To Stay or Leave? The Relationship of Emotional and Informational Support to Commitment in Online Health Support Groups

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ABSTRACT

Today many people with serious diseases use online support groups to seek social support. For these groups to be sustained and effective, member retention and commitment is important. Our study examined how different types and amounts of social support in an online cancer support group are associated with participants' length of membership. We first built machine learning models to automatically identify the extent to which messages contained emotional and informational support. Agreement with human judges was high ($r > 0.76$). We then used these models to measure the support exchanged in 1.5 million messages. Finally, we applied quantitative event history analysis to assess how exposure to emotional and informational support predicted group members' length of subsequent participation. The results demonstrated that the more emotional support members were exposed to, the lower the risk of dropout. In contrast, informational support did not have the same strong effects on commitment. We speculate that emotional support enhanced members' relationships with one another or the group as a whole, whereas informational support satisfied members' short-term information needs.

Author Keywords

Commitment, Online communities, Social support, Natural language analysis, Applied machine learning.

ACM Classification Keywords

H5.3. Information Interfaces and Presentation: Group and Organization Interfaces: Asynchronous interaction, Computer-supported cooperative work, Evaluation/methodology, Web-based interaction.

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INTRODUCTION

A large number of American Internet users participate in online health support groups to obtain informational and/or emotional support [8, 9]. A large fraction of these online support groups deal with cancer [11].

Although online support groups are popular, the scientific jury is out regarding their effectiveness in helping participants deal with health problems [20]. It is highly likely that the effectiveness of such groups depends on the communications that members exchange with one another, but surprisingly little systematic research has been devoted to specifying how the quality and quantity of such communications affect groups' outcomes and members' health-related outcomes (see [16, 25, 28] for exceptions).

This paper focuses on member retention and commitment, which are important to individual members and to the maintenance and success of the group as a whole. People who stay in an online support group longer are more likely to receive whatever benefits it provides. Moreover, members are resources in online groups. They share information, provide help, and form social ties with others. Over time, they shift from receiving support to providing it to others [27]. Continued participation, however, cannot be taken for granted. Evidence obtained in a wide variety of online groups indicates that a substantial number of participants drop out before they could plausibly contribute any benefits to the groups or receive many themselves. Thus, in order to understand the effectiveness of online support groups, a critical first step is to understand the factors that influence members' decisions to remain in them.

Maintaining membership in an online (or offline) group is a fundamental component of commitment to that group [2, 4 15]. In their model of group socialization, Levine and Moreland analyzed the antecedents and consequences of individuals' commitment to groups [e.g., 22, 24]. According to their group socialization model, members engage in an evaluation process to determine how well the group can satisfy their needs. In so doing, they consider how rewarding the group has been in the past and predict how rewarding it is likely to be in the future. The outcome of this evaluation process determines members' commitment to the group, which in turn affects the likelihood that they will remain in it and expend effort to achieve collective goals.

The specific rewards that determine commitment vary across groups and are heavily influenced by the functions that groups serve for their members. Since people join health support groups in order to cope with medical problems and the stresses surrounding their illness, the amount and type of social support they receive (as manifested in the communications they receive) are likely to function as important rewards. If so, we would expect receipt of social support to influence members' commitment to groups, as indexed by the length of time they remain in those groups.

Social Support

Of the categories of social support others have identified [10], two have received the most theoretical and empirical attention – emotional support and informational support.

Receiving emotional support. Participants in online support groups can receive emotional support either directly, through messages of caring and concern, or indirectly, through comparisons with others who have had similar experiences [3]. Cancer patients often claim that emotional support is the most helpful type of support they receive [12] and the type of support they actively seek [13]. Research suggests that peer discussion focusing on emotional support enhances cancer patients' psychological adjustment [18, 20].

Receiving informational support. Participants in online support groups also exchange informational support about the course of their disease, treatments, side effects, communication with physicians, and financial problems and other burdens. Research suggests that information available in cancer support groups is an important factor leading to improvements in psychological well-being [19].

Research Question

Our major research question is how exposure to emotional and informational support in online cancer support groups is associated with members' continued participation in these groups. The literature on commitment to groups discussed above suggests that either type of support will increase commitment, because participants are likely to consider them important benefits of participation, even though research in offline groups suggests informational that support may be more valuable, especially for women with breast cancer [19].

