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RESEARCH ARTICLE

From Monologue to Dialogue: Performative Objects to Promote Collective Mindfulness in Computer-Mediated Team Discussions

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Appendix

Details of Textual Analysis for Representing and Aligning Behaviors

Representing

The open-ended responses to the justification question for all participants within each team were aggregated into a single text file and analyzed using the Automap software (Carley et al. 2006). This software provides a semi-automated means of identifying the concepts within a body of text and the relationships (based on proximity) among those concepts. Within the aggregated text file, we grouped each participant's response to the justification question into one paragraph and began each response with the participant identifier (e.g., P1, P2, P3, P4, and P5).

Figure A1 contains a simplified version of what the justification text file might look like. In this figure, each participant's justification is represented by a single statement. This sample is much more abbreviated than were the actual justifications. In practice, most participants wrote several sentences of justification. If we were to use an actual sample, the analysis in our example would be so large that it would obscure the mechanism of the map analysis function we are attempting to explain. Thus we use this simple example for illustration purposes.

The software built a semantic network from the text by establishing relationships between the words that occurred within each response. Links were established between each participant and the words they used, which include the criteria and values most relevant to them. In cases where a participant's justifications were similar to those of another member of their team (i.e., they used the same words), links would be established across their individual responses.

With the semantic network analyzed in this study, the vertices were the participant identifiers and words participants used in their justifications. Edges exist if the vertices (i.e., words) occurred within the same paragraph of the aggregated justification text. Directional edges were constructed between vertices if they occurred within the same message, with words occurring earlier in the message pointing toward words occurring later in the message.

P1: I chose Robin because she had AP credit.
P2: I chose Paula because she was in a club.
P3: Paula's grades were too low and she didn't have any AP credit.
P4: I chose Charles because he had AP credit.
P5: I didn't like Mary because her grades were going down.

Figure A1. Simplified Justification of Text Sample

The text was imported into Automap 2.7.67. Punctuation marks were removed from all transcripts prior to processing. Doing so allows the software to recognize that GPA and G.P.A. are the same acronym and that "scores," and "scores" and "-scores" are all the same word. AutoMap's MapAnalysis function features two settings that we configured for processing the text: (1) the window size and (2) the windowing reset. The window size setting was used to configure the allowable distance between words for a relationship to be identified between them. A window size of two would indicate that only words that are next to each other can have a relationship between them. The windowing reset setting allows the user to determine the point at which the processing window will be reset (e.g., at the end of each sentence, at the end of each paragraph, or after a certain number of words). In constructing the semantic network, we set the window size to include all words until the windowing reset point and set the windowing reset to the end of each paragraph. With this setting, relationships would be identified between all the words in a given participant's response while ensuring that relationships would only be established between participants if they used the same sets of words in their justifications.

The semantic network resulting from the analysis of the sample text in Figure A1 is illustrated in Figure A2 (once again this is a simple diagram based on our simple example). The layout algorithm groups the vertices according to the number of edges between them. Neighborhoods or clusters of related vertices can be seen in the figure. For example, in the upper-left section of the figure, we can see that P1 and P4 used similar phrasing in close proximity in their sentences. In fact, their sample phrases in Figure A1 were almost identical. The concept of AP credit features prominently in the middle of the network, and bridges the P1 and P4 cluster we have been describing with the cluster of concepts included in P3's response. We can also see that the concept of grades also features prominently in the team's mental representation of the problem space.

Although these relationships among the individual representations can be determined visually, the ability to interpret the network data visually becomes more difficult as the size of the network increases. Figure A3 illustrates the complexity of the network extracted from one team's justification text that we used in our analysis. We can still observe clusters and connections among concepts. But with a network this size, we must turn to quantitative metrics from network analysis to help us understand the properties of the network.

The semantic network data from the MapAnalysis of the justification texts were imported into ORA version 1.9.5.3.5 for further analysis. To assess representing, we used the network measure of transitivity. Transitivity is a measure of clustering based on the number of triples and triangles within a network (Börner et al. 2007). A triple is a collection of three connected vertices with two edges. A triangle is a collection of three connected vertices with three edges (between v1 and v2, v2 and v3, and v1 and v3) (Friedkin 1998). As seen in FigureA4, there are 8 possible combinations of edges between vertices 1 through 3 in an undirected graph (Wasserman and Faust 1994). Four of those possible combinations (E, F, G, and H) can be described as having triples. Only one of those combinations (set H) creates a triangle.

