Talk to Me: Foundations for Successful Individual-Group Interactions in Online Communities

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ABSTRACT

People come to online communities seeking information, encouragement, and conversation. When a community responds, participants benefit and become more committed. Yet interactions often fail. In a longitudinal sample of 6,172 messages from 8 Usenet newsgroups, 27% of posts received no response. The information context, posters' prior engagement in the community, and the content of their posts all influenced the likelihood that they received a reply, and, as a result, their willingness to continue active participation. Posters were less likely to get a reply if they were newcomers. Posting on-topic, introducing oneself via autobiographical testimonials, asking questions, using less complex language and other features of the messages, increased replies. Results suggest ways that developers might increase the ability of online communities to support successful individual-group interactions.

Author Keywords

Online communities, community success, contribution, commitment, responsiveness, language, text analysis.

ACM Classification Keywords

H.5.3 Group and Organization Interfaces.

Since the 1970's, when the first Usenet news-sharing programs were created, online communities have co-evolved with computer networking. Three decades later, people share information, jokes, discussion, data, and social support in thousands of online communities across a variety of platforms such as web-based bulletin boards, e-mail distribution lists, and (still) the Usenet. People benefit from the presence and activity of others in online communities—from the information and support they provide and the conversations they participate in. Online communities are particularly well suited for adapting general information for individuals' specific needs. It is through online communities that a cancer patient can get advice relevant to her unique experiences and that a frustrated Windows user is able to learn about a work-around for his specific problem.

PREDICTING SUCCESS OF ONLINE COMMUNITIES

In order to succeed, online communities, like smaller groups, need to meet the needs of individual members and maintain themselves over time. The goal of the present article is to identify conversational, individual, and group level factors that affect two key elements of success. The first is the community's willingness to respond to a member's message, because the responses provide the content through which participants gain benefit from others in the group. The second is members' commitment to the community, which reflects their satisfaction with their experience.

To survive and thrive, online communities must provide the benefits and experiences that members seek [2, 14]. In online groups, conversation is the basic mechanism by which participants derive benefit. Whether they are explicitly soliciting information or assistance or implicitly seeking to direct the group's attention toward topics in which they are interested, individuals who attempt to start conversations are trying to increase the likelihood that the group will provide benefits they value. The community's response, if any, is what satisfies the poster's needs. Thus, community responsiveness to attempts to initiate conversations is an essential element of community success.

The viability of a community also depends on the willingness of individuals to stick with the group over time. A self-interest model of group commitment holds that people remain committed to a group only as long as the group meets their various social, instrumental, and emotional needs better than alternative uses of their time [16]. In discussion-based communities, getting talked to is a basic mechanism for getting benefit. If others fail to respond, the silence calls into question one's reason for commitment. This hypothesis is consistent with research showing that individuals who post for the first time to an online group are more likely to return when others respond to them [11]. Other research has found that receiving a response increases the speed of posting a second time, although not the probability of posting again [15].

Factors Affecting Individual-Community Interaction

Online communities consist of people and the content they exchange. While there are cases of extremely long-lived discussions involving hundreds of people, most online conversations are smaller, shorter and more focused, with a clear initiating message, a small number of participants, a limited duration, and a relatively circumscribed topic. It is through these online conversations, typically presented in threaded form, that many individuals experience an online community.

To increase the benefit that people receive from online communities, and ultimately the viability of the community itself, it is important to understand the factors that affect the interaction through which people experience the community [27]. Unlike most user interfaces through which users engage computers, discussion does not follow a designed formula. What is said (topic), how it is said (style and structure), who says it (author characteristics), and where it is said (group characteristics) all interact to shape the way that an individual's interaction with a community plays out. We begin by considering the context in which interaction occurs (features of the group and individuals who participate) and characteristics of the messages themselves. Using one year of records from a diverse sample of Usenet discussion groups, we apply textual analysis and statistical techniques to evaluate how these factors influence replies and commitment. We finish with a discussion of the implications of these results for designers of tools that support online communities.

Context

When an individual makes the decision to post a message to an online community, he or she does so within an existing context. Features of the group and characteristics of the individual shape both the message written and the type of reply it receives.

