estimates of the strength of the relationship between any two variables in the model (Daniel, Zapata-Rivera & McCalla, 2003).

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This flexible Bayesian network can be used to dynamically explore various what-if scenarios based on current evidence. For example, Figures 8 shows the state of the Bayesian network once a positive *learning outcome* has been observed. We can examine the effects on the distribution of other variables (i.e., probability distributions that would produce a positive learning outcome). Similarly, Figure 11.9 fixes *media quality* to be the high state and shows the ensuing changes in variables. This information could be used to generate instructional dialogue aimed at (a) supporting critical thinking by analyzing various cases, and (b) refining the current probabilities of the network.

Although this flexible Bayesian network was generated based on the expert's causal map, we could similarly use student data (i.e., causal maps and forum contributions) to generate student or group flexible Bayesian networks.

POSTING TO THE DISCUSSION FORUM

As noted earlier, we are not only interested in being able to view changing belief nets, but we also want to figure out where and when such changes occur. For example, suppose student-1 had no link at all (mentally, or in place in his current map) between one of the media variables and

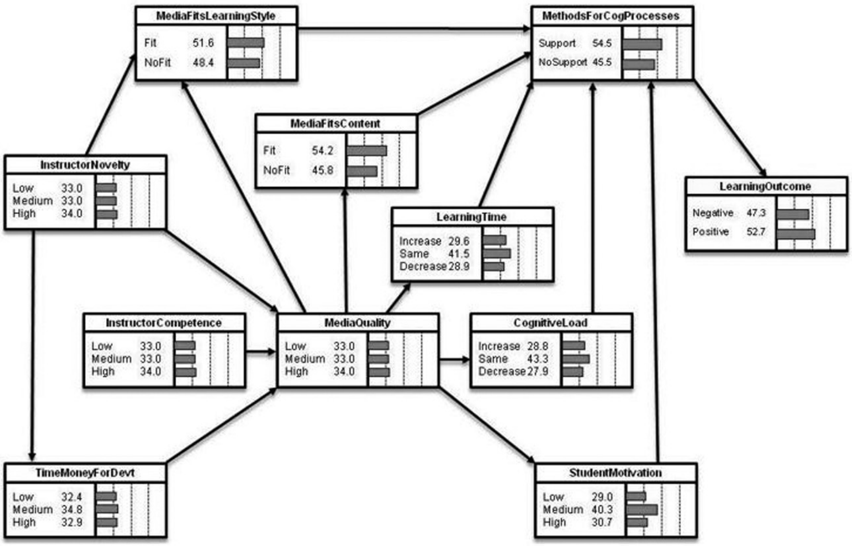

Figure 11.7. Bayes net based on the expert's map (structure and strength of relationships).

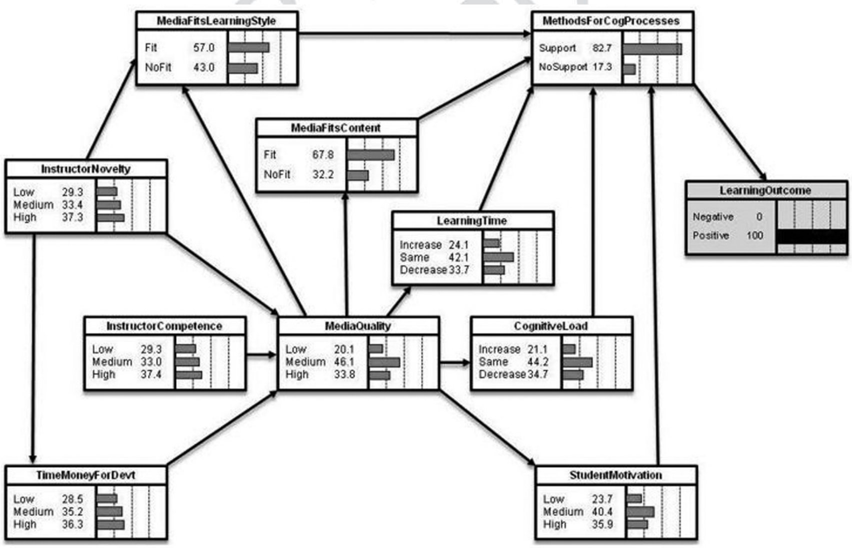

Figure 11.8. Observing a positive learning outcome and exploring the distribution of variables.

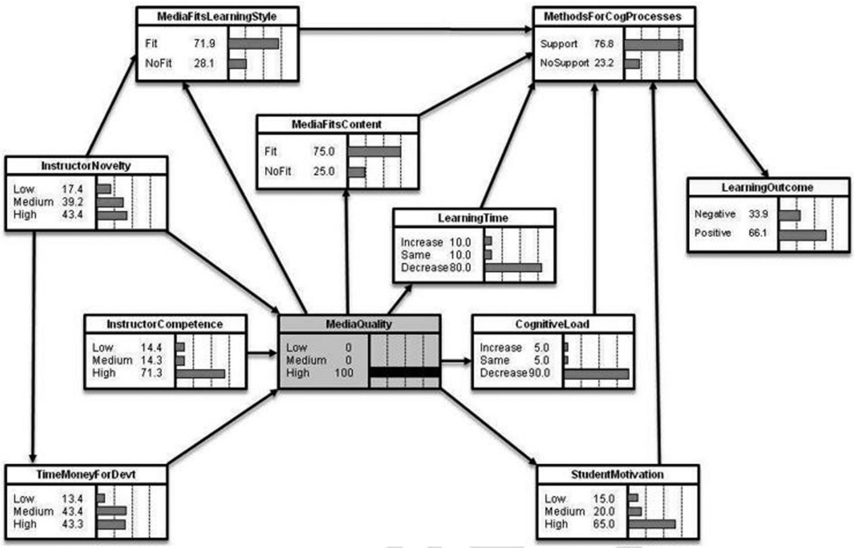

Figure 11.9. Observing high quality media and its effects on other variables.

