Modeling Student Socioaffective Responses to Group Interactions in a Collaborative Online Chat Environment

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ABSTRACT
Being able to monitor collaborative learning environments using unobtrusive measures is crucial to maximizing students' socioaffective experiences with a system. This analysis uses the cohesion of student responses to model students' feelings of power and connectedness to the group, two factors which emerge from a principal component analysis of a motivational survey.

Keywords
CSCL, educational group chat, group dynamics, power, connectedness, cohesion, Coh-Metrix, learning

1. INTRODUCTION
Understanding the dynamics of computer-supported collaborative learning (CSCL) environments is crucial to providing adaptive enhancements or supports to groups of students who are not receiving the full benefits of technology-based collaboration [5]. One important facet of any learning environment is the student's affect during the interaction, which may have a positive impact on motivation [4] or may lead to tension and competition if the group is experiencing negative emotions due to conflict [1]. Previous work on group dynamics and its impact on learning has made a sharp division between the social and informational processing parts of group discussion [6, 9], but in collaborative learning environments, these aspects may be difficult to tease apart, as there may be a cognitive component to social side of CSCL and vice versa. This may be particularly true when examining cues which assess the group's socioaffective state without interrupting the flow of conversation to ask for a self-report. Linguistic cues of a cognitive nature may be able to detect various socioaffective components of CSCL conversations, with the added advantages of being performed automatically and covertly based on the flow of conversation.

This work uses Coh-Metrix [7] to assess how discoursive deep cohesion predicts socioaffective components found in a motivational survey [8] administered to students engaged in a group chat environment. Deep cohesion is defined as the extent to which ideas in the text are cohesively connected at a deeper conceptual level that signifies causality or intentionality. Therefore, deep cohesion may be one way of exploring how cognitive aspects of language predict socioaffective outcomes in group conversation. By understanding group dynamics in CSCL environments, we may be able to intervene where group conversation stagnates or goes awry to maximize the learning experience.

2. METHODS
Seven hundred forty-eight students in two introductory-level psychology classes at the University of Texas at Austin used an online educational platform to chat with group members about assigned readings. Once logged on, students were randomly placed in groups of up to five members, given a 10-item pretest about the readings, then allowed to chat for exactly 20 minutes about the readings. Discussion questions were given to groups to facilitate discussion, but no restrictions were placed on what could be said. After the chat session, students were given a 10 item posttest and filled out a motivation questionnaire which asked about the students' perceptions of the interaction, group members, and their own role in the group. More details about this survey are given by Niederhoffer and Pennebaker [8]. All data was logged for analysis, then cleaned, parsed, and extracted from these logs. The chat contributions of each individual were processed using Coh-Metrix and then Winsorized.

3. RESULTS AND DISCUSSION
The first set of analyses conducted sought to find out the relationship between perceptions about the group interaction and learning. We conducted a principal component analysis (PCA) to create meaningful, broader variables with which to describe the students' socioaffective experience in the group. The data fit all the standard criteria for factorability (all variables intercorrelated with one of variable above .3, a Kaiser-Meyer-Olkin measure of sampling adequecy above .6, and a significant Bartlett's test of sphericity ($\chi^2(21) = 1640.31$, $p < .001$). Two components with eigenvalues greater than 1 were found, which collectively explained 66.6% of the variance. All items from the test loaded strongly onto only one component (>.4) with low cross-loadings (<.3). The items that loaded onto the first component was

concerned with the student's perceptions of how well the chat went and how much the student "clicked" with the other members; this component was therefore labeled "Connectedness". The second component was composed of items about the social status of the student and the control they exerted over the group, and thus has been labeled "Power." Feelings of power and connectedness have both been linked to qualitatively and quantitatively better performance in collaborative learning environments [2, 3]. These components were then correlated with each students' proportionalized learning gains ([Posttest - Pretest] / [1 - Pretest]). Connectedness was significantly correlated with learning $r(743) = .164$, $p < .001$, but power was not, $r(743) = .007$, $p > .05$. McGrath [6] has posited that a positive social relationship leads to better group performance, so connectedness and learning ought to be somewhat linked even in a single discussion session, but authority has also been linked to learning [3], which was not found here. However, it is possible that power component, which is based on self-reports, is not sensitive enough to pick up this relationship in a single learning session.

The second set of analyses examined how the linguistic cue deep cohesion predicted feelings of power and connectedness to the group by using mixed-effects modeling. Mixed-effects modeling was used to account for the nested structure of the data, where students are embedded within group. This random factor can therefore be controlled for in mixed-effects modeling while measuring the effects of the fixed factors. Two models were constructed for these analyses: one to examine deep cohesion's ability to predict power and one to predict connectedness. Deep cohesion was the independent variable, while student (748 levels) nested within group (183 levels) was the random factor. Deep cohesion was found to positively and significantly predict feelings of connectedness to the group, $F(1, 744.137) = 12.25$, $SE = .021$, $p < .001$, so that as a student felt more connected to the group, the deep cohesion in their language increased. The same was also true for predicting feelings of power in the group, $F(1, 746) = 11.909$, $SE = .021$, $p = .001$; as a student's feelings of power in the group increased, so did the deep cohesion in their language. This demonstrates not only that linguistic cues are a viable source of predicting socioaffective outcomes, but that the cues for detecting such outcomes need not be restricted to typical emotive cues; a person's feelings about their group experience may also emerge in the cohesion of their language, a subtler cue than, for instance, their use of emotive language.

These analyses demonstrate that cognitive linguistic cues may be of use in detecting students' socioaffective attitudes towards fellow students in CSCL environments, which may have long-term consequences for their motivation and continued use of such systems. Being able to covertly detect these attitudes may mean that interventions are possible.

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