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THE INFLUENCE OF GRAPHICAL OR TEXTUAL REPRESENTATIONS ON TEAM CONCEPT MAP FORM: FURTHER VALIDATION OF A MEASURE OF KNOWLEDGE STRUCTURE

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Abstract. This descriptive investigation seeks to extend our application of graph theoretical measures of knowledge structure (KS) by considering the question: How do graphical versus textual lesson materials influence team concept map form? To answer this, 80 team concept maps on a woodland infestation from two previous studies were reanalyzed using innovative node degree similarity measures. Lesson materials were either graphical (partial maps in a hidden profiles paradigm) or textual (propositional statements that compose those partial maps). Triads working online at a distance used the lesson materials to create a team concept map with or without awareness of the other triad members' knowledge information. As expected, the team maps derived from the graphical materials were far more like the expert and solution benchmark maps relative to the textual team maps. Also, the graphical condition led to more similar team maps (team convergence of about 51% and 55% overlap) relative to the textual condition (27% and 49% overlap). These results align with expectations and thus further validate this technology-based approach for measuring knowledge structure in lesson artifacts in order to better understand the mediating influence of lesson tasks on learning processes and outcomes.

1 Introduction

An important aspect of science is concept inter-relatedness, called structural knowledge (Goldsmith et al., 1991; Ifenthaler, 2010; Jonassen et al., 1993) and also just knowledge structure (Clariana, 2010). Measuring and assessing the knowledge structure (KS) of individuals and teams requires the capturing and analysis of key latent variables (Johnson et al., 2006). Conceptually, KS implies relationships patterns that can be represented as networks; several classes of weighted association networks provide a well-established toolset for capturing, combining, analyzing, representing, and comparing KS (Clariana, 2010).

Concept maps are a well-established measure of learning that can capture different aspects of knowledge (Ruiz-Primo, 2004) including KS (Clariana, 2010). The concept map analysis approach applied in this current investigation has been used previously to measure KS – of American students learning social science principles (Clariana et al., 2015), of German students solving pesticide problems (Clariana et al., 2013), of Dutch school children learning ecology (Fesel et al., 2015), of Dutch/English bilinguals learning archeology from English lesson materials (Mun, 2015), and of Korean/English bilinguals learning archeology from English lesson materials (Kim & Clariana, 2015). The current investigation involves German undergraduates working online in triads to create team concept maps.

This investigation seeks to further validate and extend this concept map KS measurement approach by applying it to address the question: How do graphical versus textual lesson materials influence team concept map form?

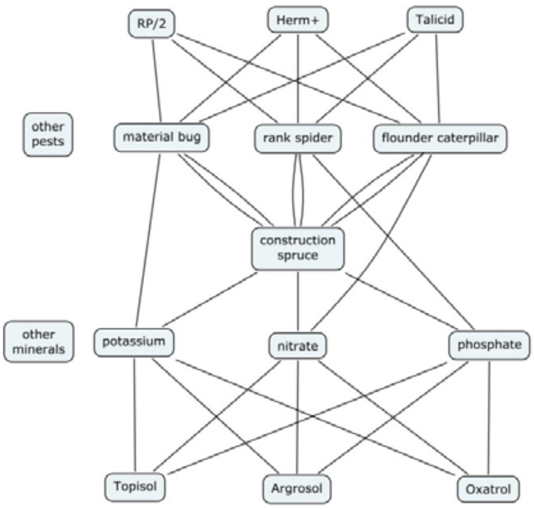
2 Methods and Results

This descriptive quasi-experimental investigation reanalyzed 80 team-created concept maps from a previous study of Engelmann and Hesse (2010) that used graphical lesson materials and from the follow-on study of Engelmann et al. (2014) that used equivalent textual lesson materials. Those two studies are otherwise identical except for the textual or graphical lesson materials. Also the precise details of the methodology are available in those two published papers, but in brief, participants were recruited from a German university with a monetary incentive; as they randomly arrived at the site, they entered separate cubicles alone and worked online in triads connected using skype audio and the CmapTools (Cañas et al., 20014) mapping tool to create a shared team map.