learning outcome. Then, while reading another student's post that contained compelling evidence strongly in support of (or opposed to) the particular relationship, that event could be identified as the trigger (or the—where and when) for such a change taking place. We are able to make this determination because of the requirement for students to establish hyperlinks to the discussion thread that influenced their linkages in their map.

To standardize the discussion and help ensure contributions by all, a comprehensive procedure was provided to the students prior to their engaging in the online debate. All students were required to review the procedures *before* posting any messages to the discussion forum. The procedure and its coding scheme are presented in Appendix 1.

Following is the scenario that students were provided before debating.

Imagine that you have joined ranks with an instructional design team to re-design this course, Introduction to Distance Learning. Your team has recently completed the task analysis, analysis of entry skills and prior knowledge, identification of behavioral objectives, and has determined the instructional sequences. Your next step is to select the media to deliver the instructional sequences.

You, the team leader, ask your team members for input on what types of media and how many different types of media should be incorporated into the course. One member is *strongly in favor of implementing multiple forms of media to enhance the effectiveness of the course. However, another member disagrees because he believes that it is not the use of media (other than print) that will really make the difference, but the choice of instructional design, methods and activities. As a result, both members of your team will have to present their arguments to determine if the use of media will really make a significant difference in this course relative to time and resources needed to develop the media.*

This week, you will participate in an online debate to both challenge and support the following claim: ***One's choice of media (text, graphics, audio, and video) significantly increases learning.***

This week's readings highlight some of the similarities and differences in media technologies in terms of their unique attributes. The attributes are often used to determine which media are most appropriate for supporting particular learning processes and outcomes (or instructional applications). However, Richard Clark believes that technology attributes do not directly contribute to students' learning. It doesn't really matter what technology we use. Learning outcomes are determined 99% by the teaching methods one chooses to use and not by the technology. However, Robert Kozma argues that media attributes do make a difference because it can affect the learning process and choice of instructional method. The arguments presented in these readings should be presented in this week's debate.

Data Analysis

The three main goals of this research included: (1) measuring changes in students' mental models via their belief nets (or causal maps), (2) determining the degree to which the changes converge on an expert's (or target) model, and (3) identifying factors (e.g., instances within the discussion forum) and measuring their impact on the changes in students' mental models. To accomplish our first two goals, we needed to develop a tool to support visual analysis of students' causal maps at the granular level. The software prototype developed for this project by Jeong (2015b) is available for download and used with Microsoft Excel™.

To get to the rendered map that is produced with jMAP, each student's individually-crafted map (as well as the expert map) was coded into an 11 x 11 transitional frequency matrix. Each observed link was recorded into the corresponding cell within the matrix with a value identifying the strength of the link (1 = weak, 2 = moderate, 3 = strong) followed by a value that identified the number of evidence nodes presented with the link. Together, this can establish the perceived strength of the link (e.g., —3–2 means that the student has linked the two nodes with the strongest link strength and included two pieces of evidence in support of the claim). Figure 11.7 shows an example of one student's original map that was drawn representing his current beliefs (and supporting evidence) on media's influence on learning outcome.

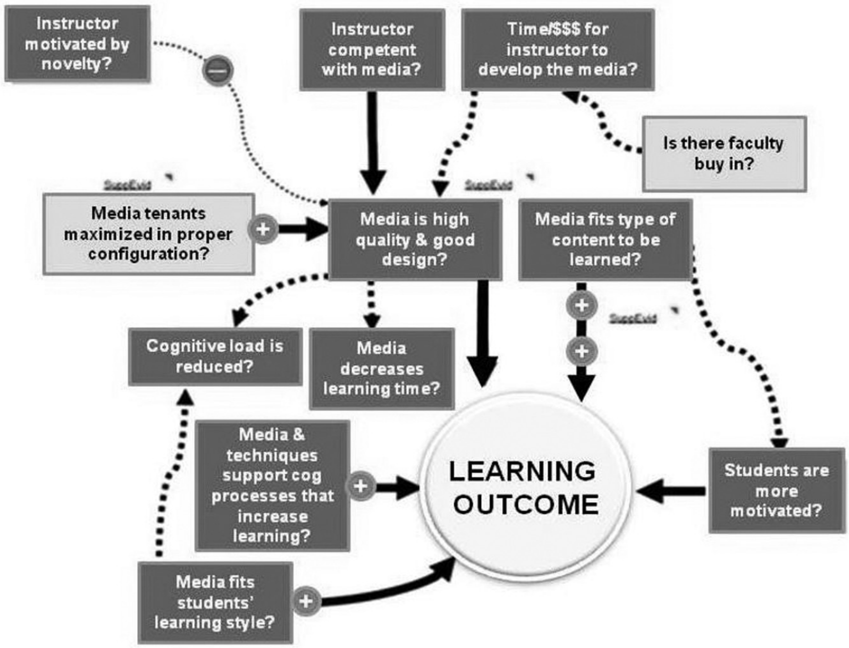

Figure 11.10. Student 8, Map 3 depicting a view of *media's relation to learning* with hyperlinked evidence (positive and negative) and differential link strengths.