RESEARCH SITE AND DATA

The study reported in this paper examines the impact of social support on continued participation in the breast cancer discussion boards[1] operated by Breastcancer.org, "a nonprofit organization dedicated to providing the most reliable, complete, and up-to-date information about breast cancer." This organization also provides a variety of communication platforms, including discussion boards and chat rooms for patients, family members, and caregivers, to exchange support. The discussion board platform is one of the most popular and active online breast cancer support groups on the Internet. It contains more than 90,000 registered members and 66 forums organized by such criteria as disease stage (e.g., Metastatic Breast Cancer), treatment (e.g., Hormonal Therapy), demographic characteristics (e.g., Women 40-60ish), and problems in living (e.g., Breast Reconstruction). In the forums, members ask questions, share their stories, and read posts from others about how to deal with their disease. This discussion board platform is a rich environment for studying the dynamics of online support groups.

We collected all the public posts, users, and their profiles on the discussion board platform from Breastcancer.org from October 2001 to January 2011. During this period there were a total of 90,242 unique users who posted 1,562,459 messages belonging to 68,158 discussion threads. The median length of a discussion thread was 6 messages (mean=23). Figure 1 depicts the distribution of the number of posts per thread. The median lifespan of a thread, from the first thread starting message to the last, was 3 days (mean=33). The distribution of lifespan of threads is shown in Figure 2. Fifty percent of thread-starting messages received a response within 24 hours, but 11% never received any response.

Sixty percent of registered members never logged in after registering. Members posted a median of zero messages and a mean of 24 messages in the forums (Figure 3). Thirteen percent of members filled in a personal profile providing additional information about themselves and their disease (e.g., age, occupation, cancer stage, diagnosis date).

Our goal in this paper was to investigate the association between the amount and type of social support exchanged in the forums and members' continued participation. Our analysis consisted of two parts. First we trained and validated machine learning models to measure the amount of emotional and informational support contained in each of the 1.5 million messages exchanged in the forums. We then used survival analysis [30] to examine how the emotional and informational support that members were exposed to in a particular week predicted their continued participation in the group.

PREDICTING SOCIAL SUPPORT

Most previous research on communication in support groups is based on hand-coding relatively small samples of messages [7, 17, 23, 28, 29]. Even Meier and colleagues' relatively ambitious effort only coded emotional and informational support in about 3,000 online messages [23]. These techniques are impractical for the 1.5 million posts in our data. Previous research has shown that it is possible to

[1] http://community.breastcancer.org/

partially automate some text analysis of conversations in online support groups, but correlations with human judgments were modest [1].

To overcome these methodological challenges, we built machine learning models to automatically identify the extent to which messages exchanged in the breast cancer discussion forums contained emotional or informational support. Machine learning algorithms use statistical procedures analogous to multiple regression to map a set of input features to a set of output categories or numerical values. In our data, the input features include linguistic information from the messages, such as the message length, presence of words from general and domain-specific dictionaries, and higher-level linguistic features such as the presence of questions or advice. The output is a numerical value representing the amount of emotional or informational support the message contained.

Building and validating the machine learning models involved three steps, which we describe in more detail below. First, human judges hand-coded the extent of emotional and informational support in a sample of 1,000 messages. Their judgments represent the "ground truth" or "gold standard" to which to compare the machine learning estimates. Second, we represented the messages as a set of linguistic features as input to the machine learning algorithms. Finally, we constructed the statistical models from part of the handed-coded data, by applying machine learning algorithms, and then evaluated the accuracy of the models on a hold-out sample of data.

Creating the Human-Coded Dataset

In order to construct a hand-coded dataset for training machine learning models, we randomly selected 1,000 messages from the breast cancer data and employed Amazon Mechanical Turk (MTurk) workers to rate each message in terms of the amount of emotional and informational support it contained.

Amazon Mechanical Turk [2] is an online marketplace for crowdsourcing. It allows requesters to post jobs and workers to choose jobs they would like to perform. Jobs are defined and paid in units of so-called Human Intelligence Tasks (HITs). Snow et al. [31] have shown that the combined judgments of a small number (about 5) of naïve annotators on MTurk lead to ratings of texts that are very similar to those of experts for content such as the emotions expressed, the relative timing of events referred to in the text, word similarity, word sense disambiguation, and linguistic entailment or implication. As we show below, MTurk workers' judgments of social support are also similar to those of highly trained, expert coders.