These two studies considered theoretical and practical issues related to content-based knowledge awareness (CoKA) in transient collaborative groups. The CoKA construct is derived from the literature base on shared mental models, common ground, and transactive memory systems. Thus the triads were randomly assigned to either a treatment condition where team members are able to see the other triad members' lesson materials or the control condition where they were not able to see the others' lesson materials. In their individual lesson materials, each member of the triad received either a partial concept map or equivalent text materials with some common information and also about 1/3rd of the total information that described a woodland infestation and possible solutions, all three portions taken together are needed to solve the infestation problem (a hidden profiles paradigm); thus 40 teams received graphical information and 40 teams equivalent textual information as propositional statements derived directly from the graphical information. Since each team created one joint team concept map in the shared virtual space, the data for this reanalysis consists of these team maps.

2.1 Convergence with Referent Maps

Using only the 15 key terms, all of the team maps were converted to 15-element node degree vectors (see Figure 1), then each team map vector was correlated with an expert map vector that contained all of the information and also with a solution sub-map vector that only had the information needed to solve the pesticide problem. Since r values are not interval data, then these r values were transformed to Fisher Z and averaged, also the estimated percent overlap of the maps is calculated as Pearson r squared of the Fisher Z inverse (see Table 1).



	Expert	Solution
construction spruce	9	6
rank spider	6	4
material bug	6	3
flounder caterpillar	6	0
nitrate	5	2
phosphate	5	2
potassium	5	0
RP/2	3	2
Argrosol	3	1
Herm+	3	0
Oxatrol	3	0
Talicid	3	0
Topisol	3	0
other minerals	0	0
other pests	0	0

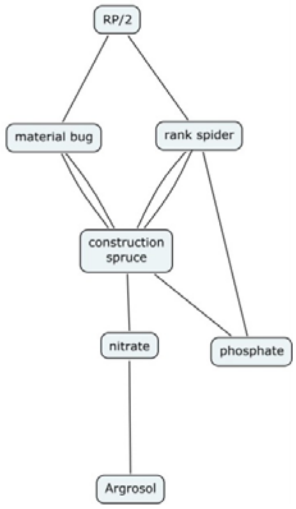


Figure 1. The full Expert map (left panel) and the Solution map (right panel) along with the node degree table for each map.

		to Expert map	to Solution map
textual	treatment	0.91 (0.46); 52.0%	0.61 (0.36); 29.6%
	control	1.26 (0.63); 72.4%	0.62 (0.37); 30.4%
graphical	treatment	1.25 (0.59); 72.0%	0.95 (0.33); 54.7%
	control	1.42 (0.62); 79.1%	0.79 (0.30); 43.4%

Table 1: Team map similarity to the expert map and to the solution sub-map as Fisher Z means and standard deviations (in parenthesis) and as map percent overlap for each condition.

This Fisher Z data were analyzed by a 2 x 2 x 2 repeated measures ANOVA, with the between subjects factors lesson form (graphic or text) and knowledge awareness treatment (can or cannot see peers' screens) and with the repeated measure similarity to the expert map and to the solution sub-map. The main effect for lesson form (as graphic or text) was significant, $F(1,76) = 7.407$, $MSe = 0.340$, $p = .008$; not surprisingly, the team maps based on the graphical lesson forms relative to those based on the textual lesson form were substantially more similar to the expert's map (Fisher $z = 1.34$ vs. 1.09; 76% vs. 63% overlap with the expert) and to the solution map (Fisher $z = 0.87$ vs. 0.62; 49% vs. 30% overlap with the solution). Also the interaction of the repeated measure similarity to the expert map and to the solution map and knowledge awareness was significant, $F(1,76) = 9.953$, $MSe = 0.108$, $p = .002$ (see Figure 2), however, although follow-up analysis of this interaction revealed no significant findings, the control group that had only their own map, the developing team map, and audio contact with their triad members developed triad team maps that were more fully developed and similar to the expert map. In contrast, the triad team maps in the knowledge awareness condition were less fully developed and tended to be more solution oriented.

