

Chapter 6

Statistical Discourse Analysis of Online Discussions: Informal Cognition, Social Metacognition, and Knowledge Creation

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Introduction

The benefits of online discussions have increased both their uses and records of their uses, which allow detailed analyses to inform design and to improve their productivity. Unlike face-to-face talk, students on asynchronous, online forums can participate at different places and times and have more time to gather information, contemplate ideas, and evaluate claims before responding, resulting in superior decision-making, problem solving, writing, and *knowledge creation* (KC; Luppicini 2007; Tallent-Runnels et al. 2006; Glassner et al. 2005). For example, studies using aggregate counts from online forum data showed how specific actions (e.g., “why” or “how” questions, explanations, evidence, summaries) are related to KC (Lee et al. 2006; Lin and Lehman 1999; Wise and Chiu 2011).

While aggregate counts provide descriptive summaries, they do not fully utilize the information relating to the time and order of collaboration and learning processes (Reimann 2009) or capture the sequential data needed to test KC hypotheses about how group members’ actions/posts/messages are related to one another (Chiu 2008a). Aggregate counts cannot illuminate the relationships among processes that contribute to knowledge creation. In contrast, analyses of sequences of messages can test whether some types of messages (e.g., asking for an explanation) or sequences of messages (different opinion followed by asking for explanation) often precede target types of messages (e.g., theorizing). These results can help us understand the temporal and causal relationships among different types of

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messages or message sequences that aid or hinder knowledge creation. We show how statistical discourse analysis (SDA, Chiu 2008b) can model these sequences to test these KC hypotheses. To explicate SDA, we introduce a specific set of data (Fujita 2009) and hypotheses to contextualize the methodological issues.

Data

In this study, we examine asynchronous, online forum messages written by students in a 13-week online graduate educational technology course delivered using Web-Knowledge Forum. These data are the second iteration of a larger design-based research study (Fujita 2009). Data sources included questionnaire responses, learning journals, and discourse in Knowledge Forum. One of the authors participated in the course both as a design researcher collaborating closely with the instructor and as a teaching assistant interacting in course discussions with students. The goals for this study were twofold: to improve the quality of online graduate education in this particular instance and to contribute to the theoretical understanding of how students collaborate to learn deeply and create knowledge through progressive discourse (Bereiter 1994, 2002).

Participants

Participants were 17 students (12 females, 5 males) (see Table 6.2). They ranged in age from mid-20s to mid-40s. Five were students in academic programs (4 M.A., 1 Ph.D.); 12 were students in professional programs (9 M.Ed., 3 Ed.D.). See Table 6.A1 in Appendix for details.

Procedure

Students were encouraged to engage in progressive discourse through three intervention activities: a reading by Bereiter (2002), classroom materials called Discourse for Inquiry (DFI) cards, and the scaffold supports feature built into Knowledge Forum. The DFI cards were adapted from classroom materials developed by Woodruff and Brett (1999) to help elementary school teachers and preservice teachers improve their face-to-face collaborative discussion. These adapted activities can model thinking processes and discourse structures in the online Knowledge Forum environment, which help online graduate students engage in progressive discourse. There were three DFI cards: *Managing Problem Solving* outlined commitments to progressive discourse (Bereiter 2002), *Managing Group Discourse* suggested guidelines for supporting or opposing a view, and *Managing*

Table 6.1 Knowledge Forum scaffolds and scaffold supports used in iteration 2

| Scaffolds | | |
|---|---|--|
| Cognition | Social metacognition | Dependent variables |
| <i>Opinion</i> (I think knowledge building takes a long time) | <i>Ask for explanation</i> (I need to understand why knowledge building has to take a long time) | <i>Theorize/explain</i> (My theory of the time needed for knowledge building is based on its sequence of parts) |
| <i>Elaboration</i> (I think knowledge building takes a lot of smaller steps) | <i>Ask about use</i> (Why do we need to understand how much time knowledge building takes?) | <i>New information</i> (Scardamalia and Bereiter's (1994) study showed that computer supports can support knowledge building in classroom learning communities) |
| <i>Anecdotal evidence</i> (Last week, our class took over an hour to come up with a good theory) | <i>Different opinion</i> (I don't think knowledge building has to take a long time. It might depend on the people) | |

Meetings provided two strategies to help students deal with anxiety. The cards were in a portable document file (.pdf) that students could download, print out, or see as they worked online.