As shown in Figure 11.10, there are two nodes of a different color in the map. New nodes were permitted in the student-generated maps, and this student chose to add two new nodes, one of which contained hyperlinked evidence in relation to its link with—high quality media. Figure 11.11 shows the matrix of raw link data that was coded from this particular map. To illustrate how to read the matrix, consider the link in the student's map (Figure 11.10) going from —media fits students' learning style (lower-left of the figure) to learning outcome. This is a strong link (value = 3) with one piece of evidence associated with it. In Figure 11.11, find the row labeled—learning style and read over to the entry for learning outcome. The value of the link is 3–1.

The jMAP software developed in this study used the matrix data from each student's map to regenerate a diagram for each student's model with visual enhancements that compare and identify similarities and differ-

Nodes	Novelty	InstructorCompetenc	$$$	MediaFitsContent	LearnStyle	QualityMedia	CognitiveProcess	DecreaseTime	CogLoad	StudentMotivation	Outcome
Novelty						1-1					
InstructorCompetence						3					
$$$						2					
MediaFitsContent										2	3-2
LearnStyle									2		3-1
QualityMedia								2	2		3
CognitiveProcess											3-1
DecreaseTime											
CogLoad											
StudentMotivation											3
Outcome											
ProperMediaCombo						3-1					
FacultyBuyIn			2								

Figure 11.11. Matrix of links and evidence data derived from Student 8, Map 3 with two new nodes data included at the bottom.

ences between a student's model and another selected model. Examples of possible comparisons include: (a) student A's map 1 versus map 2, (b) student A's map versus expert map, (c) collective representation of map 1 (produced by all the students) versus an expert model, (d) student A's map 3 versus student B's map 3, and so on. A user interface was developed to enable the software user to view the maps in real-time while choosing and changing different view options (e.g., individual student versus group view; toggle between and/or compare student's map at time 1 versus time 2; toggle between student and expert map; expert comparisons with all student's links versus only expert's links; view only links with versus without supporting evidence, and so on).

The jMAP's generated diagrams use colored links to clearly and visually identify *differences* between two selected maps (or groups of maps)—most notably between a student map and the expert map. A grey-colored link denotes missing links (i.e., links that are present in the expert map but missing in the student map), dark green link means links match with identical strength values, and light green means that links match, but their strength values differ. An example will be shown in the following section.

RESULTS

Our first two research goals were to (a) assess changes to students' causal models over the course of learning about and discussing a new topic, and (b) determine if their maps tended to converge on an expert's representation of the content area. Towards that end, we had to develop a set of tools and methods to produce dynamic visual diagrams of students' current understanding of the relationship among media variables and learning outcome. This has been accomplished with the jMAP tool, and has yielded a set of FBNs that may be viewed in various combinations and contiguously to highlight changes in links between models in terms of connections and strengths.

To illustrate, Figure 11.12 shows a screen capture of the jMAP interface examining the comparison (i.e., actual juxtaposition) of (a) student #8's third map (depicted in Figure 10), and (b) the expert map. To read this combined map, the student successfully linked the node —methods support cognitive processes to learning outcome with a strong link. The dark green color means that the connection and strength of that link are the same as within the expert map. Overall, the student identified six of the same links as in the expert model—with three of those sharing the same strength value.

In addition to the maps, the jMAP interface includes two tables, as shown above. The table on the left allows the user to easily move among all possible maps using control-key functions, showing the map, the matrix, or both, and compared to the expert model or another model, such as a group model (see table labeled—Navigational Tools to Visually Analyze Belief Networks). The table labeled —Quantitative Measures provides an indication of the similarity between the current map (in this case, student #8) and the comparison map (the expert map). Here, the percentage of shared links between the two models is 37.5%.

Our third research goal focused on examining the impact of particular patterns of discourse produced during the presentation and cross-examination of arguments and supporting evidence during the course of the weeklong debate. In particular, we are interested in beginning to identify the events or *patterns* that initiate changes in the belief nets—particularly

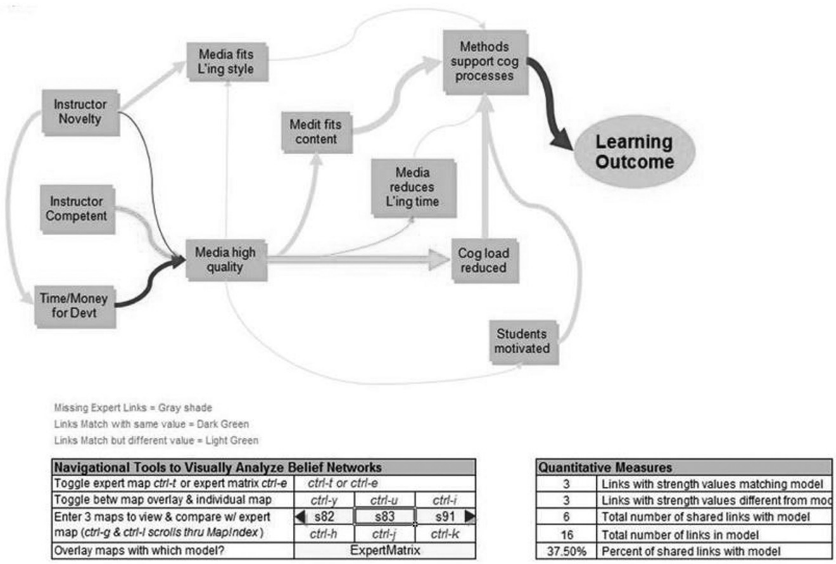

Figure 11.12. Screen capture of the jMAP interface showing a student's M3 (final causal map) overlaid on the expert's model

with regard to their effect on changing the strengths of links observed in students' evolving models.