Group-Level Factors

Group identity. Groups differ in terms of their topic, their size, and the basis of commitment to them, among other dimensions. The topics grounding the discussion in these groups are likely to affect the behavior of individuals engaged in an online group and their commitment to it. For example, Ridings and Gefen report that friendship is a much stronger motivator for continued participation in hobby and interest groups than in professional groups [28]. The basis of commitment can also vary. Social psychologists have distinguished topic-based (or identity) groups, in which members are attached to the group as a whole and the purposes for which it exists, from bond-based groups, in which members are attached to the group because of their friendships with other members [30]. Bond-based groups were found to have higher member commitment than topic-based groups. For the research reported here, we have selected communities concerned with health, politics and sports. Health groups often tend to be bond-based, while politics groups tend to be topic-based.

Cross-posting. Unlike the case in off-line groups, online participants can easily offer the same conversation to multiple groups simultaneously through cross-posting. While cross-posting affects aspects of group dynamics [33], its impact is not straightforward. Cross-posting a message enhances its visibility, increasing the chance that it will be seen by individuals who are capable of and interested in providing responses. However, a message shared with many other communities is no longer unique to a particular community, possibly reducing the incentive of other members to respond [3]. Without knowing the relative strength of these effects, it is not possible to predict whether cross-posting messages will be positively or negatively associated with the likelihood of receiving a response.

Group size and volume. People tend to be less committed to larger groups and to contribute less to them [12, 23]. In addition to the effects of size per se, the size of a group influences the amount of communication in them. Overall communication volume seems to have paradoxical effects on reading and participation in online communities. On one hand, empirical research has shown that higher communication volume lowers return rates in online groups [2, 10], consistent with the information overload argument. On the other hand, network externality and critical mass theories imply that online groups need a minimum volume of message traffic to draw and retain members [13, 19]. Too many messages, and people may not return to participate; too few, and it will be difficult to maintain the community responsiveness needed for successful interaction.

Individual-Level Factors

Newcomer status. The history of an individual within a community also plays a role in the success of individual-group interactions. Theories of reciprocity suggest that posters with a history of contribution in online communities are more likely to receive responses, because others feel obliged to return the favor [8]. As a result it is expected that newcomers who attempt to start discussions will be less successful than members who have engaged in the community in the past. Similarly, models of group involvement suggest that individuals with a history of participation will be more committed than newcomers, and as such, are more likely to continue contributing to the community in the future [22].

Message Characteristics

Rhetorical strategies

The rhetorical form in which a person frames a contribution is likely to influence how others in the community respond to it. For instance, Galegher and her colleagues [7] have shown that questions and personal histories emphasizing legitimacy were often included in initial posts by newcomers seeking to interact with online support groups. Self-disclosure, often found in these initial posts, should increase other group members' willingness to reply and can increase the poster's commitment to the group by signaling a willingness to develop trust with group members [18, 20]. Additionally, because norms of language encourage interlocutors to respond to a question with an answer [29] and because explicit requests are more likely to receive a response than indirect ones [17], questions are more likely to get a response than other types of speech forms.

Topical coherence. Conversational coherence is likely to be as desirable in the written conversation in online communities as in spoken interaction [9]. Each online community involves a limited set of topics that are related to its goal or purpose, and these conversational topics help establish and maintain the unique identity of the community. Messages that relate to these topics are perceived as being relevant to the group, whereas messages that are 'off-topic' can be treated as undesirable noise that fails to contribute to the group and may even distract other members. Although community names and formal descriptions can indicate a group's topical focus, the discussions are what reveal the interests and knowledge of the community's members. Hence posts that are topically consistent with these discussions are more likely to receive a reply than off-topic posts, because they are likely to appeal to members' interests.

Linguistic Complexity

Information overload arguments [10] imply that individuals will be sensitive to both the length and complexity of messages. Longer messages that use more complex sentences and vocabulary impose a greater cost on readers, reducing the chances that the message will be read or responded to [33].

Word choice

The vocabulary that people use in their conversation is partly constrained by the topics they are discussing. However, the word choice may also reflect their orientation towards the topic. For example, the use of words like "very," "totally," and "undoubtedly" may indicate certainty, while terms like "I think" or "wonder" may indicate uncertainty [24]. Word choice may also reflect attitudes towards the people with whom they are communicating. For example, often personal pronouns show the writer's relationship to an audience. Thus, first person plural pronouns such as "we" and "us" may express solidarity with the group, while use of third-person plural pronouns may differentiate an in group from an out group [25].

