



# Seeking and receiving social support on Facebook for surgery



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## ABSTRACT

Social networking sites such as Facebook provide a new way to seek and receive social support, a factor widely recognized as important for one's health. However, few studies have used actual conversations from social networking sites to study social support for health related matters. We studied 3,899 Facebook users, among a sample of 33,326 monitored adults, who initiated a conversation that referred to surgery on their Facebook Wall during a six-month period. We explored predictors of social support as measured by number of response posts from "friends." Among our sample, we identified 8,343 Facebook conversation threads with the term "surgery" in the initial post with, on average, 5.7 response posts (SD 6.2). We used a variant of latent semantic analysis to explore the relationship between specific words in the posts that allowed us to develop three thematic categories of words related to family, immediacy of the surgery, and prayer. We used generalized linear mixed models to examine the association between characteristics of the Facebook user as well as the thematic categories on the likelihood of receiving response posts following the announcement of a surgery. Words from the three thematic categories were used in 32.5% (family), 39.5 (immediacy), and 50.7% (prayer) of root posts. Few user characteristics were associated with response in multivariate models [rate ratios, RR, 1.08 (95% CI 1.01, 1.15) for married/living with partner; 1.10 (95% CI 1.03, 1.19) for annual income > \$75,000]. In multivariate models adjusted for Facebook user characteristics and network size, use of family and prayer words in the root post were associated with significantly higher number of response posts, RR 1.40 (95% CI 1.37, 1.43) and 2.07 (95% CI 2.02, 2.12) respectively. We found some evidence of social support on Facebook for surgery and that the language used in the root post of a conversation thread is predictive of overall response.

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## 1. Introduction

"I get by with a little help from my friends" goes the well-known Beatles lyric, and indeed there is strong evidence that social support is protective of health (Cohen and Syme, 1985; Christakis and Allison, 2006; House et al., 1988a,b; Smith and Christakis, 2008; Umberson et al., 2010) while social isolation is associated with adverse health outcomes (Durkheim, 1897; Seeman, 1996). Though some evidence suggests that social relationships are directly positive for health and well-being (Cohen et al., 2000; Thoits, 1983), other research finds that social relationships can also be associated

with negative health risk behaviors (Christakis and Fowler, 2007; Fujimoto et al., 2012). The research on social support specifically, rather than social relationships more generally, finds that increased social support lowers the risk of morbidity and even mortality (Berkman et al., 2003; Holahan et al., 1997; Holt-Lunstad et al., 2010; Mookadam and Arthur, 2004; Penninx et al., 1998; Uchino, 2004). Evidence also suggests that social support may buffer the harmful effects of stress from serious or chronic health conditions (Berkman et al., 2003; Taylor, 2011; Wheaton, 1985).

Social support has both structural and process dimensions (House et al., 1988a,b), and thus has been defined and measured in multiple ways. The structural dimension of social support can include the number of social ties or the structural characteristics of an individual's social network (House et al., 1988a,b), while process measures capture the nature of the support such as emotional support or the expression of concern, as well as instrumental or in-kind assistance.

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House and colleagues (House et al., 1988a,b) also explain that social support can vary by individual attributes including sex, age, race/ethnicity, and socioeconomic status because such factors shape differential exposure to structural barriers and opportunities in society. For example women are more likely than men to provide support to family and friends (Kessler and McLeod, 1984), but men receive more social support on average, than women (Antonucci and Akiyama, 1987; Thoits, 1995). In contrast, women report a greater number of close relationships than men (Laireiter and Baumann, 1992) and have higher levels of perceived support than men (Ross and Mirowsky, 1989). Social support appears to differ along other sociodemographic dimensions as well. For example younger and married individuals, as well as those of higher socioeconomic status, report receiving overall more social support than their counterparts (Ertel et al., 2009; House et al., 1988a,b; Schnittker, 2007; Waite and Gallagher, 2000).