In terms of changes in link strength over time, one question we can explore is: What happens when a link is missing in map 1 and then appears in map 2—does the strength of the link tend to start low and then increase upward in map 3 (e.g., as the student—firms up his or her belief with new evidence)? To assess this pattern, we examined the percentage of new links introduced in students' map 2 that either (a) increase in strength in map 3, (b) stay the same in map 3, (c) decrease in map 3, or (d) are removed in map 3.

Using another function in jMAP (called *SeqData*), the sequence of changes in link strengths between maps 1 and 2 and between maps 2 and 3 were tabulated (e.g., transitions from—Add Link in map 1 to—Increase Link Strength in map 2). These data were imported into DAT to compute the transitional probabilities between all possible events (see Appendix 2 to view the frequency matrix, transitional probabilities matrix, and *z*-scores matrix for these data). Portions of the data reported in the matrices were then used to generate the transitional state diagrams, shown in Figure 11.13. These diagrams reveal similarities/differences in patterns observed in the way links were added or removed, and link strengths were increased, decreased, or stayed the same.

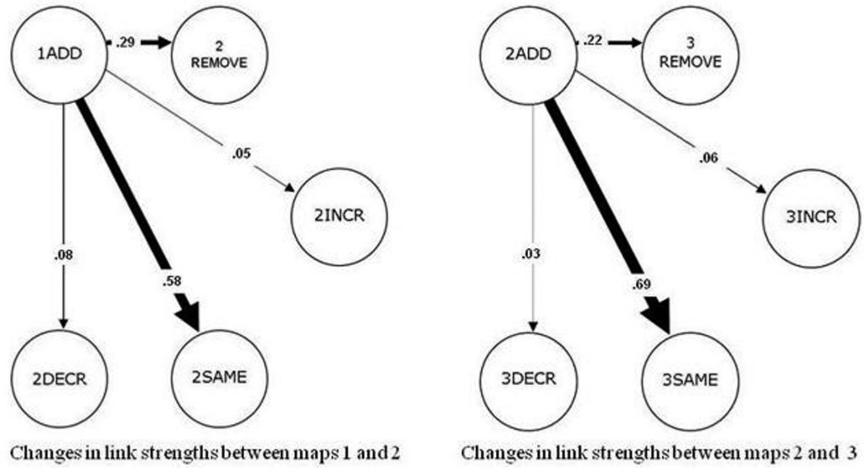

Figure 11.13. Transitional state diagrams of changes in students' link strengths across 3 maps.

The diagrams shown in Figure 11.13 indicate no observable differences in how likely link strengths changed between maps of the students in our very small pilot study. The fact that there appears to be no differences in how likely students increased and decreased link strengths suggests that students gave equal consideration for both supporting and opposing evidence, and one can hypothesize that: (a) the debate format used in the group discussion (i.e., arguing both sides of the issue) may be the reason for this finding; and/or (b) students participating in discussions that do not use a debate format may be more likely to become entrenched in their beliefs, and as a result, less likely to change the strengths of their initial links. Given the shortcomings of our pilot study (described later), we are not placing too much stock in the current —findings and instead, emphasize the capabilities of the tools that will permit researchers to engage in a whole range of valuable examinations.

Our final analysis/illustration concerns mutual links established by students in their causal maps. This can give us an idea about common beliefs (or misconceptions—if they are counter to the expert's model), that may have instructional implications. The jMAP tool lets us combine all students' causal map data into a collective model (note: users may include any subset of data for aggregation, including all students). Two matrices are presented in Figure 11.14—the group link data (on the left) and the expert's link data (on the right). The group matrix shows the mean link strengths rounded to zero decimals so that it can be overlaid easily with other maps.

To illustrate salient differences between the two, first notice that the students tend to believe that Student Motivation positively and directly

Group matrix (N = 8)

Nodes	Novelty	InstructorCompeten	Time & $$$	MediaFitsContent	LearnStyle	MediaQuality	CognitiveProcess	DecreaseTime	CogLoad	StudentMotivation	Outcome
Novelty	0	0	0	0	0	0	0	0	0	0	1
InstructorCompetence	0	0	0	0	0	2	0	0	0	0	0
Time & $$$	0	1	0	0	0	2	0	0	0	0	0
MediaFitsContent	0	0	0	0	1	0	0	0	0	1	0
LearnStyle	0	0	0	0	0	0	0	0	0	1	1
MediaQuality	0	0	0	0	0	0	1	0	0	1	0
CognitiveProcess	0	0	0	0	1	0	0	0	1	1	1
DecreaseTime	0	0	0	0	0	0	0	0	1	0	0
CogLoad	0	0	0	0	0	0	0	0	0	1	0
StudentMotivation	0	0	0	0	0	0	0	0	0	0	2
Outcome	0	0	0	0	0	0	0	0	0	0	0