Unlike the case with higher-level rhetorical strategies and linguistic complexity, we have no strong hypotheses about the way in which these low-level word choices will influence the likelihood of others responding to a message. We measured these characteristics of messages, though, for exploratory purposes.

DATA AND METHODS

The study described in this paper examines the impact of these classes of factors on individual-group interaction in a sample of Usenet newsgroups. With over 189,000 online public discussion groups involving millions of people discussing topics ranging from technical support to health, Usenet provides a rich environment for studying the dynamics of online communities [31]. While there are now other technologies, such as listservs, web forums, and content management systems, that can support online communities, archive-based, threaded discussion forums remain a key element of many online communities [14]. Thus, while in some arenas Usenet may appear to be "past its prime," it remains a valuable example of a technology and social structure that is central to the operation of most active online groups.

The groups selected for this study were chosen to enhance the generalizability of the results. We selected communities that covered a range of topics and populations. The sample of 8 newsgroups includes 2 health support groups in the alt.support domain concerned with depression and breast cancer, 3 in the alt.politics domain concerned with gun rights, liberalism, and economics, and 3 in the alt.sports domain concerned with the Liverpool Everton soccer club, the Boston Celtics basketball team, and the NY Rangers hockey team. These categories loosely correspond to 3 of the 5 main types of online communities identified by Ridings and Gefen (health/wellness, personal interest, and sports recreation) [28].

Data Collection

Our raw data contained both structural and content data from all eight newsgroups from March 2001 to March 2002. The data included the combination of individual and structural data provided by the Netscan project at Microsoft [32], and the text of the posted messages, which were downloaded from Google Groups website (http://groups.google.com/). The Netscan database provided structural information about groups, authors, and messages, such as the total number of messages posted to a group on a given day, dates of an individual's first and last posts to a group, and the number of replies that a message received. These data were combined with the results of content and language analysis of the message texts (with headers and quoted text removed) to create the measures described below.

Our sample includes records for 6,174 messages. These represent the first message that each participant in one of the sampled newsgroups posted during the study period, if it was itself not a reply to another message. That is, our focal messages all have the potential to start a thread. Approximately three-quarters (72.9%) of these messages received a reply.

Measures

Dependent Variables

Community Responsiveness is measured by a dummy variable GotReply, reflecting whether a focal message received a reply (1) or not (0). Individual commitment is measured by the dummy variable PostAgain. We are interested in the decision of a person who posted an initial message to post again, either attempting to initiate another thread or replying to another person's message. A preliminary analysis of over 200 million threads from the Netscan database shows that fewer than 5% of threads last more than two days, from their first to last message. Therefore, our measure of posting again equals 1 if initial posters posted a message at least three days after their initial message or 0 otherwise.

Independent Variables

Context. Group type is represented as 7 dummy variables for the 8 newsgroups. The breast cancer group was the default group not represented by a dummy in the analyses that follow. The differences in topics and basis for commitment will be reflected in the group dummies.

Group message volume was measured with the variable MessagesToday, which is the total number of messages, both potential thread starters and replies, posted in the newsgroup on the same day as the target message. This measure reflects both the number of people available to reply and the number of other messages competing for readers' attention. Because this variable was highly skewed, a log transformation was applied to normalize the distribution.

IsCrossposted is a dummy variable indicating whether a message is shared with other newsgroups (1) or not (0). Individual status is measured by Newcomer, a dummy variable that is 1 if an individual had never posted to the newsgroup before the start of the study period (March 18, 2001) and 0 if they had posted previously.

Rhetorical strategy. A *testimonial* is an introductory posting to a group that contains most, if not all, of the following features: the first-person pronoun (though sometimes describing the situation of a third party), the age of the poster, the acknowledgment that this message is a first-time post by the individual (e.g., "I've been lurking here for a while" or "let me start by…"), a description of the poster's situation and history ("I was diagnosed in 1994 with BC…."), and a request for advice ("If I do sit-ups every day, say 15 or so, along with some other exercises, how long until my stomach muscles show?").

We used Minorthird [6], a machine learning and text classification toolkit, to classify messages based on their rhetorical purpose. In prior research, Minorthird has been used to identify signature files, quotations [4], and speech acts from email texts [5].

