Computer Mediated Discussions:
Effects of the Previous Messages' Evaluations, Knowledge Content, Social Cues and Personal Information on the Current Message

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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.

Introduction

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; Hara, Bonk, & Angeli, 2000; Garrison, Anderson, & Archer, 2001; Schellens & Valcke, 2005). Their results showed that many students processed course information at high cognitive levels and used more critical thinking during online discussions (Garrison, Anderson, & Archer, 2000).

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 consisted of five dimensions for examining the relationships among messages in an online independent academic forum. 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 Univeristy Bulletin Board System (BBS) Website.

Five dimensions characterizing online discussion messages

Building on past studies of FTF and online discussions (Chiu, 2000; Chiu & Khoo 2003; Henri, 1992; Garrison et al., 2000), we introduce a framework for characterizing messages in online academic discussion forums along five dimensions. The detailed dimensions and their possible consequences in FTF and online discussion processes are shown in table 1. We define "e-poster" as a person who has posted a message on the online discussion board.

Table 1: Five dimensions to characterize online messages and their possible consequences in FTF and online discussions.

Messages		Possible consequences during a discussion	
Dimension	Category	FTF discussion	Online discussion
Evaluations	Agreement	Positive feeling (+)	?
	Disagreement	Disagreement (+)	Disagreement (+)
		Negative feeling (+)	Elicit response (+)
	Unresponsive / new topic	Negative feeling (+)	?
Knowledge content	Contribution	?	Disagreement (+)
			Social cue (+)
			Elicit response (+)

	Repetition	?	?
	Null content	?	?
Social cues	Positive	Positive feeling (+)	Positive feeling (+)
	Negative	Negative feeling (+)	Negative feeling (+)
		Contribution (–)	Contribution (–)
	None	?	?
Personal information	Nickname (Name)	?	?
	Personal statement (Appearance)	?	?
	Visits (Past achievement)	Agreement (+)	Agreement (+)
		Positive feeling (+)	
Elicitation	Eliciting response	?	?
	No response	?	?

"+" indicates more likely; "–": less likely; "?": unknown.

Evaluations

Evaluations characterize how the current speaker or e-poster assesses the previous action. By linking messages together, evaluations increase the coherence of interactions (Goodwin & Goodwin, 1987). Evaluations can be agreements, disagreements, or unresponsive actions.

As online discussions tend to be less personalized compared to FTF discussions, online discussion participants tend to be less concerned about one another's feelings (Brown & Levinson, 1987) and hence more likely to express their disagreements. These disagreement messages often include new information used to support its opposition. This new content, in turn, is more likely to elicit a response (often disagreement). In contrast, agreement messages that support the previous message need not add much content, thereby providing less added information for others to reference. Hence, a disagreement message is more likely to elicit response than an agreement message in online forums.

Knowledge content

The knowledge content dimension characterizes the information displayed regarding the focal topic: new contributions, old repetitions, null content (Chiu, 2000).

During online discussions, contributions provide new information which might elicit more responses than repetitions or null content, especially if the participants are focused on the content. Contributions are also more likely to elicit disagreements than agreements in online discussions. As e-posters' concerns about threats to face tend to be lower, they might express their disagreement more directly and explicitly (Dubrovsky, Kiesler, & Sethna, 1991). Finally, contributions are also more likely to attract emotional concern and involvement during online discussions (Patwardhan, 2004).

In sum, contributions during online discussions might elicit more responses, more disagreements, and more emotional responses compared to repetitions or null content messages.

Social cues

The social cues of a message differ from the formal content of subject matter (Henri, 1992). During online discussions, social cues can be positive, negative, or none. The effects of social cues on later messages in FTF and online discussions are likely similar, though the intensities might differ. In both FTF and online discussions, positive social cues tend to elicit positive social cues while negative social cues elicit negative ones. While excessive social cues might distract from focus on the task (Walther, 1996) and reduce the number of subsequent contributions, negative social cues might show a stronger negative effect than positive social cues.

Personal information

Personal information describes perceived characteristics of a person that exist prior to the FTF or online discussion. In online discussions, e-posters often portray a public image by choice of electronic name, possibly other personal information, and past activity on the specific website. Personal information typically has more surface validity in FTF discussions than in online discussions. Status effects are likely smaller in online discussions compared to FTF discussions (Dubrovsky et al., 1991).