The transitivity of a network is based on the percentage of triangles found in the network compared with the number of triples in the network (Friedkin 1998). Transitivity is calculated using the following formula (Börner et al. 2007):

$$\textit{Transitivity} = (3 \times (\textit{number of triangles}))/((\textit{number of connected triples}))$$

We can calculate the total number of connected triples by obtaining the sum of all possible combination of neighbors that a vertex i with a degree of k_i can have (Börner et al. 2007). The transitivity value of a directed network is then defined as follows (Carley and Reminga 2004):

Let G = (V, E) represent the graph of a network with V being the set of vertices and E being the set of edges.
Let $I = \{(i, j, k) \in V^3 \mid i, j, k \textit{ distinct}\}$
Let $\textit{Potential} = \{(i\ j, k) \in I \mid (i, j) \in E, \textit{ and } (i, k) \in E\}$
Let $\textit{Complete} = \{(i, j, k) \in \textit{Potential} \mid (i, k) \in E\}$

Then $\textit{Transitivity} = \dfrac{|\textit{Complete}|}{|\textit{Potential}|}$

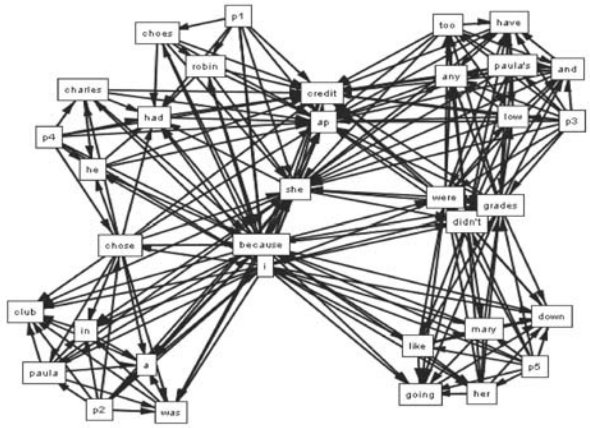

Figure A2. Semantic Network Extracted from Sample Justification Text in Figure A1

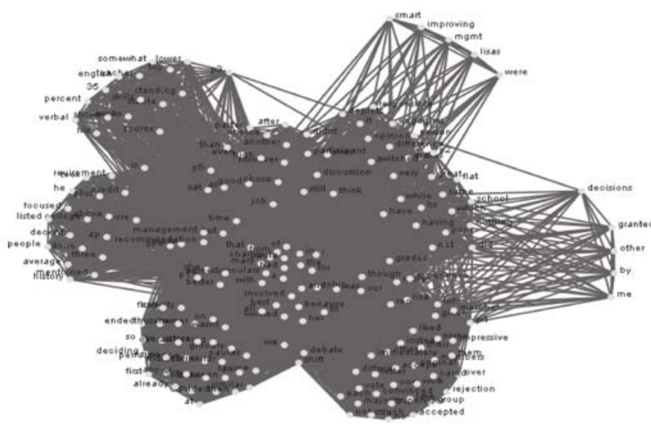

Figure A3. Visualization of a Team Justification Text

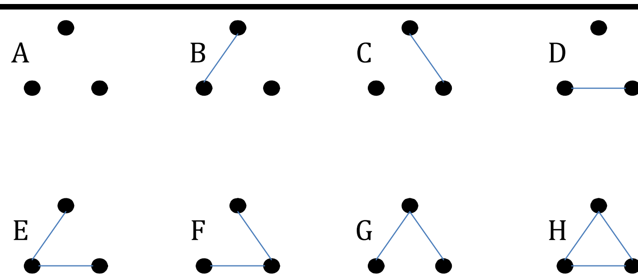

Figure A4. Possible Combinations of Edges in Triples

Transitivity is an appropriate metric for assessing the connectedness of the justification text networks. If members of the team have achieved a greater degree of shared mental models, the similarity of topics and concepts included in their individual justifications will be reflected in an increased number of triangles among the concepts across the network. If team member justifications were completely unique and exhibited no shared mental models, the network would be comprised of isolated clusters and the transitivity value would be much lower.

Aligning

We used the messages shared via the synchronous-text chat tool and the shared whiteboard tool to measure the degree of aligning among team members. Using the same MapAnalysis configuration settings within AutoMap described in the previous section, we extracted network data from the body of messages exchanged among team members. The text from the text chat transcript and the shared whiteboard transcripts were combined into a single text file for each team. Within the text chat transcript, each message was stored on a separate line with the participant identifier included at the beginning of each message. Although the participant identifiers were not visible in the shared whiteboard transcripts, the OneNote software stores the identifier of the participant who last edited a block of text within its XML structure. Using these embedded identifiers, we were able to construct a series of statements from the OneNote whiteboard that were structured in the same manner as the messages in the text chat transcripts—with a participant identifier followed by a statement. Text snippets that were deliberately proximate to each other in the shared whiteboard were grouped together in the text file. For example, if one member of the team placed a heading in the whiteboard labeled "Charles academic Information," and other members contributed their information beneath that heading, we included the heading in each member's statement.