[2] https://www.mturk.com/mturk/welcome

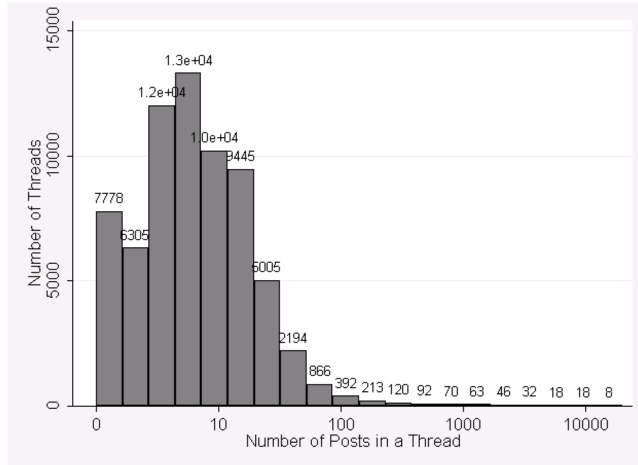

Figure 1. Distribution of Number of Posts per Thread

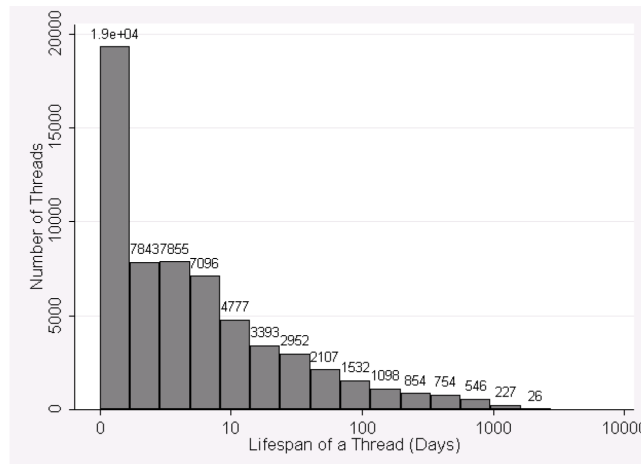

Figure 2. Distribution of Lifespan of Threads

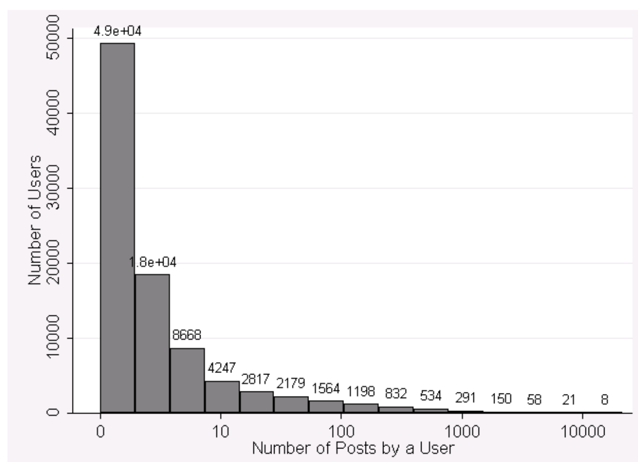

Figure 3. Distribution of Number of Posts per User

Emotional and Informational Support Annotation

The workers were given brief definitions of two kinds of social support, taken from [3]:

- ***Emotional support messages*** *provide understanding, encouragement, affirmation, sympathy, or caring.*
- ***Informational support messages*** *provide advice, referrals or knowledge.*

They were then shown a message and asked: "How much emotional support does this message provide?" and "How much informational support does this message provide?" The workers answered the two questions using a 7-point Likert scale, where 1 meant "none" and 7 meant "a great deal". To encourage workers to take the numeric rating task seriously, we also asked them to highlight words and phrases in the message that provided evidence for their ratings. To further control the annotation quality, we required that all workers have a United States location and have 98% or more of their previous submissions accepted. Ten workers rated each message, with different sets of workers rating each message. Altogether 298 workers participated in the ratings, and a subset of 29 workers completed 80% of all ratings. We paid $0.05 for rating each message.

We aggregated the 10 workers' responses for each message by averaging their ratings. Thus, each message has an average numerical score between 1 and 7 that indicates the amount of emotional and informational support it contains. Following are two examples from our final hand-coded dataset, one providing high emotional support and one providing high informational support. The example messages are lightly disguised using the techniques suggested by Bruckman [6].

- Eg. 1: emotional support=5.7; informational support=1.0

  Julie- you have had such a difficult road, but yet you still manage to do well in school.....I am truly inspired by you. Big cyber hugs and best wishes to you :>

- Eg. 2: emotional support=1.2; informational support=4.5

  Extranodal extension occurs when the tumor extends through the wall of the lymph node. This is noted on pathology reports, but in the main it isn't very significant, and isn't used in assessing cancer stage.

