What Works: Creating Adaptive and Intelligent Systems for Collaborative Learning Support

Nia M. Dowell[1], Whitney L. Cade[1], Yla Tausczik[2], James Pennebaker[3], & Arthur C. Graesser[1]

[1]Institute for Intelligent Systems, The University of Memphis, Memphis TN 38152 USA
{ndowell|wlcade|graesser}@memphis.edu

[2]Department of Social Computing, Carnegie Mellon University, Pittsburg PA 13289 USA
{ylataus}@cs.cmu.edu

[3]Department of Psychology, University of Texas at Austin, Austin TX 78705 USA
{pennebaker}@mail.utexas.edu

Abstract. An emerging trend in classrooms is the use of collaborative learning environments that promote lively exchanges between learners in order to facilitate learning. This paper explored the possibility of using discourse features to predict student and group performance during collaborative learning interactions. We investigated the linguistic patterns of group chats, within an online collaborative learning exercise, on five discourse dimensions using an automated linguistic facility, Coh-Metrix. The results indicated that students who engaged in deeper cohesive integration and generated more complicated syntactic structures performed significantly better. The overall group level results indicated collaborative groups who engaged in deeper cohesive and expository style interactions performed significantly better on posttests. Although students do not directly express knowledge construction and cognitive processes, our results indicate that these states can be monitored by analyzing language and discourse. Implications are discussed regarding computer supported collaborative learning and ITS's to facilitate productive communication in collaborative learning environments.

Keywords: collaborative interactions · learning · computational linguistics · Coh-Metrix

1 Introduction

Current educational practices suggest an emerging trend toward collaborative problem solving or group learning [1,2]. This is reflected in the more recent upsurge of computer-mediated collaborative learning or groupware tools, such as email, chat, threaded discussion, massive open online courses (MOOCs), and trialog-based intelligent tutoring systems (ITSs). The growing adoption of collaborative learning environments is supported by research that shows that, in general, collaboration can increase group performance and individual learning outcomes (see [3] for a review). The interest of educational researchers in this topic has motivated a substantial area of research aimed at identifying and improving collaborative knowledge building processes using both ITSs and computer-supported collaborative learning (CSCL) systems [4]. Previous research in the area of collaborative learning has shown that information in the interaction itself can be useful in predicting the cognitive benefits that students take away [5,6]. For instance, cognitive elaboration, quality argumentation, common ground, task difficulty, and cognitive load have been shown to influence knowledge acquisition of the individual learner and performance of the overall group [7,8,9,10]. One factor that sets collaborative learning apart from individual learning is the use of collaborative language [11,12,13]. Being the root of all computer-mediated collaboration, language, discourse, and communication are critical for organizing a team, establishing a common ground and vision, assigning tasks, tracking progress, building consensus, managing conflict, and a host of other activities [1].

However, previous research in this area has predominantly focused on asynchronous communication, such as email or discussion boards, that require no real-time interaction between the users. In contrast, synchronous communication, such as text-based IM tools and videoconferencing, involves interactions that are dynamic and constantly updated [14]. Additionally, scholars typically rely on human coding, and have only recently applied automatic or semi-automatic natural language evaluation methods [2], [5], [15,16]. Consequentially, we know little about the actual process of knowledge construction in synchronous collaborative learning interactions.

There are several advantages to utilizing textual features as an independent channel for assessing collaborative communication processes. First, in the past, it has been an arduous task to assess communication during collaborative learning due to the complex nature of transcribing spoken conversations. However, advances in technology have increased the use of computer-mediated collaborative learning (CMCL), which allows researchers to track and analyze the language and discourse characteristics in group learning environments. Second, linguistic features derived from CMCL are contextually constrained in a fashion that provides cues regarding the social dynamics and an in-depth understanding of different qualities of interaction [2], [5], [17,18]. Third, recent advances in computational linguistics have convincingly demonstrated that language and discourse features can predict complex phenomenon such as personality, deception, emotions, successful group interaction, and even physical and mental health outcomes [19,20,21,22,23,24]. Thus, it is plausible to expect a textual analysis of symmetrical collaborative learning interactions to provide valuable insights into collaborative learning processes and performance.