In order to train Minorthird to identify testimonials, we identified features of the messages, illustrated previously, that our reading suggested characterized autobiographical testimonials (e.g., mention of lurking or age). We then used machine learning to classify messages into binary categories. Minorthird provides an array of algorithms for prediction; SVMLearner gave us the best results. A comparison of the machine classification with hand-coded messages for a 10-fold cross-validation on ~200 messages gave recall of 0.89, precision of 0.89, and Kappa of 0.78. IsTestimonial is 1 if Minorthird classified the message as containing a testimonial and 0 otherwise.

A *question* is a request for something from the group. Since not all requests are made in the form of direct questions (i.e., a sentence ending with a question mark), Minorthird was used to identify question messages based on more than just punctuation. Other features include a reversed subject and verb ("Are there any herbal therapies out there that might help."), indirect questions ("I want …," "I'm looking for …," "I was wondering if …"), and references to help and information ("suggestions," "advice," "recommendations"). The dummy variable *IsQuestion* is 1 if the Minorthird analysis indicated a message contained a question.

A comparison of the machine classification with hand-coded messages for a 20-fold cross-validation on ~1000 messages gives recall of 0.70, precision of 0.72, and Kappa of 0.52. IsQuestion is 1 if Minorthird classified the message as containing a question and 0 otherwise.

Topic coherence was measured with average document frequency (the number of messages in the newsgroup in which the content words comprising the focal message appeared one or more times, divided by the number of words in the focal message) and total messages in the newsgroup. As a pre-process, we stemmed the messages [26] and removed functional terms that are poor indicators of content (i.e., *the, this, is, an,* etc.). A high *average document frequency* indicates that the language in the focal message is widely used in the newsgroup. Conversely, a lower value indicates that the language used is not common across rest of the posts. The underlying assumption is that newsgroup members share "a common language."

Linguistic complexity. Message complexity was measured by message line counts, percentage of long words, and average words per sentence. Line Count was the number of lines in the message, after headers and quotes were stripped. Because this variable was highly skewed, we logged the value to normalize the distribution. We also calculated the percentage of words in each message that were six or more characters long. Pennebaker's [24] Linguistic Inquiry and Word Count tool (LIWC) software package was used to calculate this measure. Words per Sentence, the average number of words per sentence, was also calculated

Category	Sample vocabulary
I	I, my, me
We	We, our, us
You	You, you'll, yours
3rd Person Pronouns	She, their, them
Negate	No, never, not
Assent	Yes, OK, yeah, agree
Positive emotion	Happy, pretty, good
Negative emotion	Cry, hate, nervous, enemy
Cognitive mechanisms	Cause, consider, think, know, maybe, always
Friends	Pal, buddy, coworker
Family	Mom, brother, wife, cousin
Sports	Football, game, play
Money	Cash, taxes, finance
Death	Dead, dying, coffin
Physical	Ache, heart, lust, breast, sleep
Swearing	Damn, fuck, piss

Table 1: Samples of Vocabulary Defining LIWC Categories

using LIWC. Because this variable was highly skewed, we logged the value to normalize the distribution.

Word choice. To identify low-level word choices of the message texts we assessed message content using LIWC. LIWC measures the frequency with which words from a hand-classified dictionary occur in a message to assess the extent to which the message includes such features as different types of pronouns; positive and negative affect; reference to cognitive (e.g., insight, certainty), sensory (e.g., seeing, hearing), or social processes (e.g., communication, friends, family); past or future orientation; and discussion of personal concerns (e.g., work, school, and leisure activities). The approximately 2300 words in the LIWC dictionaries account for approximately 80% of the words used in a broad sampling of texts written in American English [24]. Categories were selected from the LIWC dictionaries based on their relevance to the groups of study (Table 1). For the health groups, "I," "you," "them," "friends," "family," "death," and physical states and functions address the concerns of personal relationships, as well as the focus on illness. The political and sports groups were served by "we," "other," "negate," "assent," positive and negative emotions, cognitive mechanisms, money, sports and swear words.