Expert matrix

Nodes	Novelty	InstructorCompeten	time & $$$	MediaFitsContent	LearnStyle	MediaQuality	CognitiveProcess	DecreaseTime	CogLoad	StudentMotivation	Outcome
Novelty			2		2	1					
InstructorCompetent						2					
time & $$$						2					
MediaFitsContent							3				
LearnStyle							1				
MediaQuality				2	1			1	3	1	
CognitiveProcess											3
DecreaseTime							1				
CogLoad							3				
StudentMotivation							2				
Outcome											

Figure 11.14. Comparison of links between grouped-student and expert map data.

influences Learning Outcome (see above). In contrast, there is no corresponding link in the expert's model. Second, students do not seem to believe that the variables: Media Quality, Decreasing Learning Time, or Reducing Cognitive Load are related (read across the row labeled Quality Media in the group data matrix). In contrast, the expert model sees them as connected, especially Media Quality with Cognitive Load. Table 11.2 presents a summary of links judged to be strong and important from the expert's map, but which students do not link at all.

Table 11.2. Links That the Expert Deems Important, But the Students Collectively Do Not

Variable 1	*Variable 2*	*Expert*	*Group*
Media Fits Content	Cognitive Process	3	0
Media Quality	Cognitive Load	3	0
Cognitive Process	Learning Outcome	3	0
Cognitive Load	Cognitive Process	3	0

Some possible instructional implications from these results may be summarized. For instance, although both the expert and the group of students believe that there is a direct connection between Cognitive Process and Learning Outcome, the students seem to perceive a direct connection between Student Motivation and Learning Outcome while the expert views Cognitive Process as a mediating factor between these two variables (see

Figure 6 to view the expert map). The instructor could use this information to talk to students explicitly about the relationships among these variables and perhaps reach an agreement through negotiation.

In addition, students did not connect Cognitive Load to Cognitive Process as the expert did. Instead they linked it to Student Motivation to generate two alternate causal paths, both leading to learning outcome: (a) Cognitive Load → Cognitive Process → Outcome (expert's map), and (b) Cognitive Load → Student Motivation → Learning Outcome (students' map). Students seem to believe that there is weak evidence supporting the claim that decreasing Cognitive Load increases Student Motivation. It could also be the case that there is a label-semantics problem (i.e., students understanding of the definition of some of these concepts is different from that of the expert). The teacher could use this information to review supporting evidence offered by students and share with them the evidence that he used to support his claims.

Although the expert believes that there is a strong connection involving Novelty and (a) Time/$$$ for Development, (b) Learning Style, and (c) Media Quality, students only see a single connection involving Novelty—a weak link from Novelty to Learning Outcome. In addition, the expert links Media Quality to: (a) Media Fits Content, (b) Learning Style, (c) Decreased Learning Time, and (d) Cognitive Load. The students do not have links to any of those variables. Findings such as these could be used as the basis for targeted and additional instructional focus.

DISCUSSION

We have just begun this research stream and have presented some of our preliminary ideas, tools, and pilot data relating to the display and interpretation of students' evolving belief structures. Developing the ability to measure if and how maps change (generally), and if and how link strengths change over time (specifically) is a first and important step toward helping students evolve their mental models. We are now able to do this with jMAP. The next steps will involve adding many new features and functionality to the jMAP program that will allow us to examine students' belief nets in greater detail. For instance, we want to determine how the addition of evidence nodes into one's map (or the extent to which the evidence presented in the online discussions were challenged and cross-examined in exchanges like EVID → BUT) affect or explain observed changes in link strengths across time. By producing and juxtaposing separate transitional state diagrams (like those presented in Figure 11.13) that depict patterns in the way causal links with evidence vs. without evidence change over time, we can finally begin to conduct more micro-level analysis of the cognitive or sociocognitive processes that trigger changes in links and links strengths, particularly changes that progress towards an expert or collective group model.

In addition to providing an easy way for researchers (as well as instructors, students, and others) to examine dynamic beliefs about some topic, FBNs can be used to support student reflection. That is, once FBNs are formed (or *inferred* based on performance indicators—see Shute & Zapata-Rivera, 2008 for more on that), students can explore their maps (or others' maps, such as an expert's) and use them for formative purposes. Researchers in the area of Open Student Models are exploring effective ways of sharing student assessment information maintained by the system (e.g., supporting evidence) with students, teachers and parents (e.g., Bull & Kay, 2013; Van Labeke, Brna, & Morales, 2007; Zapata-Rivera, 2012; Zapata-Rivera, Hansen, Shute, Underwood, & Bauer, 2007).

Limitations and Future Directions

One of the limitations of the data we have is that we are not able to separate the effects of the readings that students were assigned from the effects of the discourse on students' maps. To disentangle these effects in subsequent research, we will ask that students do the readings first (or not assign any readings at all), then produce a map, and finally require students to participate in the debate while constructing maps 2 and 3. If we do not assign any readings, we would instruct students to use their own resourcefulness to gather and share supporting literature to develop their arguments.