To assess the reliability of workers' ratings, we calculated the intra-class correlation coefficients for the two types of support [21]. Intra-class correlation is appropriate to assess the consistency of quantitative measurements when all objects are not rated by the same judges. The intra-class correlations representing the reliability of the average emotional support rating and the average informational support were high (both = .92).

To assess the validity of their ratings, we also had the workers code 25 messages from the ACOR sample [23] and 25 messages from the Bambina sample [3], which had been previously coded by experts. The correlation of MTurkers' average ratings and the experts' average ratings was moderate for both emotional support (r=.70) and informational support (r=.76).

LIWC Features
Pronoun: i, we, you, she/he, they, impersonal pronoun
Tense: auxiliary verb, past, present, future
Sentiment: positive emotion, negative emotion (anxiety, anger, sadness)
Topic: cognitive mechanism, biological processes, time, religion, death
Linguistic Features
Length: sentence count, word count per sentence
Sentence type: negation, question
Part-of-speech: proper nouns, adjectives, cardinal numbers
Sentiment: strong subjectivity, weak subjectivity
Advice: advice verb, <please+VERB>, <if+you>, <you+MODAL>
Other: drug
LDA Topical Features
Pre-diagnosis, Treatment plan, Forum communication, Adjusting to diagnosis, Financial concerns, Lymphedema, Diet, Family and friends, Positive life events, Surgery, Thoughts and feelings, Chemo radiation, Family history, Emotional reaction, Tumor treatment, Spiritual, Emotional support, Routine and schedule, Hairloss and appearance, Post-surgery problems

Table 1. Summary of the Three Kinds of Textual Features

Feature Set

Writers tend to adopt different language strategies when expressing different types of social support in their messages. To capture these strategies, we identified and used three types of textual features in the machine learning models. The first type was a set of generic dictionaries developed by Pennebaker and his colleagues [26] in the Linguistic Inquiry and Word Count program (LIWC), which measures function words (especially various types of pronouns) and topics with psychological relevance (e.g., positive emotion words, negative emotion words, cognition words). Second, we included rule-based structural features of the messages, mainly based on parts of speech, to capture higher-order linguistic concepts such as the presence of questions. Finally, we created specialized, cancer-related dictionaries using Latent Dirichlet Allocation (LDA) topic modeling. We describe each set of features below, summarize the important ones in Table 1, and provide a complete list in the online appendix[3].

LIWC Features: The Linguistic Inquiry and Word Count program (LIWC) is a popular tool which calculates the frequency with which words in a text match each of 68 dictionaries representing linguistic dimensions (e.g., pronouns, tense), psychological constructs (e.g., positive

[3] http://www.cs.cmu.edu/~yichiaw/Data/CSCW2012/CSCW2012-FeatureSet.htm

emotion), and personal concerns (e.g., leisure, death) [26]. Alpers and his colleagues analyzed several hundred posts in an online breast cancer support group using a human rater and LIWC. They demonstrated a moderate correlation between the ratings assigned by the rater and LIWC scores [1]. Motivated by their work, we included LIWC scores in our machine learning models and considered them as the baseline features. LIWC dictionaries were selected based on their relevance to emotional and informational support (Table 1). For example, for emotional support, *we* (e.g., “we,” “us,” “ours”) addresses the feeling of companionship, whereas *positive emotion* (e.g., “love”) and *religion* (e.g., “pray”) express encouragement. For informational support, *impersonal pronoun* (e.g., “it”) and *present tense* are often used to describe objective facts.

Linguistic Features: *Sentence count* and *word count per sentence* are features designed to represent the length and complexity of messages. The *negation* feature is the number of sentences in a message containing negation words or phrases, such as “not”, “shouldn't”, or “did not.” The *question* feature counts the number of question sentences. Since not all questions are asked directly and end with a question mark, we applied heuristic rules to detect question sentences, including sentences starting with a modal verb (e.g., “Does anyone know …”) and indirect questions (e.g., “I am wondering if …”). Because some parts-of-speech (POS) can signal information or emotion, we counted the number of these specific part-of-speech tags. For instance, professional labels can be signaled as *proper nouns* (e.g., “Dr. Smith”), and emotional states may be signaled by *adjectives* (e.g., “happy” life). We applied the Stanford POS tagger [32] to assign POS tags for words and extracted relevant POS features. Sentiment features describe the subjectivity of a text segment. We counted the number of *strong-subjectivity words* (e.g., “reject”, “nervous”) and *weak-subjectivity words* (e.g., “idea”, “suggest”) for every message. These two features were derived from the subjectivity lexicon of OpinionFinder [33]. To identify sentences involving advice or requests, we identified several text patterns or verbs in messages. For instance, the *<you+MODAL>* is a pattern that counts the number of sentences that start with a pronoun *you* and are immediately followed by a modal verb expressing possibilities (e.g., “should”, “might”, “must”). *<please+VERB>* is a pattern which detects sentences that begin with the word *please* followed by a verb. Furthermore, the *advice verb* feature considers the occurrence of verbs like “make”, “suggest”, “wish”, etc. Finally, the number of *drug* terms in each message was counted. An exhaustive list of medicine names was collected from the Food and Drug Administration website[4].