Variable	Total (N = 6,174)		Old-timers (N = 2,423)		Newcomers (N = 3,751)	
	Mean	S.D.	Mean	S. D.	Mean	S. D.
GotReply	.73	.44	.75	.44	.72	.45
PostAgain	.49	.50	.76	.43	.32	.47
Messages today (lg)	5.19	1.18	5.19	1.14	5.20	1.20
IsCrossposted (0/1)	.25	.43	.26	.44	.25	.43
Newcomer (0/1)	.61	.49	.00	.00	1.00	.00
Topical coherence	.03	.02	.03	.02	.03	.02
IsTestimonial (0/1)	.16	.37	.13	.34	.19	.39
IsQuestion (0/1)	.32	.46	.26	.44	.35	.48
Line Count (lg)	1.28	.47	1.30	.48	1.27	.47
% words > 5 letters	21.58	8.75	21.05	8.34	21.93	9.00
Word Per Sentence	1.40	.22	1.41	.23	1.40	.22
I	3.10	3.68	2.72	3.43	3.35	3.81
We	.54	1.08	.56	1.09	.53	1.08
You	.92	1.64	.87	1.63	.96	1.65
3rd Person Pronouns	1.44	1.89	1.56	1.91	1.37	1.87
Negate	1.20	1.42	1.20	1.37	1.21	1.46
Assent	.11	.41	.13	.41	.10	.42
Positive Emotion	2.01	1.84	2.00	1.82	2.01	1.85
Negative Emotion	1.64	1.85	1.53	1.75	1.71	1.91
Cognitive Mechanisms	4.81	3.11	4.72	3.04	4.87	3.16
Friends	.11	.39	.09	.37	.12	.41
Family	.19	.58	.15	.49	.22	.63
Sports	.36	1.05	.38	1.09	.34	1.02
Money	.62	1.30	.60	1.24	.63	1.34
Death	.15	.52	.14	.49	.16	.55
Physical	1.09	1.63	1.05	1.59	1.12	1.65
Swearing	.20	.75	.21	.76	.19	.75

Table 2: Descriptive Statistics for Discussion Initiation Messages

Message size and complexity, rhetorical content, and low level content were also calculated for all of the direct replies that each initiating message received. Measures of reply characteristics were then constructed by averaging these values for every reply the original post received.

ANALYSIS AND RESULTS

Descriptive Analysis

To examine community responsiveness to overtures from individual participants, we constructed a dataset containing measures for the 6,174 posts that had the potential to instantiate a thread (i.e., messages that were not replies to other messages). Of these, 2,423 posts from were old-timers who had posted previously and 3,751 from newcomers. Table 2 shows the means and standard deviations for variables used in the following analyses for the entire data set and for both old-timers and newcomers.

Predicting whether a message gets a reply

To examine the contextual and message factors affecting community responsiveness, our analyses focused on models that predicted the likelihood that a non-reply message posted to a newsgroup would elicit a response (see Table 3 for regression results). Continuous variables have been standardized, but binary variables have not. We used a probit analysis for modeling the binary dependent variable. The coefficients in Table 3 represent the change in probability of getting a reply with a change in the independent variable, when all continuous variables are at their mean level and dummy variables are set to zero (i.e., old-timers, no cross posting, no question, no testimonial). The dummy variables for the specific newsgroup were included in all the models, although they have been omitted from Table 3 for reasons of space. Because messages within a single newsgroup are not independent of each other, we conducted the analysis using the cluster feature in Stata's probit procedure, which adjusts the standard error of the coefficients to account for non-independence of observations.

Contextual factors. Model 1 in Table 3 represents contextual factors—the environment to which a participant posts a message. Although the coefficients representing specific groups are omitted in Table 3, the group identity had a large impact on getting a reply (Pearson $\chi^2(8) = 217.2$, $p<.000$). Overall, 72.9% of the 6,174 messages received a reply, but the probability ranged from a low of 63.6% in the liberalism discussion group to a high of 81.6% in the depression group.

Who the poster was also made a difference. Newcomers were about 4% less likely to get a reply than individuals who had posted to the group in the past.

Unlike research by Jones and his colleagues [10], we found no evidence in this dataset that attention overload associated with high message volume led to messages being ignored. The effect of cross-posting was also weak. Messages posted to multiple groups were 9% more likely to receive replies, but the effect was not statistically significant.