A number of psychological models of discourse comprehension and learning, such as the construction-integration, constructionist, and indexical-embodiment models, lend themselves nicely to the exploration of how knowledge is constructed in collaborative learning interactions. These psychological frameworks of comprehension have identified the representations, structures, strategies, and processes at multiple levels of discourse [7], [25,26]. Computational linguistic tools that analyze discourse patterns at these multiple levels, such as Coh-Metrix (described later), can be applied in collaborative learning interactions to gain a deeper understanding of the discourse patterns useful for individual and group performance [7], [27,28]. This endeavor also holds the potential for enabling substantially improved collaborative learning environments both by providing real-time detection of students and group performance and by using this information to develop the student model and trigger collaborative learning support as needed.

In the current study, we employ computational linguistic techniques to systematically explore chat communication during collaborative learning interactions in a large undergraduate psychology course. Specifically, we identify the discourse levels and linguistic properties of collaborative learning interactions that are predictive of learning. Further, we examine how these relations may differ for individual students and overall group level discourse. A more general overarching goal of this paper is to illustrate some of the advantages of automated linguistics tools to identify pedagogically valuable discourse features that can be applied in collaborative learning ITS and CSCL environments.

1.1 Brief Overview of Coh-Metrix

Coh-Metrix is a computer program that provides over 100 measures of various types of cohesion, including co-reference, referential, causal, spatial, temporal, and structural cohesion [27,28,29]. Coh-Metrix also has measures of linguistic complexity, characteristics of words, and readability scores. Currently, Coh-Metrix is being used to analyze texts in K-12 for the Common Core standards and states throughout the U.S. More than 50 published studies have demonstrated that Coh-Metrix indices can be used to detect subtle differences in text and discourse [28], [30].

There is a need to reduce the large number of measures provided by Coh-Metrix into a more manageable number of measures. This was achieved in a study that examined 53 Coh-Metrix measures for 37,520 texts in the TASA (Touchstone Applied Science Association) corpus, which represents what typical high school students have read throughout their lifetime [29]. A principal components analysis was conducted on the corpus, yielding eight components that explained an impressive 67.3% of the variability among texts; the top five components explained over 50% of the variance. Importantly, the components aligned with the language-discourse levels previously proposed in multilevel theoretical frameworks of cognition and comprehension [7], [25,26]. These theoretical frameworks identify the representations, structures, strategies, and processes at different levels of language and discourse, and thus are ideal for investigating trends in learning-oriented conversations. Below are the five major dimensions, or latent components:

- **Narrativity.** The extent to which the text is in the narrative genre, which conveys a story, a procedure, or a sequence of episodes of actions and events with animate beings. Informational texts on unfamiliar topics are at the opposite end of the continuum.
- **Deep Cohesion.** The extent to which the ideas in the text are cohesively connected at a deeper conceptual level that signifies causality or intentionality.
- **Referential Cohesion**. The extent to which explicit words and ideas in the text are connected with each other as the text unfolds.

- **Syntactic Simplicity**. Sentences with few words and simple, familiar syntactic structures. At the opposite pole are structurally embedded sentences that require the reader to hold many words and ideas in working memory.
- **Word Concreteness**. The extent to which content words that are concrete, meaningful, and evoke mental images as opposed to abstract words.

2 Methods

2.1 Participants, Materials, and Procedure

The participants were 851 undergraduates (62.4% female) in two introductory-level psychology courses at a large Midwestern university. Caucasians accounted for 49.6% of participants while Hispanic/Latino accounted for 22.4%, Asian American for 16.1%, African American 4.2% and less than 1% identified as either Native American or Pacific Islander. Twelve participants were discarded as outliers or due to computer failure, resulting in $N = 839$.

Students logged into an education platform managed within the University at specified times to complete the group interaction task. The education platform was an online course center where students filled out surveys, took quizzes, completed writing assignments, and participated in group chat. Prior to logging into the system, students were instructed that, in order to complete the assignment, they would need to read supplementary material on a few psychological theories (e.g. 10 pages of the text-book).