Knowledge Forum, an extension of the CSILE (Computer Supported Intentional Learning Environment), is specially designed to support knowledge building. Students work in virtual spaces to develop their ideas, represented as “notes,” which we will refer to in this chapter as “messages.” It offers sophisticated features not available in other conferencing technologies, such as “scaffold supports” (labels of thinking types), “rise above” (a higher-level integrative note, such as a summary or synthesis of facts into a theory), and a capacity to connect ideas through links between messages in different views. Students select a scaffold support and typically use it as a sentence opener while composing messages; hence, they self-code their messages by placing yellow highlights of thinking types in the text that bracket segments of body text in the messages. At the beginning of the course, only the Theory Building and Opinion scaffolds built into Knowledge Forum were available. Later, in week 9, two students designed the “Idea Improvement” scaffolds (e.g., What do we need this idea for?) as part of their discussion leadership (see Table 6.1). The Idea Improvement scaffolds were intended by the student designers of the scaffolds to emphasize the socio-cognitive dynamics of “improvable ideas,” one of the 12 knowledge building principles (Scardamalia 2002) for progressive discourse. In this study, we focus our analysis on tracing messages with scaffold supports that build on or reply to one another. Types of scaffold supports relevant to our hypotheses are organized and renamed (*italicized*) in terms of cognition, social metacognition, and dependent variables.

Table 6.2 Hypotheses regarding the effects of classroom problem solving processes on the outcome variables *new information* and *theorizing*

| Explanatory variable | → dependent variable | |
|-----------------------------|----------------------|------------|
| <i>Cognition</i> | New information | Theorizing |
| Opinion | + | + |
| Elaboration | | + |
| Anecdotal evidence | | + |
| <i>Social metacognition</i> | | |
| Ask about use | + | + |
| Ask for explanation | | + |
| Different opinion | | + |

Symbols in *brackets* indicate expected relationship with the outcome variables: positive and supported [+], hypothesized but not supported

Hypotheses

We test whether recent cognition or social metacognition facilitate new information or theoretical explanations (Chiu 2000; Lu et al. 2011). Introducing new information and creating theoretical explanations are both key processes that contribute to knowledge building discourse. New information provides grist that theoretical explanations can integrate during discourse to yield knowledge creation. As students propose integrative theories that explain more facts, they create knowledge through a process of explanatory coherence (Thagard 1989). Hence, new information and theoretical explanations are suitable target processes to serve as dependent variables in our statistical model.

Researchers have shown that many online discussions begin with sharing of opinions (Gunawardena et al. 1997). Students often activate familiar, informal concepts before less familiar, formal concepts (Chiu 1996). During a discussion, comments by one student (e.g., a key word) might spark another student to activate related concepts in his or her semantic network and propose a new idea (Nijstad et al. 2003). When students do not clearly understand these ideas, they can ask questions to elicit new information, elaborations, or explanations (Hakkarainen 2003). Also, students may disagree (different opinions) and address their differences by introducing evidence or explaining their ideas (Howe 2009). Whereas individual metacognition is monitoring and regulating one's own knowledge, emotions, and actions (Hacker and Bol 2004), *social metacognition* is defined as group members' monitoring and controlling one another's knowledge, emotions, and actions (Chiu and Kuo 2009). Specifically, we test whether three types of cognition (informal opinion, elaboration, and evidence) and three types of social metacognition (ask for explanation, ask about use and different opinion) increase the likelihoods of new information or theoretical explanations in subsequent messages (see Table 6.2). To reduce omitted variable bias, additional individual and time explanatory variables were added. For example, earlier studies showed that males were more likely than females to make claims, argue, elaborate, explain, and critique others (Lu et al. 2011).