Studies of social support and health also find that how individuals seek social support can be as important as the overall type or amount of support received (Heller, 1979; House, 1987). Social networking sites (SNSs) such as Facebook provide a new way to seek and receive social, particularly emotional, support for health-related issues (Centola, 2013; Moorhead et al., 2013). Originally proposed by Granovetter (Granovetter, 1973), some argue that technological and other social changes affect the way people relate to one another, such that “many meet their social, emotional, and economic needs by tapping into sparsely knit networks of diverse associates rather than relying on tight connections to a relatively small number of core associates” (Rainie and Wellman, 2012). A recent survey by the Pew Internet & American Life Project found that 11% of adult SNS users (approximately 5% of U.S. adults overall) have posted about health matters (Fox, 2011). Initial studies have found that participants in chronic disease groups on Facebook provide emotional support to one another (Greene et al., 2011). Online communities have been found to be a beneficial source of peer support for specific patient groups (Moorhead et al., 2013; Coulson et al., 2007) and potentially as effective as face-to-face support groups (Winzelberg et al., 2003). However, an understanding of social support for health among a non-patient population on SNSs is lacking (Moorhead et al., 2013).

While there is a dearth of studies of online social support for health in general (i.e., non-patient) populations, studies of social support on SNSs more generally do exist. In a survey study of undergraduates at one university, Ellison, Steinfield, and Lampe (Ellison et al., 2007) found that the intensity of Facebook use (measured with a scale of self-reported items including number of Facebook “friends,” amount of time spent on Facebook, and attitudes toward Facebook as a part of daily life) is positively associated with social capital, including the perception of available social support (see also Hampton and Wellman, 2003; Williams, 2006). Other studies of social well-being on SNSs explore how user characteristics affect the extent of supportive interaction in the SNS, and then whether such interaction is associated with actual well-being. For example, Burke, Marlow and Lento (Burke et al., 2010) found that the amount of “directed communication” on SNSs is associated with more perceived emotional support (bonding social capital) and less loneliness using a Facebook survey of  $n = 1,193$  respondents. Another study using a snowball sample of adults, found that more (SNS) friends is associated with more supportive interaction on the SNS, which was associated with well-being (Oh et al., 2014).

Our study aims to begin to fill the literature gap on social support for health in a non-patient SNS population by using a large sample of Facebook users’ conversations over a six-month observation period collected by the Harris Interactive Research Life-streaming Panel (HRLP). Given that the benefits of social support

are particularly important during times of acute stress such as in response to a major health event or significant illness (Mookadam and Arthur, 2004), we restrict our attention to conversations that begin with a post about a surgical event and measure the extent of response (number of response posts received) generated in the subsequent conversation as a measure of received social (emotional) support. Received support differs from perceived support both conceptually and operationally, and research suggests that the impact of each on health may also differ (see, e.g., Barrera, 1986; Lakey and Cohen, 2000). A recent meta-analysis of the relationship between received and perceived support found a correlation of  $r = 0.35$  (Haber et al., 2007). A number of studies of social support on SNSs have found a positive relationship between measures of received support and perceptions of support (e.g., Burke et al., 2010; Ellison et al., 2007; Oh et al., 2014). In contrast to earlier studies of social support for health on SNSs, these users are not restricted by membership in a patient support group. Our sample is also distinctive from previous studies of social support on SNSs more generally in that it is not based in a particular sub-population such as college students.

In line with findings for offline social support, we hypothesized that individual characteristics of younger age, female sex, married status, and higher socioeconomic status, as well as having a greater number of Facebook friends, would be associated with receiving a greater amount of emotional support (receipt of response posts) for a post about surgery on Facebook.

## 2. Methods

### 2.1. Data source

This study was determined to be exempt from institutional board review by the Committee for the Protection of Human Subjects at Dartmouth College.

We used data collected by the HRLP to examine the use of Facebook for social support. Participants to the HRLP are a subsample of the Harris Poll that give Harris permission to record their private conversations on the SNSs Facebook and Twitter. The HRLP continually recruits participants and as of June 2011, there were 33,326 adults.

On Facebook, each user creates a personalized profile and has what is known as a Wall that provides a place for conversing with others in the user’s online network. For the purposes of this study, we operationally defined a conversation thread as a collection of posts on their Wall where the Facebook user initiated the conversation. We refer to the initial post of a Facebook conversation thread as the root post and follow-up posts as response posts herein (Fig. 1).