LDA Topical Features: The features just described are generic, not tailored to the content of cancer support.

LDA Topic	Sample Vocabulary
Pre-diagnosis	Told, appointment, wait, back
Treatment plan	Clinical, risk, medicine, therapy
Forum communication	Post, read, help, thread
Adjusting to diagnosis	Understand, trying, experience
Financial concerns	Insurance, plan, company, pay
Lymphedema	Arm, pain, swelling, fluid, area
Diet	Eat, weight, food, exercise, body
Family/Friends	Daughter, sister, wife
Positive life events	Love, nice, happy, enjoy, fun
Surgery	breast, surgeon, mastectomy
Thoughts/Feelings	Think, remember, believe
Chemo radiation	Chemo, radiation, treatment
Family history	Mom, children, age, young
Emotional reaction	Better, lucky, scared
Tumor treatment	Biopsy, nodes, positive, report
Spiritual	Love, god, prayer, bless, peace
Emotional support	Hope, hug, glad, sorry, best, luck
Routine/Schedule	Today, night, sleep, work
Hairloss/Appearance	Hair, wig, grow, head
Post-surgery problems	Pain, blood, tamoxifen, symptom

Table 2. Samples of Vocabulary in LDA Topic Dictionaries

Research on analyzing the text in support groups suggests that different topics can signal different types of social support [7]. For example, when messages use surgery-related terms, such as “reconstruction”, “skin”, “surgeon”, they are likely to provide information to others. Latent Dirichlet Allocation (LDA) is a statistical generative model that can be used to discover hidden topics in documents as well as the words associated with each topic [5]. We first trained a LDA model using 30,000 breast cancer messages randomly selected from the entire dataset. The model was set to derive 20 latent topics. For each topic, we chose the 500 words most likely to correspond to that topic and used them to build a topic dictionary. Two experts familiar with cancer manually assigned a label to each topic (Table 2). Examples of topics derived from the LDA analysis include *Emotional Support* (e.g., “hope”, “hug”, “glad”), *Post Surgery Problems* (e.g., “pain”, “blood”, “tamoxifen”) and *Spiritual* (e.g., “love”, “god”, “prayer”). Table 2 shows the sample vocabulary for each LDA topic dictionary. Each LDA topical feature calculates the frequency of words in a message matching its corresponding dictionary.

Construction and Performance of ML Models

Our task is a machine learning regression problem. Given the input feature representation of a message, we built two machine learning regressors, one of which outputs a numerical value indicating the amount of emotional support in the message, whereas the other outputs the amount of informational support. We used Weka [34], a machine

[4] http://www.fda.gov/Drugs/

learning toolkit, to build the regression models. The 1,000 messages coded by MTurk workers were randomly partitioned into training (80%), development (10%), and test (10%) sets. The training set was used to build the models. The development set was used to evaluate the accuracy of different configurations of the models and variations in the features used. Once the models achieved good performance on the development data, we used the test set to evaluate how well the final regressors performed. We evaluated the predictions using the Pearson correlation between the human-coded ratings and predicted amounts of support for the 100 messages in the test sample. Table 3 shows the evaluation results and the twenty most important features of the emotional and informational support models.

Given the adequate validity of these two models (as indicated by the correlations of .76 and .80 for emotion and information, respectively), we then applied them to measure the emotional and informational support contained in the 1.5 million messages in the Breastcancer.org dataset.

