Effects of Previous Messages' Evaluations, Knowledge Content, Social Cues and Personal Information on the Current Message During Online Discussion

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Abstract: This study of the flow of online discussions examined how previous messages affected the current message along five dimensions: (1) evaluations (agreement, disagreement, or unresponsive actions); (2) knowledge content (contribution, repetition, or null content); (3) social cues (positive, negative, or none); (4) personal information (number of visits); and (5) elicitation (eliciting response or not). Using dynamic multilevel analysis (DMA) and a structural equation model (SEM), this study analyzed 131 messages of 47 participants across seven topics in the mathematics forum of a university Bulletin Board System (BBS) Website. Results showed that a disagreement or contribution in the previous message yielded more disagreements and social cue displays in the current message. Unlike face-to-face discussions, online discussion messages that disagreed with a previous message elicited more responses. Together, these results suggest that teachers can use and manage online discussions to promote critical thinking, facilitate discussion of controversial topics, and reduce status effects.

Studies on FTF discussions have shown that the actions of earlier speakers can affect those of the current speaker. For example, a person is more likely to agree if the previous speaker agreed (Chiu & Khoo, 2003). Hence, earlier messages might also affect later messages in online forums. By understanding how online discussions evolve message by message, educators can improve their quality and facilitate student learning.

Most previous studies on online discussions examined the *individual* properties of each message (Tallent-Runnels et al., 2006; De Wever, Schellens, Valcke, & Van Keer, 2005; Hara, Bonk, & Angeli, 2000; Schellens & Valcke, 2005). Their results showed that many students processed course information at high cognitive levels during online discussions, supporting the claim that online discussion can promote active and critical thinking (Garrison, Anderson, & Archer, 2000, 2001).

Using data on 131 messages by 47 respondents on seven topics, we extend this line of research in three ways. First, we propose a framework for examining the *relationships* among messages in an online independent academic forum. Our framework consists of an online message's evaluation of the previous message (agreement, disagreement, or unresponsive actions), its knowledge content (contribution, repetition, or null content), its social cues (positive, negative, or none), displayed personal information (number of visits, nickname, and personal statement), and its elicitation of other messages (eliciting response or not). Second, we explicate a new methodology for analyzing these relationships, a modified version of Chiu and Khoo's (2005) dynamic multilevel analyses. Lastly, we apply this revised method to test how earlier messages' evaluations, knowledge content, social cues, and personal information affected the properties of each message in a mathematics forum on a Bulletin Board System (BBS) Website.

Data and Analyses

In this data set, 47 participants posted 131 reply messages across seven topics. These topics were among the most popular discussions on the mathematics board of Peking University BBS Website (URL: bbs.pku.edu.cn) from May to October, 2004. Peking University students are among the best students of China and are usually 18 to 30 years old (from undergraduate to postgraduate). Gender information was unknown.

The set of variables (see table 1) for a single message included number of visits by each e-poster and the following binary variables: agreement, disagreement, contribution, repetition, social cue, negative social cue, and elicitation. Values of zero for Agreement and Disagreement indicate an unresponsive action. Likewise, values of zero for Contribution and Repetition indicate Null content. Also, values of one for Social cue and zero for Negative social cue indicate Positive social cue.

Table 1: Message properties to be examined in the study.

Message properties	Example
Agreement	"I agree with you."; "Good answer. Can you say more?"
Disagreement	"I *don't* think so."; "That's partially right, *but*, …"
Unresponsive / new topic	"This reminds of an interesting story …"
Contribution	"*In my opinion*, …"; "we can *multiply rate times time*"
Repetition	"Yes, you're right. Two times six is twelve, not ten."
Null content	"Yes"; "Thank you"; "I don't understand"
Positive social cue	"Excellent!"
Negative social cue	"That's ridiculous!"
Non-personal social cue	"Two times three equals six"
Visits	E-poster's visits on the BBS website, e.g., *791*.

This analysis uses three sets of variables: properties of the current message (0), properties of earlier messages variables in the same thread (-n, where n = 1, 2, 3, …), and properties of the next message (+1) in the same thread. For example, contribution (0) indicates whether the current message includes a new idea. Likewise, repetition (-1) indicates whether the previous message in the thread repeated an earlier message. Lastly, elicitation (+1) indicates whether or not a message responded to the current message.