Table 6.3 Statistical discourse analysis strategies to address each analytic difficulty

| Analytic difficulty | Statistical discourse analysis strategy |
|--|--|
| <i>Data set</i> | |
| Missing data (0110??10) | Markov Chain Monte Carlo multiple imputation (Peugh and Enders 2004) |
| Nested data (messages within topics) | Multilevel analysis (hierarchical linear modeling, Bryk and Raudenbush 1992; Goldstein 1995) |
| Tree structure of messages (Λ) | Store preceding message to capture tree structure |
| <i>Dependent variables</i> | |
| Discrete variable (yes/no) | Logit/probit |
| Infrequent variable | Logit bias estimator (King and Zeng 2001) |
| Similar adjacent messages ($m_3 \sim m_4$) | I^2 index of Q-statistics (Huedo-Medina et al. 2006) |
| Multiple dependent variables (Y_1, Y_2, \dots) | Multivariate outcome models (Goldstein 1995) |
| <i>Explanatory variables</i> | |
| Sequences of messages (X_{t-2} or $X_{t-1} \rightarrow Y_t$) | Vector auto-regression (VAR, Kennedy, 2004) |
| Indirect, multilevel mediation effects ($X \rightarrow M \rightarrow Y$) | Multilevel M-tests (MacKinnon et al. 2004) |
| False-positives (type I errors) | Two-stage linear step-up procedure (Benjamini et al. 2006) |
| Robustness | Single outcome, multilevel models for each outcome Testing on subsets of the data Testing on original data |

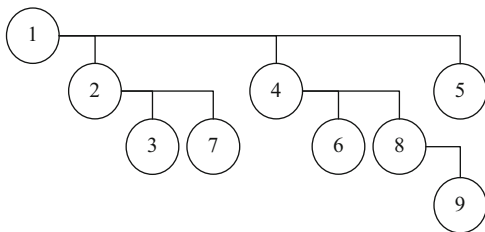
Analysis

To test the above hypotheses, we must address analytic difficulties involving the data, the dependent variables, and the explanatory variables (see Table 6.3). Data issues include missing data, nested data, and the tree structure of online messages. Difficulties involving dependent variables include discrete outcomes, infrequent outcomes, similar adjacent messages, and multiple outcomes. Explanatory variable issues include sequences, indirect effects, false-positives, and robustness of results. SDA addresses each of these analytic difficulties, as described below.

SDA addresses the data issues (missing data, nested data, and tree structure of online messages) with Markov Chain Monte Carlo multiple imputation (MCMC-MI), multilevel analysis, and identification of the previous message. Missing data can reduce estimation efficiency, complicate data analyses, and bias results. By estimating the missing data, MCMC-MI addresses this issue more effectively than deletion, mean substitution, or simple imputation, according to computer simulations (Peugh and Enders 2004).

Messages are nested within different topic folders in the online forum, and failure to account for similarities in messages within the same topic folder (vs. different topic folders) can underestimate the standard errors (Goldstein

Fig. 6.1 Tree structure showing how nine messages are related to one another



1995). To address this issue, SDA models nested data with a multilevel analysis (Goldstein 1995; cf. hierarchical linear modeling, Bryk and Raudenbush 1992).

Unlike a linear, face-to-face conversation in which one turn of talk often follows the one before it, an asynchronous message in an online forum might follow a message written much earlier. Still, each message in a topic folder and its replies are linked to one another by multiple threads and single connections in a tree structure. See Fig. 6.1, for an example, of a topic message (1) and its 8 responses (2, 3, . . . , 9).

These nine messages occur along three discussion threads: (a) $1 \rightarrow 2 (\rightarrow 3; \rightarrow 7)$, (b) $1 \rightarrow 4 (\rightarrow 6; \rightarrow 8 \rightarrow 9)$, and (c) $1 \rightarrow 5$. Messages in each thread are ordered by time, but they are not necessarily consecutive. In thread (b), for example, message #6 followed message #4 (not #5). To capture the tree structure of the messages, we identify the immediate predecessor of each message. Then, we can reconstruct the entire tree to identify any ordinal predecessor of any message.

SDA addresses the dependent variable difficulties (discrete, infrequent, serial correlation, and multiple) with logit regressions, a logit bias estimator, I^2 index of Q-statistics, and multivariate outcome analyses. The dependent variables are often discrete (a justification occurs in a conversation or it does not) rather than continuous (e.g., test scores), so standard regressions such as ordinary least squares can bias the standard errors. To model discrete dependent variables, we use a logit regression (Kennedy 2008). As infrequent dependent variables can bias the results of a logit regression, we estimate the logit bias and remove it (King and Zeng 2001).