Once students logged into the educational platform, they were directed to the first quiz. The quiz was 10 multiple-choice questions and tested students' knowledge of the reading material. After completing the quiz, they were randomly matched with other students currently waiting to engage in the chatroom portion of the task. When there were at least 2 students and no more than 5 students ($M = 4.59$), individuals were directed to an instant messaging platform that was built into the educational platform. The group chat began as soon as someone typed the first message and lasted for 20 minutes. The chat window closed automatically after 20 minutes, at which time students took a second 10 multiple-choice question quiz. Each student contributed 154 words on average ($SD = 104.94$) in 19.49 sentences ($SD = 12.46$). As a group, discussions were about 714.8 words long ($SD = 235.68$) and 90.62 sentences long ($SD = 33.47$).

2.2 Performance

On average, students scored better on the posttest after the group discussion than on the pretest. Pretest and posttest scores, for both the individual and group, were converted to proportions based the number of correct answers. Group performance was then operationalized as the average group members' score on the pretest and posttest.

2.3 Data Treatment and Computational Evaluation

The educational platform logged all of the students' contributions. Prior to analysis, the logs were cleaned and parsed to facilitate two levels of evaluation. First, for the individual-level analyses, texts files were created that included all contributions from a single student, resulting in 839 text files. Second, we combined all group members' contributions into a text file for group-level analyses. All files were then analyzed using Coh-Metrix. Following the Coh-Metrix analysis, the scores were normalized by removing any outliers. Specifically, the normalization procedure involved Winsorising the data based on each variable's upper and lower percentile.

3 Results and Discussion

A mixed-effects modeling approach was adopted for all analyses due to the nested structure of the data (e.g., learners embedded within groups). Mixed-effects modeling is the recommended analysis method for this type of data [31]. Mixed-effects models include a combination of fixed and random effects and can be used to assess the influence of the fixed effects on dependent variables after accounting for any extraneous random effects. The lme4 package in R [32] was used to perform the requisite computation.

The primary analyses focused on identifying discourse features (namely, the five dimension used to generally describe texts in Coh-Metrix: Narrativity, Deep Cohesion, Referential Cohesion, Syntax Simplicity, and Word Concreteness) of the chat data that are predictive of learning. We also tested whether prior knowledge moderated the effect of discourse on learning performance. Separate models were constructed to analyze discourse at the individual learner and group levels in order to isolate their independent contributions on learning performance. Therefore, there were two sets of dependent measures in the present analyses: (1) individual learners' performance on the multiple-choice posttest and (2) overall groups' performance on the multiple-choice posttest. The independent variables in all models were the 5 discourse features of interest, as well as proportional pretest performance scores, which were included to control for the effect of prior knowledge. The random effects for the individual learner models were participant (839 levels), while the group model used participant (839 levels) within group (183 levels) as the random effect.

Table 1 shows the discourse features that were predictive of learning performance for both the individual and group level models. As can be seen from this table, learners' deep cohesion and syntax are predictive of individual learning performance. Specifically, we see that learners who engaged in deeper cohesive integration and generated more complicated syntactic structures were significantly more likely to score higher on the posttest than learners who used simpler syntax and less deep cohesion. Discourse cohesion, defined as the extent to which the ideas in the text are cohesively connected at a deeper conceptual level that signifies causality or intentionality, is a central component in a number of processes that facilitate individual learning and comprehension [7]. With regard to the findings for deep cohesion, this suggests that students who are learning are engaging in deeper integration of topics with their background knowledge, generating more inferences to address any conceptual and structural gaps, and consequentially increasing the probability of knowledge retention. The finding for syntactic structure might provide evidence for the cognitive explanation hypothesis [17]. In general, this suggests that students who are producing denser sentence compositions are high verbal and/or are engaging in increased effort, inferences, and elaboration.

The analysis of collaborative group interaction discourse revealed that narrativity and deep cohesion were predictive of learning performance. In particular, the group-level results indicated that collaborative groups who engaged in more expository, or informational, style interactions significantly outperformed those with more narrative discourse. Initially, these findings seem counterintuitive based on previous research which found that narrative text is substantially easier to read, comprehend, and recall than informational text [7], even when the familiarity of the topics and vocabulary are controlled. However, students were instructed to talk about what they read in their textbook, which could suggest that groups that learned more were mirroring their textbook's more expository nature. Additionally, [29] noted that informational texts tend to have higher cohesion, as compared with narratives, and thus cohesion plays an important role in in compensating for the greater difficulty of expository style discourse. Deep cohesion was also predictive of learning performance in the group-level interaction analysis.