From our small pilot study, we have identified a number of features and functions which we plan to develop and employ in future research. One important new feature includes the development of software to automatically code students' maps into the transitional frequency matrices. For this project, we entered the data into matrices manually. In addition, we would like to modify the map-creation program so that students can easily include evidence in their maps to establish both the—impact as well as the—likelihood of impact (or plausibility). Alternatively, we may just try to focus students' attention to identifying the level of causal impact between nodes.

In future studies, we also plan to create, in advance, discussion threads for each of the 10 nodes (see Table 11.1) presented in the students' causal model template. Our pilot study used only two threads—one to post arguments to support the claim (that choice of media increases learning), and the other thread to post arguments to oppose the claim. That particular structure can support a debate (pros and cons), but does not direct the discussion to focus directly on identifying and establishing causal relationships between factors that influence/determine the effects of media. In addition, and directly in the aforementioned template, we want to insert into each node (in advance) direct links to the designated discussion threads. This will make the students' hyperlinking efforts much easier, and will enable us to apply sequential analysis to identify patterns of discourse and test the relationship between the observed discourse patterns with observed changes in links and link strengths. Finally, we plan to make the primary focus of the discussion to be an in-depth exploration and discussion (as opposed to a debate) of the causal factors behind the use of media that produces gains in student learning.

Another problem we identified in the pilot study is that we just used one expert model (from the instructor of the course). In the future, we want to be able to produce aggregate models of two or more experts and use that as the basis for comparison. And regarding student maps, recall that the students were able to introduce new nodes to their maps. When a new node is placed between nodes that have been specified in the expert model (as a mediating variable), the student/expert map comparisons will increase the reported number of missing links. As a result, the software will need to include a function that can identify instances where students progressively link two expert nodes separated by one or more new mediating nodes, and accordingly, adjust the number of reported missing links.

Additional global measures/indicators that could be automatically tallied and presented by software in the future include:

- *Direct causes* which can be identified from the matrix by looking down the last column of the table (Learning Outcome) to reveal the factors that link to (and thus are believed to directly influence) Learning Outcome.
- Number of *intermediate nodes* (mediating factors) which can be determined by identifying the number of incoming arrows for a given factor (within the factor's column), and by determining the number of outgoing arrows from the same factor (links reported within the factor's row).
- The same approach can be used to identify *root causes* (factors with no parents) by simply locating the factors with no links listed in the factor's column.
- The number of *new nodes* created in a given map can be identified and inserted into the matrix after the list of original nodes.

Some of the new design features we will be including in the next version of the jMAP program include the following: (a) show links regardless of direction (to avoid confusion about the directionality of the links where some students may use arrow to explain that B happens because of A, and others may use arrows to explain that A leads to B), (b) remap links by omitting new mediating nodes; and (c) reduce density of maps—especially when there is a large number of nodes and a large number of directional links with varying densities/strengths between nodes (as in aggregate maps of a group of students). A couple of solutions to handle maps that are too crowded and difficult to read include: compute a group matrix with cell values representing the sum of cell values (strength of link = 0, 1, 2, or 3) across all individual student matrices; and/or use the singular value decomposition algorithm (or latent semantic analysis) to generate coordinates to produce a two-dimensional bi-plot (closest nodes are assumed to be linked). A limitation of this approach is that the location of the nodes changes when viewing the bi-plots for each individual, or each group, making it difficult to visually compare maps between individuals and/or groups. An alternative is to stick with the use of a map template (where the node positions do not change from individual to individual) and allow the viewer various options such as the ability to:

- Selectively omit/hide links that do not meet a certain criteria (e.g., hide or fade out links that were produced by less than 33% of the students), or show only those links that occur at higher than expected frequencies based on *z*-scores produced with the same methods used in DAT.
- Ignore the directionality of links so that the total number of possible links between all nodes is cut in half
- Reduce the relative density of all links by a specified percent or multiplier because sometimes, the probabilities are so similar that the state diagrams do not reveal patterns, thus you need to magnify the arrows to make it easier to visually identify differences and similarities between state diagrams.
- Reduce the number of nodes by selecting out specific nodes considered as mediating factors (as opposed to root causes), then extend links across mediating nodes and adjust link values to the weakest of the combined links (given the assumption the chain is only as strong as its weakest link).

The final shortcoming of the program is that it is not able to discern all of the information included in the matrix (e.g., data entered in the format of strength-of-link and number-of evidence-nodes attached to the link, such as—3–2). Given that it is time consuming to locate the nodes in students' maps (given that the positions of each node vary from map to map), using shorthand codes is something we might use to expedite the process of manually coding and entering student map data, especially if we were to apply the same data entry procedures used with the DAT software. But very soon, we plan to write a program to automatically identify and code the links presented in each students' maps.

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APPENDIX 1: INSTRUCTIONS ON HOW TO POST MESSAGES TO THE DEBATE

In this debate, you will defend your team's arguments and challenge your opponent's arguments by posting specific types of messages to perform specific functions or roles (e.g. argument, challenge, support with evidence, explain/justify). Each message you post to the debate must address *one and only one function* at a time, and the appropriate label (ARG, BUT, EVID, EXPL) must be inserted at the beginning of the message's subject heading to identify its function and team position (+ or –). Furthermore, each message you post must support your team's position, and not the position of the opposing team.

Figure 1 illustrates how the debate will look when message labels are used. If you post a supporting argument and you want to include evidence to support the argument, you must reply to the argument and present the supporting evidence in a separate reply/message.