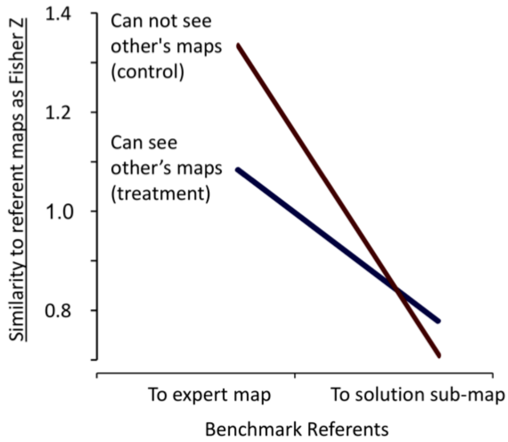


Figure 2. Significant interaction of team map similarity to the benchmark referents and knowledge awareness.

2.2 Team Convergence

Team convergence here is a measure of how similar team maps are to each other, rather than to the expert or solution maps described above. To measure team map convergence, each team map node degree vector was correlated to *every* team map vector, and the obtained Pearson r values were transformed to Fisher Z values and then averaged across all conditions, including lesson form and knowledge awareness (see Table 2). The diagonal in the table indicates with-in condition similarity while the off-diagonal compares team maps across conditions. Regarding with-in team map similarity, the teams that received graphical materials and could not see their members' screens (no CoKA) attained the most similar within-team maps, with a 55% average overlap, relative to the teams that received textual materials and could see the members' screens (KoCA) attained the least similar team maps, with a 27% average overlap. Regarding across-team map similarity, in every case, triad team member knowledge awareness (CoKA) led to *less similar maps* relative to their complementary group that is without such content knowledge awareness (control). Perhaps CoKA engenders greater within triad expression of idiosyncratic individual mental models? It remains to be determined whether CoKA leads to mental model convergence of members in the same team, but these results show that team maps developed with content-based knowledge awareness are relatively *less similar* to other team maps. Further, although not as striking as this CoKA influence, as would be expected the team maps derived from lesson concept maps generally were more similar to each other than team maps derived from lesson texts.

	Textual		Graphical	
	can see	can't see	can see	can't see
Textual – can see	**27%**	38%	35%	36%
Textual – can't see	38%	**49%**	45%	50%
Graphical – can see	35%	45%	**51%**	51%
Graphical – can't see	36%	50%	51%	**55%**

Table 2: Average team map convergence measured as percent overlap of team map node degree vectors.

3 Summary

The team maps derived from the graphical lesson materials were far more like the expert map and the solution benchmark maps relative to the textual lesson team maps. Also, the graphical lesson materials led to more similar team maps (e.g., team convergence of about 51% and 55%) relative to the textual lesson materials (27% and 49% overlap). The means that using concept maps as lesson materials engendered fundamentally different knowledge structures, relative to text-based lesson materials. This seems pretty important.

This investigation seeks to further validate and extend a concept map knowledge structure measurement approach. The observed results aligned with expectations and thus further validate this technology-based approach for measuring knowledge structure in team lesson artifacts in order to better understand the mediating influence of lesson tasks on learning processes and outcomes. The concept map KS measures used in this investigation are fairly easy to prepare and can be fully automated. Note for instance that it handles missing terms by using a zero in the vector element. Further, CmapTools could be easily modified to output map node degree data like this that can then be compared to expert referent maps and also to other team members' maps (map convergence). Thus if further validated, the approach could be of great value to researchers and teachers as complementary and objective measures of learning.

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