Elicitation

Elicitation indicates whether or not other e-posters responded to a specific message. As the mirror image of evaluations (which link backwards to earlier turns), elicitations link forward to later turns to increase the coherence of the discussion. As e-posters can respond to any message at any time, some messages receive many responses, others receive none. In Thomas's (2002) study on 69 undergraduate students' online discussion, he showed that over half students' contributions received no response, making the discussion incoherent and

inefficient. So, an e-poster who asked a question but didn't get response might feel frustrated during the discussion. Hence, elicitation reflects the importance of a message and its impact on the subsequent discussion.

Method
Data

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. Messages on the seven topics ranged from 11 to 33. The discussion durations of the seven topics ranged from 14 hours to 106 hours. 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.

Each of the seven topics focused on a problem proposed in the topic message. The topic message and its reply messages are linked to each other by multiple threads, single connections, and quotes of the previous message. See figure 1 for the relationship of messages in one of the seven topics. "0" in the circle indicates the initial topic message; "1" to "12" indicate 12 reply messages in order of posting time.
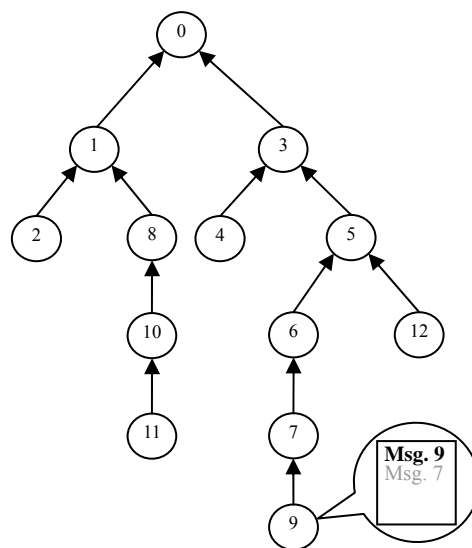

Figure 1. Relationship of messages in one of the seven topics.

Multiple threads. The topic message and 12 reply messages occur along five threads: (a) 0→1→2, (b) 0→1→8→10→11, (c) 0→3→4, (d) 0→3→5→6→7→9, (e) 0→3→5→12. Messages in each thread are ordered by time, but they were not necessarily consecutive. In thread (d) for example, message 9 followed message 7 and message 5 followed message 3.

Single connections. All messages in the topic were linked together by single connections. The forum's interface design constrained each of them to respond to only one earlier message. For example, message 9 only responded to message 7.

Quotes of the previous message. Along each single connected discussion thread, every reply message quoted the previous message to which it responded. Both messages can be read in the same computer window. For example, message 9 quoted message 7 under it, with message 7 in a lighter color.

Variables

The set of variables 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.

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.

Current Variables (0)

Current variables (0) were the variables that measured the property displayed in the current message, e.g. contribution (0). The current variables (0) in this study are shown in table 2. Number of visits (0) was an integer.

Table 2: 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*.

Lag Variables (-n)

Past variables (-n) or lag variables (-n) (where n = 1, 2, 3, …) measured the properties of messages posted before the current message (except the topic message) in the same thread. Respectively, lag variables (-1) measured the property of previous message such as repetition (-1) to which the current message responded; lag variables (-2) measured the property of message two turns prior (to which the previous message responded); lag variables (-3) measured the property of the message three turns prior; and so on.

This study examined variables up to lag (-4) of each message as shown in table 2, as FTF research suggests that lag variable effects can last for at least 3 turns (Chiu & Khoo, 2003). However, as variable (-n) required data from earlier messages, they might not be available for some specific messages. For example, no messages occurred before the topic message, so the topic message did not have any lag variables (-n).

Next Message Variable (+1)

This study examined only one next message variable (+1), elicitation (+1). It measured whether the current message elicited a later response or not and thus is a binary variable. A message eliciting no response ends a thread.

Analyses

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. Applied to nested data, OLS often underestimates the standard errors of regression coefficients (Goldstein, 1995). For discrete variables, OLS is inefficient and yields biased results. Lastly, if the time-series relationships are not modeled properly, the model residuals can be serially correlated, resulting in inefficient parameter estimates and biased estimates of the parameters' standard errors (Enders, 1995).

Thus, we address these difficulties by 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.