As adjacent messages often resemble one another more than messages that are far apart, failure to model this similarity (serial correlation of errors) can bias the results (Kennedy 2008). An I^2 index of Q-statistics tested all topics simultaneously for serial correlation of residuals in adjacent messages (Huedo-Medina et al. 2006). If the I^2 index shows significant serial correlation, adding the dependent variable of the previous message as an *explanatory* variable often eliminates the serial correlation (e.g., when modeling the outcome variable *theory*, add whether it occurs in the previous message [*theory* (-1)], Chiu and Khoo 2005; see paragraph below on vector auto-regression, Kennedy 2008).

Multiple outcomes (*new information, theorizing*) can have correlated residuals that can underestimate standard errors (Goldstein 1995). If the outcomes are from different levels, separate analyses must be done at each level, as analyzing them in the same model overcounts the sample size of the higher-level outcome(s) and biases standard errors. To model multiple outcomes properly at the same level of analysis, we use a multivariate outcome, multilevel analysis (Goldstein 1995).

Furthermore, SDA addresses the explanatory variable issues (sequences, indirect effects, false-positives, robustness) with vector auto-regression, multilevel M-tests, the two-stage linear step-up procedure, and robustness tests. A vector auto-regression (VAR, Kennedy 2008) combines attributes of sequences of recent messages into a local context (*micro-time context*) to model how they influence the subsequent messages. For example, the likelihood of *new information* in a message might be influenced by attributes of earlier messages (e.g., *different opinion* in the previous message) or earlier authors (e.g., *gender* of the author of the previous message).

Multiple explanatory variables can yield indirect, mediation effects or false-positives. As single-level mediation tests on nested data can bias results downward, multilevel M-tests are used for multilevel data – in this case, messages within topics (MacKinnon et al. 2004). Testing many hypotheses of potential explanatory variables also increases the likelihood of a false-positive (type I error). To control for the false discovery rate (FDR), the two-stage linear step-up procedure was used, as it outperformed 13 other methods in computer simulations (Benjamini et al. 2006).

To test the robustness of the results, three variations of the core model can be used. First, a single outcome, multilevel model can be run for each dependent variable. Second, subsets of the data (e.g., halves) can be run separately to test the consistency of the results for each subset. Third, the analyses can be repeated for the original data set (without the estimated data).

Analysis Procedure

After MCMC-MI of the missing data to yield a complete data set, each online message's preceding message was identified and stored to capture the tree structure of the messages. Then, we simultaneously modeled two process variables in students' messages (*new information* and *theorizing*) with SDA (Chiu 2001).

$$\mathbf{Process}_{ymt} = \beta_y + \mathbf{e}_{ymt} + \mathbf{f}_{yt} \quad (6.1)$$

For $\mathbf{Process}_{ymt}$ (the process variable y [e.g., new information] for message m in topic t), β_y is the grand mean intercept. The message- and topic-level residuals are \mathbf{e}_{mt} and \mathbf{f}_t , respectively. As analyzing rare events (target processes occurred in less than 10 % of all messages) with logit/probit regressions can bias regression coefficient estimates, King and Zeng's (2001) bias estimator was used to adjust them.

First, a vector of student demographic variables was entered: *male* and *young* (**Demographics**). Each set of predictors was tested for significance with a nested hypothesis test (χ^2 log likelihood, Kennedy 2008).

$$\begin{aligned}
 \text{Process}_{y_{mt}} = & \beta_y + \mathbf{e}_{y_{mt}} + \mathbf{f}_{y_t} + \beta_{ydt} \text{Demographics}_{y_{mt}} \\
 & + \beta_{yxt} \text{Schooling}_{y_{mt}} + \beta_{yjt} \text{Job}_{y_{mt}} \\
 & + \beta_{yxt} \text{Experience}_{y_{mt}} + \beta_{ypt} \text{Previous}_{y_{mt}}
 \end{aligned} \tag{6.2}$$

Next, schooling variables were entered: *doctoral student*, *Masters of Education student*, *Masters of Arts student*, and *part-time student* (**Schooling**). Then, students' job variables were entered: *teacher*, *postsecondary teacher*, and *technology* (**Job**). Next, students' experience variables were entered: *KF experience* and *number of past online courses* (**Experience**).