For example, Figure A5 includes a block of text from a OneNote whiteboard used by one of the teams in our analysis. The information is organized under the heading of "Mary." The underlying XML in the OneNote file reveals that most of this block was written by P4, but that the fourth line in the block was written by P5. Figure A6 illustrates the coding for this text block. This coding allows each comment included under a heading to be teamed together while also associating each contribution with the participant who made it.

Figure A7 shows a sample of text from a text chat transcript. It can also be seen in Figures A5 and A6 that punctuation marks were removed from the text (as was done for the justification text).The semantic network resulting from the analysis of the sample text is illustrated in Figure A8.

The participant identifiers and the words of each message were used as vertices in the semantic network. Directional edges were constructed between vertices if they occurred within the same message, with words occurring earlier in the message "pointing toward" words occurring later in the message. Figure A8 shows the network extracted from the text chat sample in Figure A7. Once again, this is just a small sample to illustrate the analysis technique.

Once these texts were prepared, *network centralization* of the extracted semantic network was used to measure the degree of aligning among team member contributions. Network centralization refers to the extent to which the connectedness within a network is organized around a core set of vertices (i.e., the extent to which the network has a centralized structure) (Scott 1991). The formal definition of centralization relies on the vertex-level measure of in-degree centrality. The in-degree centrality of a vertex refers to the number of edges directed at that vertex (Freeman 1978; Monge and Contractor 2003). Vertices with a high in-degree centrality form hubs within a network (Kleinberg 1999). The in-degree network centralization calculates the differences between the in-degree centrality of each vertex and the largest in-degree centrality within the network and divides the sum of those differences by the maximum possible in-degree (n-1) (Scott 1991), where n equals the number of vertices in the network. More formally, we can define the in-degree network centralization as $\left(\sum_{1<i<n} \overline{d} - d_i\right) \Big/ (n-1)$ where d_i = *the in degree centrality of vertex i* and $\overline{d} = max\{d_i \mid 1 \le i \le n\}$.

The in-degree centralization provides an appropriate metric for assessing aligning in semantic networks based on texts developed through team discussions. Using in-degree centrality rather than total degree centralization prevents the participant identifiers from overweighting the network analysis. If we had utilized the total degree centralization, the participant identifiers (P1, P2, P3, P4, and P5) that occurred at the beginning of each message would have comprised a significant component of the structural core of the network and would have biased the results of the analysis. Within the networks considered in this study, the vertices with the highest in-degree centrality are those words that are preceded by the greatest variety of words across the messages. This set of vertices makes up the structural core of the network.

During the course of a team discussion, words within the structural core make up a cluster of topics which serve to anchor the team discussion. This core includes words conceptually related to the task (e.g., grades, success, credit, trend) as well as commonly occurring connecting words (e.g., a, the, and). Although one may argue that only the task-related words should make up the core, dialogue is reflected in the alignment and mutual use of both structure (i.e., the same connecting words and phrases) and content (i.e., task specific words) in discussion (Pickering and Garrod 2004). The extent to which words contributed by team members are connected to this core reflects the degree of aligning being carried out by members of the team. A sample visualization from a semantic network used to assess aligning is illustrated in FigureA9. The size of the nodes corresponds to their in-degree centrality.

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Mary: NO AP Classes
-3.2 GPA
-Not as high SAT scores
- Some club - treasurer
- Out of state
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Figure A5. Sample Text Block from OneNote Whiteboard