Rhetorical strategy. Model 2 adds variables dealing with rhetorical strategy–asking questions, providing autobiographic testimonials and talking on-topic. The Akaike (AIC) and Bayesian Information Criteria (BIC) assesses whether adding new variables to the model improves explanatory power. A lower number indicates improvement. Since these information criteria penalize models with additional parameters, they balance parsimony with the fit of a model to the data [1].

Over and above the structural features of the environment, the rhetorical content of the initial message had a large impact on whether the community responded to it. Posts that included testimonials or make requests were more likely to get a reply than those that did not. Testimonials are one method of expressing one's legitimacy to the audience of potential responders, by explicitly indicating one's connection to the topic of discussion and to the community. Posts that included testimonials were about 10% more likely to receive a reply than those that did not. Questions, especially explicit ones, invoke linguistic norms that questions are followed by answers. In this dataset, posts containing questions were 6% more likely to receive a reply than those that did not. Being on-topic, a strategy to stay related to the interests of the groups, also increased the likelihood of a reply by about 10%.

Linguistic complexity. Model 3 adds the variables representing linguistic complexity. They improve the model, according to the Akaike and Bayesian Information Criteria. Messages with longer sentences or longer words were less likely to receive replies, suggesting that the potential responders were put-off by the cognitive difficulties that these factors represented. However, inconsistent with research by Jones, Ravid and Rafaeli [10], message size was not associated with a decrease in the likelihood of getting a reply.

Word choice. Model 4 adds the low-level message features of word choice. The addition of these variables improves the model (i.e., reduces both the AIC and BIC information criteria). Sentences containing more first person singular pronouns and third person pronouns got more replies than those that contained fewer of these words. Use of words reflecting mental processes also increased the likelihood of getting a response. Words expressing either positive or negative emotion were also more likely to get a reply.

Because these low-level message features are in part the mechanism through which posters express their rhetorical intent, and in particular because Testimonials are characterized by extensive use of the pronoun "I" ($r=.60$, $p<.001$ and $r=.20$, $p<.001$ respectively), including the word-choice variables reduced the impact of both Testimonials and Questions on the reply rate.

Predicting whether a poster returns

To examine the impact of individual-group interactions on individual commitment, we estimated models predicting whether the initial posters would return to the group to post again. In this analysis, we began with a base model that controlled for the variables listed in Table 3, Model 3, under the assumption that the context and content of the initial post might reflect the poster's existing commitment to the group and likelihood to post again. Across all groups, 49.1% of the individuals in the sample posted at least one additional time after their initial post. Again, the groups varied widely in the rates with which people posted again, ranging from a low of 39.1% in the gun rights group to a high of 63.5% in the group discussing the Boston Celtics.

GotReply	Model 1		Model 2		Model 3		Model 4	
	Context		Rhetoric		Complexity		Word Choice	
	dF/dx	S. E.	dF/dx	S. E.	dF/dx	S. E.	dF/dx	S. E.
Messages today (lg)	.01	.02	.02	.02	.01	.02	.01	.02
IsCrossposted (0/1)	.09	.06	.12*	.05	.13**	.04	.14**	.04
Newcomer (0/1)	-.04*	.02	-.05***	.01	-.04***	.01	-.04***	.01
Topical coherence			.10***	.02	.09***	.01	.07***	.01
IsTestimonial (0/1)			.10***	.02	.07**	.03	.04*	.02
IsQuestion (0/1)			.06***	.01	.06***	.01	.05***	.01
Line Count (lg)					-.01	.02	-.02	.01
% words > 5 letters					-.03*	.02	-.01	.02
Word Per Sentence					-.02***	.00	-.02***	.00
I							.03**	.01
We							.00	.01
You							-.01	.01
3rd Person Pronouns							.04***	.01
Negate							.01	.01
Assent							.01	.00
Positive Emotion							-.01*	.01
Negative Emotion							.03**	.01
Cognitive Mechanisms							.02**	.01
Friends							.00	.00
Family							.00	.00
Sports							-.01	.01
Money							.01	.01
Death							.01	.00
Physical							-.01	.00
Swearing							-.01	.01
Fit Statistics (smaller is better)								
AIC	6957.0		6756.1		6720.2		6572.7	
BIC	6977.2		6796.4		6767.3		6619.8	

Note: Dummy variables representing the newsgroup were included in the model, but not shown for reasons of space.