Support	Emotion	Information
Correlation	0.76	0.80
Most Important Features (Regression Weight)	***sentence count* (.59)** ***emotional support* (.45)** ***we* (.42)** ***you* (.40)** ***she/he* (-.37)** ***spiritual* (.28)** ***<if+you> (-.26)*** ***positive life events (-.26)*** ***adjusting to diagnosis (.24)*** ***time (-.24)*** ***word count per sentence (.21)*** ***strong subjectivity (.20)*** ***positive emotion (.19)*** ***present tense (-.19)*** ***drug (-.19)*** ***emotional reaction (.18)*** ***anger (.18)*** ***financial concerns (-.18)*** ***treatment plan (-.17)*** ***religion (.14)***	***sentence count (.89)*** ***word count per sentence (.41)*** ***strong subjectivity (-.24)*** ***<if+you> (.23)*** ***i (-.22)*** ***spiritual (-.21)*** ***we (-.20)*** ***post surgery problems (.20)*** ***forum communication (-.17)*** ***religion (-.16)*** ***anxiety (-.16)*** ***<please+VERB> (-.16)*** ***thoughts and feelings (-.15)*** ***treatment plan (.15)*** ***death (-.15)*** ***anger (-.15)*** ***impersonal pronoun (-.15)*** ***diet (.14)*** ***past tense (.14)***

Table 3. Performance of Social Support Regressors and Top Ranked Features

PREDICTING COMMITMENT TO THE GROUP FROM SUPPORT

We applied survival analysis to test the hypothesis that people who were exposed to more support remain in the forums longer, controlling for the non-support communication they receive. Survival analysis is a statistical technique for investigating influences on time-related outcomes, such as whether an event occurs or when it occurs. In the present research, the event of interest is the time until a member leaves the group (or conversely, the length of time the person continues participating in the group). More specifically, our goal is to understand whether the amounts of emotional or informational support that an individual is exposed to in an online support group can predict that person's length of participation. We use survival analysis because standard regression procedures produce biased estimates. They do not take into account the truncated nature of time-to-event data (i.e., at the time of data collection, some people who will eventually leave the group have not yet left). Because, in many online groups, the probability of leaving is much higher early in members' tenure in the group than later on, we used parametric regression survival analysis to examine influences on length of participation. We assumed a Weibull distribution of survival times, which is generally appropriate for modeling survival.

Data and Methods

The breastcancer.org data does not contain information about which messages people read, but only those they posted. To estimate the amount of support people were exposed to, we assumed that they read all of the messages in the threads to which they posted in the week they posted. This assumption probably underestimates the support individuals received, because they could glean information or compare themselves with others by reading messages without posting. Therefore, our analyses are likely to underestimate the importance of the relationship between social support and people's participation length in the group.

To conduct the analysis, we included only the 30,301 group members who contributed one or more posts, because without overt behavior it is impossible to estimate the amount of support that they viewed. We defined the time intervals as weeks. We considered the timestamp of the first post by each member as her starting date for participating in the breast cancer discussion forums and the date of the last login as the end of participation unless it was within three months before the end of data collection.

Dependent variable

- **Failure:** We consider a user to have left the group if she failed to post within 12 weeks of her last post. According to this definition, a user can drop out from the group and rejoin it multiple times. Because people whose last post was within 12 weeks of end of data collection could still be participating, we treated them as right censored in the analysis. The conclusions we report below are the same if we assume that people leave the group only once.

Control variables

- **HasProfile:** This is a binary measure that describes whether a user had created a profile page (1) or not (0). 31% of the 30,301 subjects had done so.
- **ThreadStarter:** Because people who start conversations may be different from those who participate in conversations started by others, we calculated the percentage of an individual's posts that were thread

starters. This is the number of thread starters a user posted in a week divided by the total post number for that user in that week.

Independent variables

- **PostCountByUser:** This is the number of messages a member posts in the forums in a week.
- **PostCountExposure:** We calculated the total number of posts a user was exposed to by assuming that people read all the messages posted in a thread during weeks when they also posted to the threat. This variable is the count of all posts in the threads in a week in which the user had posted. Since PostCountExposure is inferred from PostCountByUser, they are highly correlated (r=.67). In order to avoid multicollinearity problems, we only included PostCountExposure in the final models.
- **Emotional Support Exposure (EmoSupportExp):** This variable measures the average emotional support per message a user was exposed to in a week. It was calculated by summing all the emotional support in the threads in a week where the user had posted, dividing by the total post number that the user was exposed to in that week.
- **Informational Support Exposure (InfoSupportExp):** This variable measures the average informational support per message a user was exposed to in a week. It was calculated by summing all the informational support in the threads in a week where the user had a post, divided by the total post number that the user was exposed to in that week.

Except for the binary variable HasProfile, all the numerical control and independent variables were standardized, with a mean of zero and standard deviation of one. Table 4 reports the descriptive statistics for the variables entered into the survival regression models before standardization (except PostCountByUser, which, as noted above, was not included in the models).