Then, attributes of the previous message were entered: *opinion* (−1), *elaboration* (−1), *anecdote* (−1), *ask about use* (−1), *ask for explanation* (−1), *different opinion* (−1), *new information* (−1), *theory* (−1), and *any of these processes* (−1) (**Previous**). The attributes of the message two responses ago along the same thread (−2) were entered, then, those of the message three responses ago along the same thread (−3), and so on until none of the attributes in a message were significant.

Structural variables (**Demographics, Schooling, Job, Experience**) might show moderation effects, so a random effects model was used. If the regression coefficients of an explanatory variable in the **Previous** message (e.g., evidence; $\beta_{ypt} = \beta_{y_t} + f_{y_t}$) differed significantly ($f_{y_t} \neq 0?$), then a moderation effect might exist, and their interactions with processes were included.

The multilevel M-test (MacKinnon et al. 2004) identified multilevel mediation effects (within and across levels). For significant mediators, the percentage change is $1 - (b'/b)$, where b' and b are the regression coefficients of the explanatory variable, with and without the mediator in the model, respectively. The odds ratio of each variable's total effect (TE = direct effect plus indirect effect) was reported as the increase or decrease (+TE % or −TE %) in the outcome variable (Kennedy 2008). As percent increase is not linearly related to standard deviation, scaling is not warranted.

An alpha level of .05 was used. To control for the false discovery rate, the two-stage linear step-up procedure was used (Benjamini et al. 2006). An I^2 index of Q-statistics tested messages across all topics simultaneously for serial correlation, which was modeled if needed (Goldstein et al. 1994; Huedo-Medina et al. 2006; Ljung and Box 1979).

Conditions of Use

SDA relies on two primary assumptions and requires a minimum sample size. Like other regressions, SDA assumes a linear combination of explanatory variables. (Nonlinear aspects can be modeled as nonlinear functions of variables [e.g., age^2] or interactions among variables [*anecdote* × *ask about use*].) SDA also requires independent residuals (no serial correlation as discussed above). In addition, SDA has modest sample size requirements. Green (1991) proposed the following heuristic sample size, N , for a multiple regression with M explanatory variables and an expected explained variance R^2 of the outcome variable:

$$N > \left(\left\{ 8 \times \left[\frac{(1 - R^2)}{R^2} \right] \right\} + M \right) - 1 \quad (6.3)$$

For a large model of 20 explanatory variables with a small expected R^2 of 0.10, the required sample size is 91 messages: $= 8 \times (1 - 0.10)/0.10 + 20 - 1$. Less data are needed for a larger expected R^2 or smaller models. Note that statistical power must be computed at each level of analysis (message, topic, class, school . . . country). With 1,330 messages, statistical power exceeded 0.95 for an effect size of 0.1 at the message level. The sample sizes at the topic level (13) and the individual level (17) were very small, so any results at these units must be interpreted cautiously.

Results

Summary Statistics

In this study, 17 students wrote 1,330 messages on 13 topics, organized into folders in the forum. Students who posted more messages on average than other students had the following profile: older, enrolled in Masters of Arts (M.A.) programs, part-time students, not teachers, worked in technology fields, or had Knowledge Forum (KF) experience (*older*: $m = 47$ vs. other $m = 37$ messages; *M.A.*: 64 vs. 36; *part-time*: 47 vs. 27; *not teachers*: 55 vs. 36; *technology*: 54 vs. 39; *KF*: 44 vs. 32). Students posted few messages with the following attributes (see Table 6.4, panel B): new information (1 %), theory (4 %), opinion (5 %), elaboration (2 %), anecdotal evidence (1 %), ask for explanation (9 %), ask about use (2 %), and different opinion (1 %). Most messages were none of the above (83 %). (As some messages included more than one of these attributes, these percentages do not sum up to 100 %.)

Explanatory Model

As none of the second-level (topic) variance components were significant, a single-level analysis was sufficient. All results discussed below describe first entry into the regression, controlling for all previously included variables. Ancillary regressions and statistical tests are available upon request.