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P4 Mary NO AP Classes
P4 Mary 3point2 GPA
P4 Mary Not as high SAT scores
P5 Mary Some club treasurer
P4 Mary Out of state
```

Figure A6 Sample Coding fro Whiteboard Text Block

P2 the only thing against lisa
P2 is the dropping grades
P3 Charles was ranked 35% in her class
P3 but had no extracurricular
P5 her gpa was and test scores were average
P2 which is explainable by the age and the urban setting
P2 but her grades are still the best
P5 i would say charles robin mary

Figure A7. Sample Transcript Text

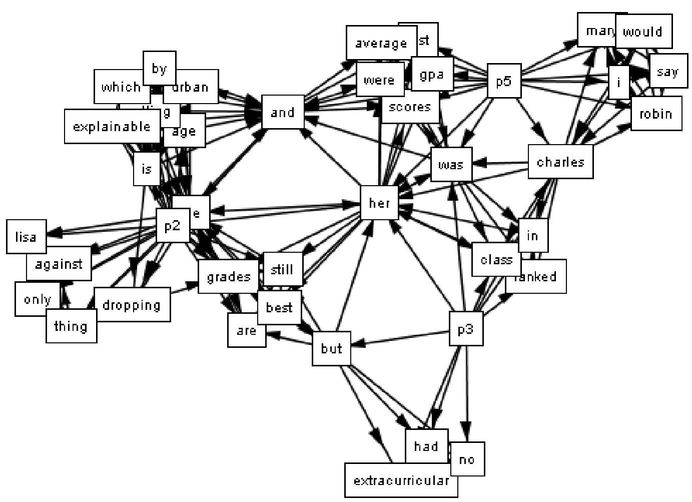

Figure A8. Semantic Network Extracted from Sample Text Chat Text

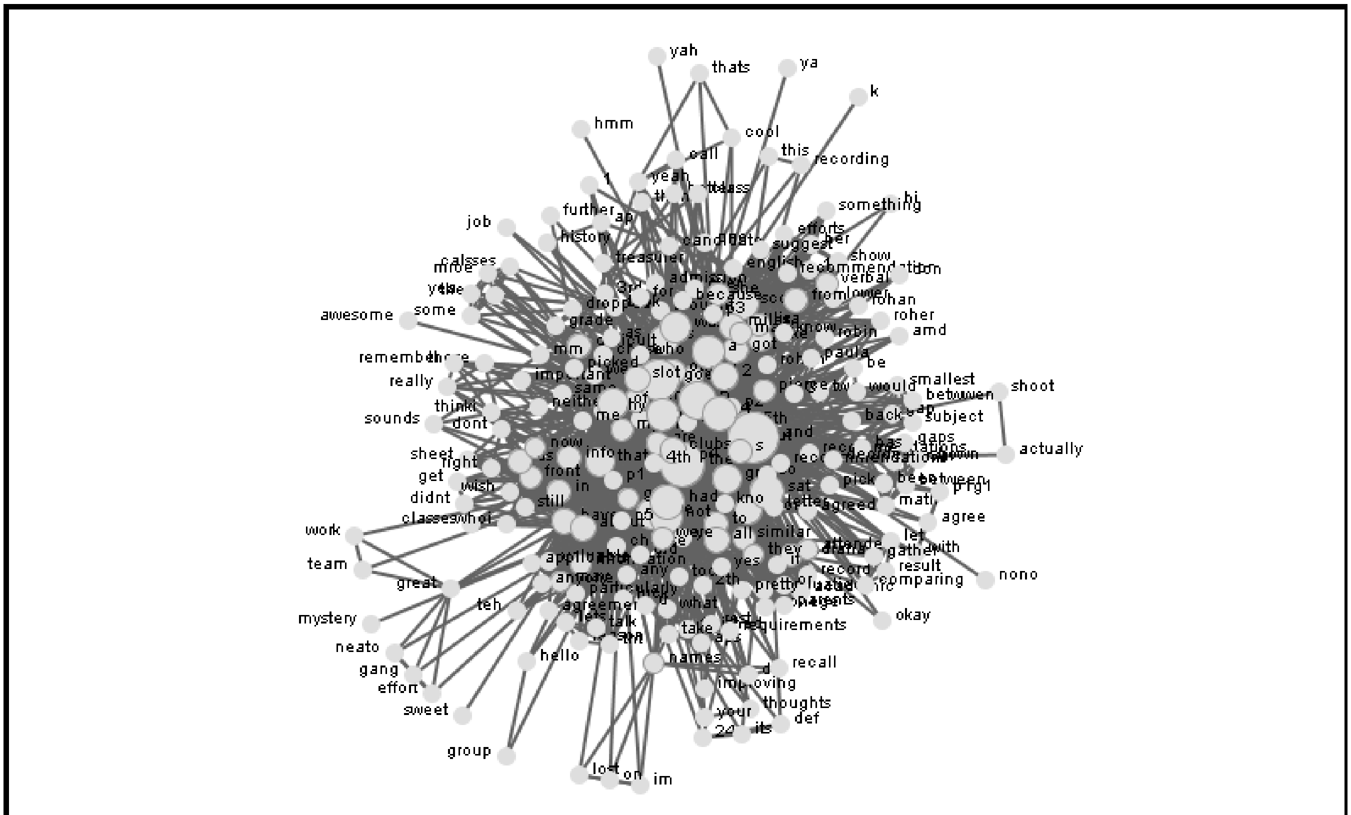

Figure A9. Aligning Network with Nodes Sized by In-Degree Centrality

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