To statistically analyze interactions among online messages, we must address three major concerns. First, e-posters' behaviors and effects differ across topics, yielding nested data. Second, most variables in this study are discrete, not continuous. Third, messages are often similar to recent events in time-series data, so the values of variables tend to depend on the values of these variables from recent messages.

Ordinary least squares (OLS) regressions do not address these difficulties (Goldstein, 1995; Enders, 1995). We address these difficulties using an extension of *dynamic multilevel analysis* (Chiu & Khoo, 2003, 2005). We test for topic differences, build an explanatory model, test for serial correlation, and model direct and indirect effects. Extending Chiu and Khoo (2005), we also use a structural equation model to test all predictor effects simultaneously.

Results and Discussion

The multi-level variance components analysis showed that topics did not differ significantly (variance at the topic level was not significant), so single-level analyses were adequate. Based on dynamic multilevel analysis results, we used an SEM to test the direct and indirect effects of the earlier messages. Non-significant effects in the SEM were removed. The final model is shown in figure 1.

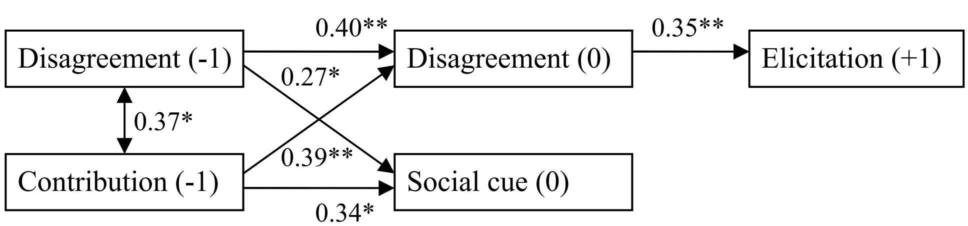

Figure 1. Structural equation model for predictors of disagreement, social cue and elicitation with significant standardized parameter estimates (χ^2 [df = 5, N = 109] = 8.19, p = .146).

As expected, disagreements often occurred after prior disagreements and contributions in this study. A message that disagrees with an earlier message yielded further disagreements, consistent with Chiu and Khoo's (2003) FTF interaction result. Unlike FTF interactions however, disagreements did not seem to threaten the continuation of the discussion, as disagreements raised the likelihood of later e-posters' responses. These effects suggest that online discussions are suited to controversial topics.

Both disagreement and contribution in the previous message positively predicted a social cue in the current message. This result suggests that in online discussions, disagreements and new ideas tend to cause stronger emotional responses and engagement compared to other types of messages. Also, disagreements and contributions elicited more responses, suggesting that messages are more provocative and engaged students to respond. Furthermore, these results showed that messages with critical thinking were more popular, which supports the claim that online discussion forum can promote critical thinking (Garrison et al., 2000, 2001).

There were also several notable non-significant results. Contrary to Walther's (1996) and Henri's (1992) arguments, social cues did not substantially affect the behaviors studied. Furthermore, status in the form of number of visits was linked to more contributions, suggesting that experienced e-posters elicited more contributions. However, agreements did not occur more often after messages by e-posters with more visits. Likewise disagreements were not less likely after messages by e-posters with more visits. Together, these results support our hypothesis that status effects are weaker in online discussions than in FTF discussions.

Implications

This study showed that disagreements and contributions affected the likelihoods of later disagreements, social cues and responses. If future studies support the results of this study, then educators and researchers might use online academic discussion in three ways: (1) *Developing controversial discussions on online forums*. As shown in this study, participants were likely to engage in and sustain online discussion on topics that involved many disagreements. This result suggests that educators might help students learn and think critically by using online forums for discussion of controversial topics, e.g., new hypotheses or problems with contested answers. (2) *Reducing status effects*. This study showed that experience status effects are much weaker in online discussions than in FTF discussions. If status effects are a serious problem in classroom interactions, online discussions among multiple classes (or schools) or perhaps with pseudonyms might mitigate these status effects. (3) *Managing online discussions at message level*. This study suggested that the property of previous messages may affect the current messages in a discussion thread. It implies that, in addition to encouraging student to participate, teachers may also manage the online academic discussions for specific purposes at message level.

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