Reasons for Using Message Labels

AU: No reference for Jonassen & Howland citation. Please add. ---------->

In this activity, you are required to label your messages in order to receive participation points for this activity because the labels can help you visualize the structure and organization of a discussion and monitor the status of each presented argument, and helps the instructor evaluate students' performance. Jonassen and Howland (2003), in their book "Learning to Solve Problems with Technology", describe this technique as a way to scaffold conversations in structured computer conferences.

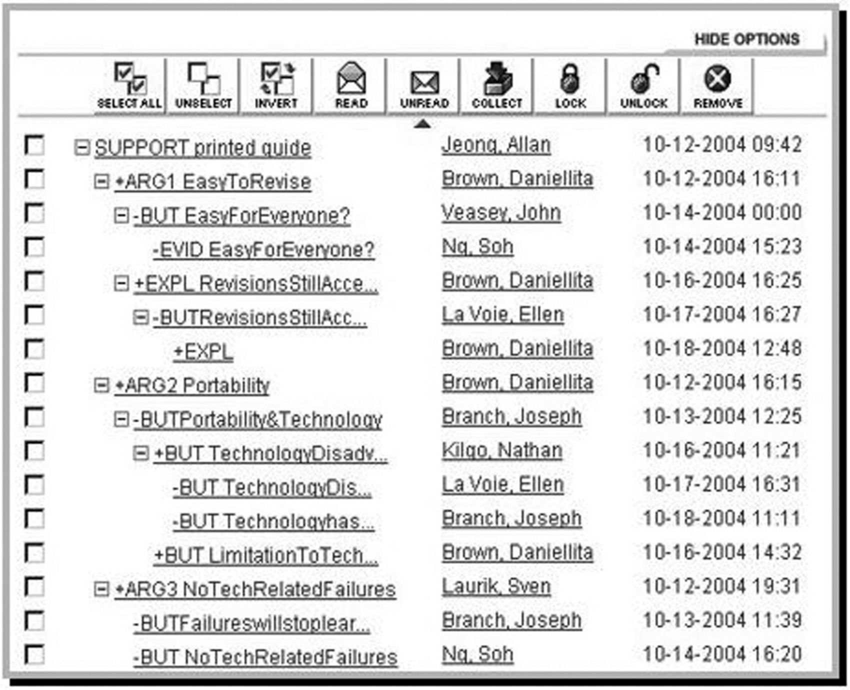

Figure 1 Example debate with labeled messages.

Table 1. Message Label Definitions and Notations

Symbol	*Description of Symbol*
+	If you are on the SUPPORTING team, ALL your posted messages must include the + tag before each message label
–	If you are on the OPPOSING team, ALL your posted messages must include the - tag before each message label.
ARG1 ARG2 ARG3	ARGUMENT: Identifies a message that presents <u>one and only one</u> argument or reason to support your team's position. Number each posted argument by counting the number of arguments already presented by your team. Example argument supporting use of threaded discussions over use of chat rooms: +ARG*2 ProducesDeeperDiscussions*
EXPL	EXPLANATION: Identifies a response that provides additional support or sub arguments, explanation, clarification, or elaboration in response to a previous message: *+EXPL CanParticipateInMultipleThreads*
BUT	CHALLENGE: Identifies a response that questions/challenges the merits, logic, relevancy, validity, accuracy or plausibility of a claim or challenge*:* *-BUT MultipleThreadsProducesCognitiveOverload*
EVID	EVIDENCE: Identifies a response that provides proof or evidence to verify or establish the validity of an argument or challenge: *+EVID DiscussionThreadsAre50%LongerOnAverage*

> *Online communication presumes that students can … meaningfully participate in conversations. In order to do that, they must be able to interpret messages, consider appropriate responses, and construct coherent replies. Most teachers realize that not all students can engage in cogent and coherent discourse. Why can't they? For one thing, most students have rarely been asked to contribute their opinions about topics. They have been too busy memorizing what the teachers tell them. So, it may be necessary to support students' attempts to converse. A number of online communication environments have been designed to support students' discourse skills ... e.g. CSILE, CaMILE & Shadow netWorkspace. (Jonassen & Howland, 2003 p. 83)*

Learning the Message Labeling Procedures

As you learn to label your messages, you will make mistakes along the way. You can return to a message to correct an error by clicking on the—modify button. At first, you may find this procedure restrictive and difficult to use, so allow yourself time to learn and adjust to the procedures. If you have a question, please post it to the Q&A forum to request help.

How to Label Your Messages: (e.g., +ARG2 ProducesDeeperDiscussions)

1. Type in —+ or —–— and then the message label; use ALLCAPS for label. If the label is an ARG, include the argument number (based on current number of arguments already posted in the corresponding discussion thread).
2. Type in one blank space.
3. Then enter a message title that accurately reflects the main point of your message. Omit spaces between words in the title so that the title is fully displayed in the message forum.

Detailed Example of a Debate with Messages Labels *Note: Message titles have been extended in length for illustrative purposes only.* (See Figure 2 on next page.)