New Information

The attributes of previous messages were linked to new information in the current message. After an opinion, new information was 7 % more likely in the next message. After a question about use three messages before, new information was 10 % more likely. Together, these explanatory variables accounted for about 26 % of the variance of new information. See Fig. 6.2.

Table 6.4 Summary statistics at the individual level (panel A) and message level (panel B)

| A. Individual variable (<i>N</i> = 17) | | |
|--|------|---|
| | Mean | Description |
| Man | 0.28 | 28 % of participants were men. 72 % were women |
| Young (under 35 years of age) | 0.50 | Half of the participants were under 35 years of age |
| Doctorate | 0.22 | 22 % were enrolled in a Ph.D. or an Ed.D. program |
| Masters of Art | 0.22 | 22 % were enrolled in M.A. program |
| Masters of Education | 0.50 | 50 % were enrolled in M.Ed. program |
| Part-time student | 0.78 | 78 % were part-time students. 22 % were full-time students |
| Teacher | 0.67 | 67 % worked as teachers |
| Postsecondary teacher | 0.28 | 28 % taught at the postsecondary level |
| Technology | 0.22 | 22 % worked in the technology industry |
| Knowledge Forum (KF) | 0.83 | 83 % had used Knowledge Forum previously |
| Past online courses | 2.89 | Participants had taken an average of 2.89 online courses. SD = 2.74; min = 0; max = 8 |
| B. Message variable (<i>N</i> = 1330) | | |
| | Mean | Description |
| Man | 0.26 | Men posted 26 % of all messages. Women posted 74 % |
| Young (under 35) | 0.44 | Young participants posted 44 % of all messages |
| Doctorate | 0.20 | Ph.D. students posted 20 % of all messages |
| Masters of Art | 0.33 | M.A. students posted 33 % of all messages |
| Masters of Education | 0.47 | M.Ed. students posted 47 % of all messages |
| Part-time | 0.86 | Part-time students posted 86 % of all messages |
| Teacher | 0.57 | Teachers posted 57 % of all messages |
| Postsecondary teacher | 0.23 | Postsecondary teachers posted 23 % of all messages |
| Technology | 0.28 | Those working in technology posted 28 % of all messages |
| Knowledge Forum (KF) | 0.87 | Those who used KF before posted 87 % of all messages |
| Past online courses | 3.35 | SD = 2.21; min = 0; max = 8. The average number of author's online courses, weighted by number of messages |
| New information | 0.01 | 1 % of the messages had at least one new information |
| Theorize | 0.04 | 4 % of the messages had theorizing |
| Opinion | 0.05 | 5 % of the messages gave a new opinion |
| Elaboration | 0.02 | 2 % of the messages had an elaboration of another's idea |
| Anecdotal evidence | 0.01 | 1 % of the messages gave evidence to support an idea |
| Ask for explanation | 0.09 | 9 % of the messages had a request for explanation |
| Ask about use | 0.02 | 2 % of the messages had a request for a use |
| Different opinion | 0.01 | 1 % of the messages had a different opinion than others |
| Any of the above processes | 0.17 | 17 % of the messages had at least one of the above features |

Note: Except for past online courses, all variables have possible values of 0 or 1

Theorize

Gender and attributes of previous messages were significantly linked to theorizing. Men were 22 % more likely than women to theorize. Demographics accounted for 5 % of the variance in theorizing.

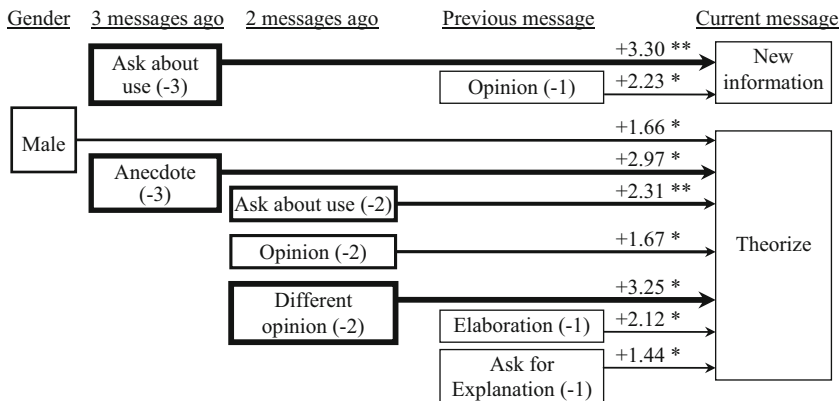


Fig. 6.2 Path diagram for new information and theorize. *Thicker lines* indicate stronger links. * $p < .05$, ** $p < .01$, *** $p < .001$