N= 6172; * p<.05, ** p<.01, *** p<.001

Table 3: Predicting and Getting Reply to an Initial Post

Newcomers were much less likely to post again than old-timers. Only 27.8% of newcomers posted again, compared to 72.2% of old timers. According to a comparison of BIC statistics, no other features of the context or messages predicted posting again (BIC = 7298 for a model including only the dummy variables for newcomer status and newsgroup identity versus a BIC = 7324 for one including all the other context and message characteristics listed in Model 4 of Table 3.)

Adding the variable *GotReply*, whether anyone in the community replied to the initial post, improves the model (i.e., BIC declines from 7324 to 7309). Independent of the context and content of the initial post, receiving a reply increased the probability of posting again in the group by about 6% (dF/dx= .062, se= .024, p<.02).

Once the context and content of the initiating message was taken into account, the topic, rhetorical purpose, and language of the reply had modest effects on the likelihood of posting again. Adding features of the reply to the base model decreased both the AIC and BIC information criteria, indicating a better fitting model. As previously noted, getting a reply increased posters' probability of posting again by about 6.2% Replies from people who were themselves newcomers and replies comprised of longer sentences depressed the influence of getting a reply, and therefore decreased the likelihood of posting again among those who received a reply by 1.8% and 4.9%, respectively. In contrast, replies containing many words expressing positive emotion increased the likelihood of posting again by about 1.7%.

DISCUSSION

This study identified factors at the group, individual and message levels that impact community responsiveness and individual commitment. The results suggested that context, content, and source of a message all play important roles in determining whether a message will successfully initiate conversation, and that getting a response influences whether a new poster will reappear in the group.

Limitations and Directions for Future Work

Although the analysis is based on a diverse sample of groups, its limited size and focus place bounds on the generalizability of the results. These communities are relatively active in terms of message volume, and relatively large in terms of number of participants. Small groups and those with less activity may face different challenges with respect to responsiveness and commitment. Also, while the sample includes a variety of groups (health, sports, politics), there are other group types (technical support, professional) not considered here. These communities may work differently. Finally, we examined only one type of technology infrastructure, Usenet newsgroups. It could be that other technologies result in different response patterns. Further research can better understand the role of specific technologies in shaping responsiveness and commitment by studying groups that use technologies such as listservs, web forums, or blogs.

Another limitation of this work relates to the tools that were used to characterize the language and rhetorical feature of the messages. The topical coherence and low-level text features were both assessed using methods that rely on relatively primitive "bag of words" approaches to language understanding. These tools assume that the meaning and function of text arises simply from the sum of its words, independent of how those words are syntactically or semantically organized. For example, the topic coherence variable measures the similarity of a message to others in the newsgroup only at the level of lexical choice; a message is similar to others in the newsgroup if content words in it appear in a large number of other messages in the newsgroup. The LIWC measures similarly attempt to assess concepts with psychological meaning by calculating percentages of words in a message that come from dictionaries representing that concept. While it can provide some indication of the function or meaning, the bag of word approach ignores syntax and many other subtle features of a document. While they are themselves not without limitation, the machine learning approaches used in this study to identify testimonials and questions incorporate aspects of the text overlooked by the more primitive tools. Not only do they suggest alternative strategies for analyzing language, they are also a possible basis for providing recommendations for individuals seeking to engage a community based on higher level rhetorical features. Thus, after analyzing a message which is unlikely to receive a reply, a computational agent might recommend to the author that the message be revised to tell an autobiographical story (i.e., a testimonial) or make a more explicit request.

Other factors may contribute to the likelihood of getting responses and individual commitment. This study examined a limited set of factors of interest. However, future research can examine other factors at either group, individual or message level. Millen and Patterson [21], for instance, suggested that channeling mechanisms and notification services enhanced online community participation. Individuals' prior technology experience and time use habits increased participation. Also, topics differed in their potential in generating discussions.

Finally, while we think it is plausible that the relationships we have identified in this paper between messages and the likelihood of getting a reply and between getting a reply and posting again are causal ones, which can be the basis of interventions to improve the success of online groups, our data are correlational and therefore do not necessarily prove causal relationships.