Who Stays in Groups?

Results of three survival models are shown in Table 5. Effects are reported in terms of the hazard ratio (HR), which is the effect of an explanatory variable on the risk or probability of participants' leaving the group. Because all the explanatory variables except HasProfile have been standardized, the hazard rate here is the predicted change in the probability of dropout from the group for a unit increase in the predictor (i.e., HasProfile changing from zero to one or the continuous variable increasing by a standard deviation when all the other variables are at their mean levels).

	Mean	Median	Std. Dev.	Min	Max
HasProfile	.31	0	.46	0	1
ThreadStarter	.10	0	.27	0	1
PostCntByUser	5.91	2	15.39	1	923
PostCntExp	78.96	25	151.04	0	3790
EmoSupportExp	2.77	2.73	0.65	1	7
InfoSupportExp	2.87	2.91	0.69	1	7

Table 4. Descriptive Statistics for the Variables in the Survival Analysis

Model 1 reports the effects of the control variables and participants' overall exposure to messages. The hazard ratio value for HasProfile means that members' survival in the group is 54% (100% - (100% * 0.46)) higher for those who have entered profile information compared to those who have no profile. Similarly, the hazard ratio for PostCountExposure indicates that survival rates are 39% higher for those who saw a standard deviation more messages than average. Starting a thread in a week has no additional effect.

Model 2 shows that when controlling for characteristics of these members and the total messages they were exposed to, both emotional support and informational support influenced the survival rates, but in different directions. Those who were exposed to messages containing an average of one standard deviation more emotional support (EmoSupportExp) were 16% more likely to *remain* in the group. In contrast, those who were exposed to messages containing an average of one standard deviation more informational support (InfoSupportExp) were 10% more

	Model 1		Model 2		Model 3	
Control/Indep. Variable	**HR**	**Std. Err.**	**HR**	**Std. Err.**	**HR**	**Std. Err.**
HasProfile	0.457***	0.009	0.474***	0.010	0.511***	0.010
ThreadStarter	1.003	0.005	0.875***	0.011	0.853***	0.010
PostCountExposure	0.614***	0.019	0.801***	0.016	0.343***	0.012
EmoSupportExp			0.844***	0.007	0.665***	0.008
InfoSupportExp			1.102***	0.009	1.048***	0.012
PostCountExposure X EmoSupportExp					0.493***	0.011
PostCountExposure X InfoSupportExp					0.953*	0.020

*: p<0.05, **: p<0.01, ***: p<0.001

Table 5. Results of the Survival Analysis

likely to *leave* the group. That is, more emotional support was associated with staying, whereas more informational support was associated with leaving. At 3 months, participants exposed to one standard deviation more emotional support than average were 190% more likely to still be in the group than those exposed to a standard deviation more informational support than average.

Model 3 adds the interaction between the number of messages participants were exposed to and the average amount of emotional and informational support in those messages (PostCountExposure X EmoSupportExp and PostCountExposure X InfoSupportExp). Compared to those exposed to an average number of messages at the average amount of emotional support, members who were exposed to a standard deviation more messages that contained a standard deviation more emotional support than average were 89% more likely to remain on the site[5]. In contrast, members who were exposed to a standard deviation more messages that contained a standard deviation more informational support than average were only 66% more likely to remain on the site[6]. That is, receiving many messages filled with emotional support was much more likely to keep members participating on the site than was receiving many messages filled with informational support. However, when members received few posts, it mattered less when these posts were filled with emotional or informational support. Figure 4 illustrates these results graphically, showing five survival curves. The middle curve shows survival with the number of posts and support exposure at their mean level. The top two curves show survival when the number of posts and average emotional support exposure (or informational support exposure) in the posts were both one standard deviation above the mean, and the two bottom curves show survival when the number of posts was one standard deviation below the mean, and the average emotional support exposure (or informational support exposure) in the posts was one standard deviation above the mean.

DISCUSSION AND CONCLUSIONS

In this paper we built accurate machine learning models to identify the extent to which messages in online breast cancer support groups contained emotional and informational support. We then examined the relationship between types and amounts of social support and commitment. The results demonstrated that the more emotional support members were exposed to, the lower the risk of dropout. In contrast, informational support did not have the same strong effects on commitment.