SUPPORT use of live chats over use of the threaded forums because…
+ARG1 chats allows for higher frequency of exchanges between students
+EXPL and that's because students can respond to one another in very short periods of time
-BUT such exchanges usually exhibit lower levels of critical analysis
+BUT not if the chats are adequately moderated by instructor
+EXPL and that's because instructor can allow for more time for students to collect thoughts
-EVID proof of this lies in studies by XXX that show synch discussion produced 50% fewer…
+BUT not if the objective of discussion is to simply share information (not analyze info)
+ARG2 receive responses quickly
-BUT this argument is redundant b/c ARG1 is the product/outcome/result of ARG2
+ARG3 produces a higher sense of social present
+EXPL therefore the impact of this is higher student motivation from the presence of peer pressure
+EVID studies by XXX show that student's self-reported level of motivation increased by ??% when…

OPPOSE use of live chats over use of threaded forums because…
-ARG1 threaded forums does not require students to speak in turn
+EXPL as a result, it is easier for all students to contribute their ideas
+BUT turn-taking is not always necessary because students can still run multiple conversations at the same time
+EXPL and that is because conversations in chats are also written in text and can therefore be reviewed
-BUT the pace of chats makes it very difficult to follow multiple threaded even if they are in text
-EXPL and that's b/c the text in chats windows are continuously scrolling, and prevents review of text
-ARG2 students can develop and extend a discussion thread at any time
-EXPL as a result, threaded discussions can produce deeper and more substantive discussions
+BUT how often does that really happen and are the differences really that significant?
-EVID studies by XXX showed that threaded discussions produced XX% more…
+BUT tracking development of multiple discussion threads can produce cognitive overload
+BUT this argument is a product of ARG1, therefore ARG1 should not be considered as a main argument
+EXPL in other words, students can contribute to any thread at any time because no turn taking is required
-ARG3 students have more time & opportunity to contribute to each thread
-ARG4 the quality of each posted message in threaded discussions is more likely to be more substantive
+BUT ARG4 is the direct outcome of ARG3 and therefore, ARG3 should not be counted as a main argument
+EXPL in other words, quality increases b/c students have more time to compose their thoughts/messages

Figure 2. Detailed example of a debate with messages labels.

APPENDIX 2: MATRICES OF DATA ANALYZED BY THE DAT TO PRODUCE THE TRANSITIONAL STATE DIAGRAM OF CHANGES TO LINK STRENGTHS…

Frequency matrix

	1NONE	1ADD	2NONE	2ADD	2INCR	2SAME	2DECR	3NONE	3ADD	3INCR	3SAME	3DECR	Replies	No Replies	Givens	% replies	% givens
1NONE	0	0	1519	148	0	0	0	0	0	0	0	0	1667	0	787	.63	.22
1ADD	0	0	27	0	5	54	7	0	0	0	0	0	93	0	93	.04	.03
2NONE	0	0	0	0	0	0	0	746	27	0	0	0	773	773	1546	.29	.44
2ADD	0	0	0	0	0	0	0	24	0	6	74	3	107	41	148	.04	.04
2INCR	0	0	0	0	0	0	0	0	0	0	0	0	0	5	5	.00	.00
2SAME	0	0	0	0	0	0	0	0	0	0	0	0	0	54	54	.00	.02
2DECR	0	0	0	0	0	0	0	0	0	0	0	0	0	7	7	.00	.00
	0	0	1546	148	5	54	7	770	27	6	74	3	2640	1760	3520		

Transitional probabilities matrix

	1NONE	1ADD	2NONE	2ADD	2INCR	2SAME	2DECR	3NONE	3ADD	3INCR	3SAME	3DECR	Replies	No Replies	Givens	Reply Rate
1NONE	.00	.00	.91	.09	.00	.00	.00	.00	.00	.00	.00	.00	1667	0	787	1.00
1ADD	.00	.00	.29	.00	.05	.58	.08	.00	.00	.00	.00	.00	93	0	93	1.00
2NONE	.00	.00	.00	.00	.00	.00	.00	.97	.03	.00	.00	.00	773	773	1546	.50
2ADD	.00	.00	.00	.00	.00	.00	.00	.22	.00	.06	.69	.03	107	41	148	.72
2INCR	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	0	5	5	.00
2SAME	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	0	54	54	.00
2DECR	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	.00	0	7	7	.00
	0	0	1546	148	5	54	7	770	27	6	74	3	2640	1760	3520	.20

Z-Scores identify the probabilities that are higher/lower than expected

	1NONE	1ADD	2NONE	2ADD	2INCR	2SAME	2DECR	3NONE	3ADD	3INCR	3SAME	3DECR	
1NONE	-0.01	-0.01	44.45	9.57	-2.93	-3.72	-3.47	-43.16	-6.84	-3.21	-11.42	-2.27	1667
1ADD	0.00	0.00	-5.89	-2.39	11.71	38.86	13.86	-6.30	-1.00	-0.47	-1.67	-0.33	93
2NONE	-0.01	-0.01	-39.30	-8.06	-1.44	-4.78	-1.70	48.98	8.12	-1.58	-5.61	-1.12	773
2ADD	0.00	0.00	-12.55	-2.57	-0.46	-1.53	-0.54	-1.57	-1.07	11.93	42.45	8.43	107
2INCR	0.00	0.00	-0.01	0.00	0.00	0.00	0.00	-0.01	0.00	0.00	0.00	0.00	0
2SAME	0.00	0.00	-0.01	0.00	0.00	0.00	0.00	-0.01	0.00	0.00	0.00	0.00	0
2DECR	0.00	0.00	-0.01	0.00	0.00	0.00	0.00	-0.01	0.00	0.00	0.00	0.00	0
	0	0	1546	148	5	54	7	770	27	6	74	3	2640