Because we know the temporal ordering of the conversational events, we can rule out some threats to causal inference often characteristic of correlational data. In particular, because the posters' construction of the messages precedes others' decision to reply to them or not, we can rule out the possibility that getting a reply caused posters to construct particular types of messages. Similarly, because the presence of a reply precedes the decision to post again, we can rule out the possibility that the likelihood of posting again caused the community to respond to an initial post in a particular way. However, we cannot rule out the possibility that the relationships between messages and the likelihood of getting a reply and between getting a reply and posting again are artifacts, conditions on the existence of some unmeasured additional variables that cause both the independent variables and outcomes. For example, it is possible that some unmeasured features of the group, post or messages are correlated with the messages-level variables in Table 3 and directly influence the likelihood of a message getting a reply.

Implications

Engaging a community is difficult. What you say, how you say it, who you are, and where you are all affect the likelihood of successfully interacting with an online community. Infrastructures designed to support the formation of viable communities that are usable by a wide audience must help individuals engage communities in a way that is likely to prompt beneficial responses and build commitment.

The context matters. Different groups have evolved different interaction patterns, including the likelihood of response to individual messages. Among the groups considered in the current research, participants in the two health groups were more willing to respond to others' initial posts than participants in other groups (dF/dx=8.5%, z=2.41, p=.01). Compared to participants in the other groups, they were especially responsive to newcomers (for the interaction, dF/dx=6.0%, z=4.43, p<.001). However, the small number of health groups examined in this research makes us hesitant to give much credence to this result until we replicate it. Other research has found large group differences in the likelihood of responding to newcomers. For example, as part of his Netscan project, Marc Smith has noted that technical support groups are more responsive to newcomers than many other types of groups.

Newcomers were responded to less often than old-timers. Either familiarity and reputation effects or learning effects might account for this difference. Because mere repeated exposure causes people to like others more [34], old-timers' prior posts may have increased familiarity, leading other members of the community to like them and be willing to respond to them.

In addition, by participating in the group in the past, old-timers may have learned how to form their messages so that they are more likely to elicit responses from others. However, two pieces of evidence are inconsistent with this hypothesis. First, in the current study, newcomers rather than old-timers were more likely to include in their messages features associated with getting a reply, including testimonials, questions, and first-person pronouns, for example. Secondly, in related work, Lampe and Johnson found no evidence that participants who had lurked in an online community longer before posting their first messages, and thereby had more time to learn the community's standards, were able to elicit replies better than people who posted during their first visit [15].

Characteristics of messages mattered for community responsiveness. Rhetorical features of the message - ones that are linked to a poster's communicative intent - influence whether it gets a reply. Posts that included testimonials or requests were more likely to receive a reply. Including self-references ("I"), third-person pronouns, describing cognitive states and process, and expressing either positive or negative emotions all increased the likelihood that a message received a response. The topical coherence of a message with respect to other recent discussions in the community also affected the likelihood of getting a reply. Some online communities use moderators to ensure that messages are on-topic [9]. By themselves these results suggest that assisting individuals with message construction, whether through examples, guidelines, or automated feedback, could help improve their experience within an online community. When combined with the finding that receiving a response significantly increases commitment, these results suggest that helping users engage the community successfully will also serve to strength the community itself.

Because most newcomers are most likely to visit an online community once and then disappear, community developers should pay special attention to ensuring that newcomers who attempt to engage the group receive responses. These methods can be managerial (e.g., greeters to welcome first-time posters; [14]) or technological. Computational agents might identify initiating posts from newcomers and intervene if others are not responding within a reasonable time frame. For example, if a newcomer tells her testimonial story in a cancer support group and then asks a question, but no one responds, the agent might forward the initial post to someone else in the group it observed who had previously answered questions and posted on similar topics. Alternatively, the agent might recognize that the testimonial did not include an explicit request and provide the first-time poster with a sample of initial posts containing this feature that have worked in the past.

CONCLUSION

In this study we examined factors at several levels of analysis that affect online community success by shaping its ability to respond to and retaining active participants. Our results suggest that efforts to develop technology to support the formation of viable and effective online communities can do more than simply provide access to an infrastructure that allows for sharing and structuring ongoing group discussion. Tools can be developed to help members use appropriate rhetorical strategies, at the right time, and in the right place to effectively benefit from and contribute to online communities - and in doing so, to improve both the experience for the individual and the success of the community as a whole.

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