In addition to the previously mentioned benefits of deep cohesion for learning, cohesion also aids processes important for collaboration, including establishing and maintaining common ground [33], negotiating references [7], and coordinating group members' mental models [34]. High cohesion dialogue may indicate more thorough collaboration and learning in building a shared mental model. This is similar to the way high cohesion text can aid learners in building a solid mental model (relative to low cohesion text). In the context of group interactions, our findings support research showing that collaborative learners may create and preserve shared conceptions of a topic, and this social co-construction facilitates optimal collaboration for knowledge building [35]. We also tested whether prior knowledge moderated the effect of discourse on learning by assessing whether the prior knowledge x discourse feature interaction term significantly predicted posttest scores. However, the interaction term was not significant (p > .05) for any of the models.

Table 1. Descriptive Statistics and Mixed-Effects Model Coefficients

Measure	**Learner Model**				**Group Model**			
	M	*SD*	*B*	*SE*	*M*	*SD*	*B*	*SE*
Narrativity	.15	.79	.01	.01	.53	.34	**-.04***	.02
Deep Cohesion	.87	1.68	**.01****	.003	1.29	.75	**.03****	.01
Referential Cohesion	-.52	1.52	-.003	.005	-1.64	.42	.01	.02
Syntax Simplicity	.69	.81	**-.01***	.01	1.30	.37	-.001	.02
Word Concreteness	-2.07	1.07	-.01	.001	-2.67	.41	-.03	.01

Note: * p < .05; ** p < .001. Standard error (*SE*).

4 General Discussion

This paper explored the possibility of using discourse features to predict student and group performance during collaborative learning interactions. Although students do not directly express knowledge construction and cognitive processes, our results indicate that these states can be monitored by analyzing language and discourse. This suggests that it takes a more systematic and deeper analysis of dialogues to uncover diagnostic cues of the knowledge construction. Overall, the findings suggest that automated analyses of linguistic characteristics can provide valid representations of individual and group processes that are beneficial for knowledge construction during collaborative learning. In particular, students and collaborative groups can achieve new levels of understanding during collaborative learning interactions where more complex cognitive activities occur, such as analytical thinking, elaboration and integration of ideas and reasoning.

It is also interesting to note that it takes an analysis of both the student and collaborative group interaction to obtain a comprehensive understanding of the linguistic properties that influence knowledge acquisition during collaborative group interactions. These findings stimulate an interesting discussion because, until recently, most research on groups has concentrated on the individual people in the group as the cognitive agents [36]. This traditional granularity uses the individual as the unit of analysis both to understand behavioral characteristics of individuals working within groups and to measure performance or knowledge-building outcomes of the individuals in group contexts. However, the present findings support the claims of many in the CSCL community to also consider group levels of granularity in discourse tracking.

The present research has important implications for CSCL and collaborative learning-focused ITSs. In order to tailor interaction feedback to student needs, a system has to be able to automatically evaluate student interactions and to provide adaptive support. The support should be sensitive to these evaluations and also follow models of ideal collaboration. While the field has started to recognize the benefits of automated language evaluation, thus far, this technology has only been used effectively in limited ways (e.g. classifying the topic of conversation or speech acts) [37]. Some research has attempted to address the issue of evaluating dialogue by relying on more shallow measures like participation to trigger feedback. Unfortunately, these approaches make it difficult to give students feedback on *how* to contribute, which may ultimately be more valuable. Computational linguistics facilities, like Coh-Metrix and the Linguistic Inquiry and Word Count (LIWC) tool, could be used to alleviate some of the burdens of capturing these important processes. Additionally, systems that are based on underlying cognitive frameworks of knowledge construction have the advantage of being applicable in diverse contexts.

The present findings suggest that these systems have the capability of identifying linguistic features beneficial for knowledge construction on multiple levels, including individual learners and overall collaborative group interaction. Information gleaned from such analyses could be useful for those in pursuing CSCL and collaborative learning-focused ITSs. For instance, a system could provide accurate real time support for learners using an interface that delivered suggestions via a simple pop up window or a more sophisticated intelligent agent. However, the value of such enhancements awaits future work and empirical testing.

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