To test if the outcome variables significantly varied across topics, we used the software MLn (Rasbash & Woodhouse, 1995) to create a multi-level Logit variance components model (Goldstein, 1995). Consider a two-level model with an outcome variable, Y_{ij} (e.g., disagreement) at message i of topic j and a Logit link function:

$$Y_{ij} = \beta_0 + e_{ij} + f_{0j}$$

$$\pi_{ij} = p\,(y_{ij} = 1) = F\,(\beta_0 + f_{0j}) \;= \frac{1}{1 + e^{-(\beta_0 + f_{0j})}}$$

The level-2 variation parameter f_{0j} represents the deviation of topic j from the overall mean. The probability (π_{ij}) that an event (e.g. a disagreement) occurs at message i of topic j is determined by the expected value of the outcome variable and the Logit link function. Multi-level models separate unexplained error into message (level one) and topic (level two) components, thereby removing the correlation among error terms resulting from messages nested within topics. If the variance components model shows significant variation at the topic level, then topics are heterogeneous and differ significantly from one another. Then, a two-level logit model and a two-level structural equation model (SEM) would be needed. If not, single level logit and SEM are sufficient.

For the outcome variable disagreement (0), we first added a vector (**X**) of x lag variables (-1) at the message level: visits (-1), agree (-1), disagree (-1), contribute (-1), repeat (-1), social cue (-1), and negative social cue (-1).

$$\pi ij = F(\beta 0 + \beta xjX(i-1)j + f0j)$$

We tested whether this set of predictors was significant with a nested hypothesis test ($\chi 2$ log likelihood, Cohen & Cohen, 1983). Then, we tested for interaction effects among pairs of significant variables. Non-significant variables and interactions were removed from the specification. Next, we tested if the regression coefficients differed significantly (Goldstein, 1995) at the topic level. If yes, we kept these additional parameters in the model. Otherwise, we removed them.

Then, we entered variables measuring the property of earlier messages, first lag variables (-2), then lag variables (-3), and lastly, lag variables (-4). For example, the lag variables (-2) were: visits (-2), agree (-2), disagree (-2), contribute (-2), repeat (-2), social cue (-2), and negative social cue (-2). We repeated the above procedure used on lag variables (-1) for lag variables (-2), lag variables (-3) and lag variables (-4).

$$\pi_{ij} = F(\beta_0 + \beta_{xj}\mathbf{X}_{(i-1)j} + \phi_{xj}\mathbf{X}_{(i-2)j} + \gamma_{xj}\mathbf{X}_{(i-3)j} + \eta_{xj}\mathbf{X}_{(i-4)j} + f_{0j})$$

The likelihood ratio test for significance of additional explanatory variables is not reliable for this estimation method, so we used Wald tests (Goldstein, 1995). Only significant variables were retained for subsequent regressions. We used an alpha level of .05 for all statistical tests. Doing many tests on one set of data can yield spurious correlations. To address this issue, we used Hochberg's (1988) variation on Holm's (1979) method.

We used Ljung & Box (1979) Q-statistics to test for serial correlation (up to order 4) in the residuals for all topics. If the residuals are not serially correlated, the parameter estimates are efficient and standard error estimates are likely unbiased (Enders, 1995). Otherwise, we add lagged outcome variables as explanatory variables or model the serial correlation directly (see Goldstein, Healy, & Rasbash, 1994, for details).

We repeated the above procedure for three more outcome variables: contribution (0), social cue (0) and elicitation (+1). These regression results served as an initial candidate for the multilevel structural equation model, which estimates all predictor effects at the same time. Non-significant parameters were removed. To help the reader interpret these results, we converted the total effects of each predictor to odds ratios (Judge, Griffiths, Hill, Lutkepohl, & Lee, 1985).

Results

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. See table 3 for regression results predicting disagreement, contribution, social cue, and elicitation. Aside from the predictors discussed below, all other predictors showed non-significant effects.

Table 3: Significant, unstandardized parameter coefficients of sequential set binary Logit regressions predicting disagreement, contribution, social cue and elicitation (with standard errors in parentheses).

Predictor	Regressions predicting…						
	Disagreement (0)		Contribution (0)		Social cue (0)		Elicitation (+1)
	1	2	1	2	1	2	1
Disagreement (0)							0.924*
							(0.400)

Disagreement (-1)	1.552*** (0.415)	1.383** (0.434)			1.104* (0.439)	0.910* (0.455)	
Contribution (-1)		1.379** (0.472)				1.063* (0.436)	
Visits (-1)			0.448* (0.190)	0.441* (0.195)			
Social cue (-2)				-0.941* (0.470)			
Nagelkerke R^2	0.172	0.267	0.092	0.151	0.083	0.153	0.066

Note: significant constant term is omitted.
*$p < .05$, **$p < .01$, ***$p < .001$*

Predicting disagreement

If the previous message was a disagreement (-1) or a contribution (-1), the current message was more likely to include a disagreement. Disagreement (-1) and contribution (-1) explained about 27% of the disagreement variance at the message level. Disagreement in the previous message explained at most 17% of the disagreement variance in the current message. Contribution in the previous message accounted for about 10%.