Attributes of earlier messages up to three messages before were linked to theorizing. After an explanation or an elaboration, theorizing was 21 % or 39 % more likely, respectively. If someone asked about the use of an idea, gave an opinion, or gave a different opinion two messages before, theorizing was 21 %, 54 %, or 12 % more likely, respectively. After anecdotal evidence three messages before, theorizing was 34 % more likely. Altogether, these explanatory variables accounted for 38 % of the variance of theorizing.

Other variables were not significant. As the I^2 index of Q-statistics for each dependent variable was not significant, serial correlation was unlikely.

Discussion

During asynchronous, online discussions, students have more time to gather information, contemplate ideas, and evaluate claims, so they often display higher levels of knowledge creation than during face-to-face discussions (Hara et al. 2000; Luppini 2007; Tallent-Runnels et al. 2006). Extending this research beyond aggregate attributes of *separate messages*, this study examined the *relationships among messages* with a new method, statistical discourse analysis. Both individual characteristics and the micro-time context of recent messages’ cognition and social metacognition affected the likelihoods of subsequent new information and theorizing.

Demographics and Job

Past studies of primary and secondary school students had shown that individual differences in gender accounted for little of the variance in discussion behaviors

(Chen and Chiu 2008), but this study showed that these men were more likely than these women to theorize. Gender accounted for five percent of the variance. This result is consistent with the research that boys are more active than girls during online discussions in high school (e.g., Lu et al. 2011).

Micro-time Context of Recent Messages

Beyond the effects of individual characteristics, both cognitive and social metacognitive aspects of recent messages showed micro-time context effects on subsequent messages. These results showed that asynchronous messages are more than simply lists of individual cognition (Thomas 2002); instead, these messages influence and respond to one another.

Informal cognition (opinions, elaborations, anecdotes) often preceded formal cognition (new information, theorizing). After a message containing an opinion, messages containing new information and theorizing were more likely to follow. Anecdotes and elaborations were also more likely to be followed by theorizing. Together, these results are consistent with the views that familiar, informal cognition is often activated before more formal cognition (Chiu 1996) and that the former can facilitate the latter through spreading activation of related semantic networks both in the individual and among group members (Nijstad et al. 2003). This order of informal cognition before formal cognition also reflects the social nature of knowledge building discourse; individuals share their informal experiences, which group members consider, reshape, and integrate into formal, public, structured knowledge. For educators, these results suggest that students often share their ideas informally and teachers should encourage students to use one another's ideas to create formal knowledge.

Social metacognition, in the form of questions and different opinions, also affected the likelihoods of new information and theorizing. Reflecting students' knowledge interests, their questions identify key goals and motivate knowledge building. Questions about use of a particular idea had the largest effect on inducing more new information, showing their power to influence other's behaviors, which is consistent with Bereiter and Scardamalia's (2006) conceptions of "design mode" teaching and earlier research (e.g., Chen et al. 2012). Furthermore, both types of questions elicited more theorizing, which is also consistent with earlier studies (e.g., Lu et al. 2011). These results suggest that educators can design instruction to give students autonomy or "collective cognitive responsibility" (Scardamalia 2002; Zhang et al. 2009) so that students can create their own learning goals (or at least subgoals) and ask questions to motivate themselves and their classmates to build knowledge that is meaningful to them. Lastly, a different opinion had the largest effect on a subsequent theory, consistent with past disequilibrium research showing that disagreements provoke explanations (e.g., Chiu and Khoo 2003). Together, these results suggest useful prompts that a teacher might encourage students to use during online discussions, for example, through brief cue cards or direct teacher questioning.