Although the results for emotional support strongly confirm our hypothesis that social support is associated with increased group commitment, the results for informational

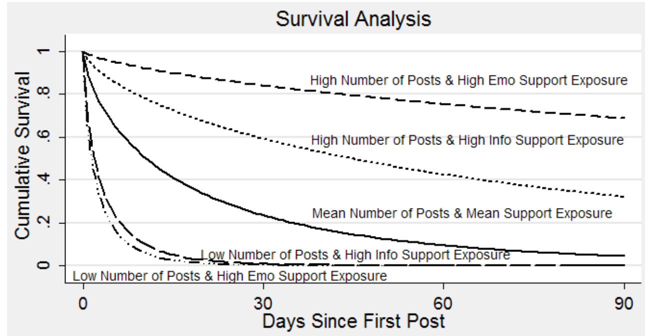

Figure 4. Survival Curves for Members Exposed To Different Levels of Number of Posts and Social Support

support do not. This contrast between the effects of two types of support is interesting, showing how social interaction can have different effects depending upon the content of the communication being exchanged.

How might we explain the unanticipated finding that increased informational support showed a weaker association with commitment than did emotional support? Although our account is necessarily speculative, we would suggest two possible explanations.

First, it may be that many information needs are short term. As a result, people who have information needs and receive informational help from others have these immediate needs met and have little reason to stay in the group, just as one might not continue perusing a dictionary after looking up a definition. On the other hand, the need for emotional support may be longer term and require multiple interactions to be fulfilled.

Second, factual information exchanged in unmoderated health support groups may lack the accuracy, credibility, and usefulness of information from other sources, such as physicians or sites run by the National Cancer Institute or the American Cancer Society. For this reason, people may leave health support groups because they perceive that the information they receive there is not helpful, and the more such information they receive, the more likely they may be to leave.

In contrast, emotional support obtained in a support group is likely to be perceived as more helpful than emotional support obtained elsewhere, because support group providers share many experiences with support group recipients. Moreover, emotional support obtained in a support group may lead recipients to develop relationships with providers or the group as a whole, which in turn increases their feelings of commitment to the group.

Limitations and Directions for Future Work

An important limitation of this study is that, even though we use longitudinal data, our findings are correlational. We examined how the support people were exposed to in one week was associated their subsequent participation in the support groups. The results are consistent with the

[5] 89% = (1-exp(-1.069-0.408-0.708))*100%

[6] 66% = (1-exp(-1.069+0.046-0.049))*100%

assumption that support exposure changes commitment. However, they can also be interpreted in terms of pre-existing differences between those who seek emotional versus informational support. For example, it may be that those seeking emotional support are also seeking long term relationships, while those seeking informational support are not. Only random-assignment experiments will allow us to definitively determine whether exposure to support actually changes commitment. A second limitation is that the reported analysis is based only on the people who had posting experience. It therefore does not shed light on the reason(s) that lurkers continue to participate in these groups. To study the behavior of lurkers, we will need to have detailed records of the activities of all users, such as their browsing and clicking logs. Moreover, because we had no direct measures of reading, we could only estimate exposure during weeks when people posted in the site. This confound led to the high correlation between the two measures and renders the interpretation of the effects of PostCountExposure in Table 5 ambiguous.

We see additional directions for future work. First, although our findings suggest that the effects of social support on commitment vary as a function of the kind of support that one receives, the cause of the difference is still not clear. A natural next step is to conduct surveys or interviews which ask participants in the group why they stay or leave.

Furthermore, although our current analysis was based on a large corpus of data from 66 forums, we only examined one type of disease (breast cancer) in one online health support group. Other online health support groups might produce different commitment levels or patterns given exposure to social support. For example, the positive effect of emotional support on commitment in a prostate cancer support group may be much weaker because men care less about emotional support. Further research studying other online support groups can help us better understand and confirm our findings.

Finally, this research examined only the association between support and commitment to the group. It would therefore be useful to examine the extent to which social support and commitment in online support groups affect participants' health quality of life.

Implications

The impressive performance of our machine learning models for predicting social support implies that it is feasible to utilize computer programs to automatically analyze the conversations in online support groups. In particular, we believe that the proposed feature set can be easily applied to build predictive models for social support for other health support datasets. LIWC and Linguistic features can be directly adopted, since these two types of features are generic in the sense that they are not tailored to any specific data. The only change one might need to make is to recreate LDA topical dictionaries customized to the data of interest, and this step can be done with little effort.

Although we used machine learning models of social support to understand behavior in health support groups, similar models could be the basis for active interventions. For example, it should be possible to assess in real time whether people who tell their disease stories are receiving the emotional support they are seeking or whether those asking a questions are receiving the informational support they are seeking. If not, their posts could be routed to volunteer moderators or to others in the community who have a history of providing the appropriate support.

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