Predicting contribution

Visits (-1) and social cue (-2) significantly predicted a contribution in the current message. If the previous message was posted by an e-poster with many visits (visits[-1]), the current message was more likely to have a contribution. Meanwhile, a social cue (-2) ago reduced the likelihood of a contribution in the current message. These two predictors explained about 15% of the contribution variance at the message turn level. Previous e-poster's visits (-1) explained at most 9% of the contribution variance. Social cue (-2) accounted for about 6%.

Predicting social cue

Disagreement (-1) and contribution (-1) in the previous message positively predicted a social cue in the current message. These two predictors explained about 15% of the social cue variance at the message turn level. Disagreement in previous message explained at most 8% of the social cue variance. Contribution in previous message accounted for about 7%.

Predicting elicitation

Fifty-five percent of the messages received responses, while forty-five percent did not. Disagreement and contribution in the current message entered alone into the regression were significant, but together, only disagreement was significant. Disagreement and contribution in a message were significantly correlated (r [131] $= 0.37$, $p < 0.01$). Disagreement in the current message explained at most 7% of the elicitation variance.

Predicting disagreement, social cue and elicitation in an SEM

Based on the above 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 2. The SEM showed a good fit (χ^2 [df = 5, N = 109] = 8.19, incremental fit index (IFI) = 0.97, comparative fit index (CFI) = 0.97, non-normed fit index (NNFI) = 0.95, root mean squared error of approximation (RMSEA) = 0.07, standardized root mean residual [SRMR] = 0.04; for discussion of fit criteria, see Hu & Bentler, 1999). As expected, the SEM effects were consistent with the regression results. Disagreement (-1) and contribution (-1) in previous message had direct positive effects on disagreement and social cue in current message. Disagreement and contribution in a message were also significantly correlated in the model (r [109] = 0.37, $p < 0.05$). Only disagreement in the current message showed a direct effect on elicitation (+1). Disagreement (-1) and contribution (-1) in the previous message affected the current message's elicitation indirectly.
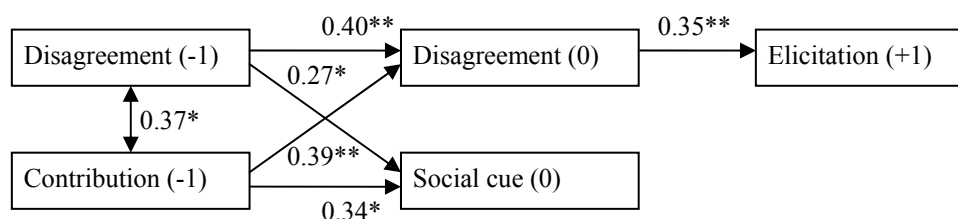

Figure 2. Structural equation model for predictors of disagreement, social cue and elicitation with significant standardized parameter estimates (χ^2 [df = 5, N = 109] = 8.19, p = .146).

Discussion

Previous studies explored *individual* aspects of online discussion messages in course related forums (e.g., Hara et al., 2000; Garrison et al., 2001; Schellens & Valcke, 2005). Extending this line of research, we examined how evaluations, knowledge content, social cues and personal information in earlier messages affected later messages to identify the *relationships* among them and to characterize the flow of the online discussion. Specifically, we examined online discussions in an independent and voluntary academic forum on a university BBS Website. The results showed that disagreement, contribution, social cue, and past visits of an e-poster in earlier messages can affect the properties of a subsequent message. After discussing these results, we consider their implications for improving online discussions.

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. Like Chiu & Khoo's (2003) FTF interaction result, disagreements also occurred more often after contributions, showing that proposing a new idea is more likely to receive a critical response rather than supportive one. Also, the SEM showed that disagreement and contribution in the previous message were significantly correlated when predicting current disagreement. It implies that if an e-poster is about to disagree, he or she often anticipates a disagreement and thus often elaborates with more information. Together, these results are consistent with the claim that online discussion forums can promote critical thinking (Garrison et al., 2000, 2001).

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 Walter'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 suggested that teachers and researchers might use online academic discussion in three ways.

Developing controversial discussions. As participants were likely to engage in and sustain online discussion on topics that involved many disagreements, teachers 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.

Reducing status effects. As 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.

Managing online discussions at message level. In addition to encouraging student to participate, teachers may also manage the online academic discussions for specific purposes at message level. For example, teachers can post anonymous messages containing disagreements and contributions to elicit more student responses.

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