Statistical Discourse Analysis

This study showcases a new methodology for analyzing relationships among individual characteristics and nonlinear, asynchronous messages during an online discussion. Such analyses must address analytic difficulties involving the data, the dependent variables, and the explanatory variables. First, data issues include missing data, nested data, and the tree structure of online messages. Second, difficulties involving dependent variables include discrete outcomes, infrequent outcomes, similar adjacent messages, and multiple outcomes. Lastly, explanatory variable issues include sequences, indirect effects, false-positives, and robustness of results.

SDA addresses each of these analytic difficulties as follows (see Table 6.3). First, SDA addresses the data issues (missing data, nested data, tree structure of online messages) with Markov Chain Monte Carlo multiple imputation (MCMC-MI), multilevel analysis, and identification of the previous message. Second, SDA addresses the dependent variable difficulties (discrete, infrequent, serial correlation, and multiple) with logit regressions, a logit bias estimator, I^2 index of Q-statistics, and multivariate outcome analyses. Lastly, SDA addresses the explanatory variable issues (sequences, indirect effects, false-positives, robustness) with vector autoregression, multilevel M-tests, the two-stage linear step-up procedure, and robustness tests.

Conclusion

This study extends the online discussion research beyond aggregated attributes of *separate messages* to *relationships among messages* by showcasing a new methodology, statistical discourse analysis. The results showed that both individual characteristics and the micro-time context of recent messages' cognition and social metacognition affected the likelihoods of subsequent new information and theorizing. Unlike past studies of students, this exploratory study with a few students suggests that gender in adults might account for substantial differences in online behaviors. Specifically, men were more likely than women to theorize. Rather than simply being lists of individual cognition, asynchronous messages create a micro-time context that affects subsequent messages. Informal cognition (opinions, anecdotes, elaborations) facilitates more formal cognition (new information and theoretical explanations). Meanwhile, social metacognition, in the form of questions and different opinions, had the strongest effects on subsequent new information and theoretical explanations.

Appendix: Ancillary Data

Table 6.A1 Student demographics

| Name | Gender | Age | Degree | Reg | Job | Residence | Familiar with KF | Previous online courses |
|-----------|--------|-------|--------|-----|-----------------------------------|-------------------|------------------|-------------------------|
| Adam | M | 26-35 | M.A. | P/T | Graduate student | Toronto, ON | Yes | 5 |
| Anne | F | | M.Ed. | P/T | Secondary teacher | Newmarket, ON | No | 0 |
| Belinda | F | 36-45 | M.Ed. | P/T | Postsecondary instructor | Kelowna, BC | Yes | 5 |
| Chloe | F | 36-45 | M.Ed. | P/T | Software trainer | Toronto, ON | Yes | 4 |
| Christine | F | 26-35 | M.A. | P/T | Postsecondary instructor | Taiwan | Yes | 5 |
| Dylan | M | 36-45 | M.Ed. | P/T | Postsecondary instructor | Toronto, ON | Yes | 0 |
| Evelyn | F | <25 | M.Ed. | F/T | Graduate student | Toronto, ON | Yes | 0 |
| Gail | F | 36-45 | Ed.D. | P/T | Elementary school principal | Simcoe County, ON | Yes | 3 |
| Ian | M | 26-35 | M.Ed. | P/T | Secondary teacher | Toronto, ON | Yes | 0 |
| Jeff | M | 26-35 | M.Ed. | P/T | Elementary teacher | Toronto, ON | Yes | 3 |
| Kelly | F | 26-35 | M.Ed. | P/T | Teacher | Toronto, ON | No | 0 |
| Laurel | F | 26-35 | Ed.D. | P/T | Educational technology consultant | Markham, ON | Yes | 6 |
| Maria | F | | MA | F/T | Postsecondary instructor | Toronto, ON | No | 0 |
| Megan | F | 36-45 | Ph.D. | F/T | Postsecondary instructor | Millbrook, ON | Yes | 8 |
| Sharon | F | 26-35 | M.A. | P/T | Elementary teacher | Toronto, ON | Yes | 2 |
| Paul | M | 36-45 | Ed.D. | F/T | Information and planning analyst | Peterborough, ON | Yes | 7 |
| Yvonne | F | 36-45 | M.Ed. | P/T | Educational technology consultant | Ottawa, ON | Yes | 4 |

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