We retrospectively collected HRLP Facebook data from December 15, 2010 to June 16, 2011 and identified 8,343 conversation threads from 3,899 adult study participants’ Facebook Walls where the root post included the term “surgery” (Tables 1 and 2).

To account for variations in grammar and spelling of the term “surgery”, we used methods based on regular expression to identify all root posts containing the term surgery (Nadkarni et al., 2011). In our sample of 8,343 Facebook conversation threads, the mean number of response posts following a root post that used the term “surgery” was 5.7 (SD 6.2) and the mean number of words in root posts was 12.4 words (SD 7.5) (Table 2). Some study participants had more than one conversation thread with a root post containing the term surgery. We account for the clustering of multiple threads to an individual HRLP participant in the analytic methods, described in detail below.

Upon a study participant’s entrance to the Harris Poll, socio-demographic characteristics are collected including age, sex, race/



Fig. 1. Example of Facebook conversation thread pertaining to a surgery.

**Table 1**  
Characteristics of study participants.

Characteristic	Total, mean, or %
No. of study participants, total	3,899
Age, mean years (SD)	45.5 (12.7)
<b>Sex, %</b>	
Male	20.0
Female	80.0
<b>Race/ethnicity, %</b>	
Non-Hispanic White	88.6
Other/multiple races	11.4
<b>Marital status, %</b>	
Single, never married	23.7
Married/living with partner	60.8
Divorced/separated	15.5
<b>Education, %</b>	
Less than high school	14.7
High school	41.8
Some college	21.9
College or more	21.5
<b>Annual Income US dollars, %</b>	
<\$35,000	28.9
\$35,000 to \$75,000	39.1
>\$75,000	31.9

Abbreviations: SD, standard deviation.

**Table 2**  
Characteristics of Facebook conversation threads examined in this study.

Characteristic	Total, mean, median, or %
No. of Conversation Threads, total	8,343
<b>Root post</b>	
Mean No. of words (SD)	12.4 (7.5)
Median No. of words [IQR]	11.0 [10.0]
% Included family terminology	32.5
% Included immediacy terminology	39.5
% Included prayer terminology	50.7
<b>Response</b>	
Mean No. of posts (SD)	5.7 (6.2)
Median No. of posts [IQR]	4.0 [7.0]
Mean No. of words per post (SD)	29.6 (27.9)
Median No. of words per post [IQR]	22 [25]

Abbreviations: SD, standard deviation; IQR, interquartile range.

had a high school education or less and roughly a third of the sample were in each of the three annual income categories.

## 2.2. Analyses

We set out to analyze whether the extent of emotional support received to a post about surgery is related to the characteristics of the Facebook user, including individual socio-demographic characteristics defined above (age, sex, race/ethnicity, education, income), number of Facebook friends, and also the nature of the post itself. To measure the number of responses that root posts about surgery receive (dependent variable), we counted the total number of separate responses to the surgery root post in a conversation thread.

To analyze the nature of the root post, we used text mining techniques similar to Latent Semantic Analysis (LSA) from the field of natural language processing to identify the most common words used in the posts as related to the extent of responses in our sample of Facebook conversation threads. LSA utilizes what is known as a *document-term matrix*, an  $m \times n$  matrix where  $n$  is the number of

ethnicity, marital status, level of education, and annual income. Additionally, Harris records the size of their online social network (i.e. the number of Facebook “friends”). We used socio-demographic characteristics as well as Facebook network size (number of friends) as independent variables in our analyses.

In our sample of 3,899 Facebook users who had one or more root posts with the term surgery, the mean age was 45.5 years (SD 12.7) and 80 percent were female (Table 1). Given the potential nonlinear effect of age, we include age in years and also age using a quadratic term (years<sup>2</sup>) in the analyses below. Nearly 90 percent of our sample was Non-Hispanic White and approximately 61 percent were married or living with their partner. Over half of our sample

documents in the corpus (the collection of all documents) and  $m$  is the number of terms (words) in the dictionary of all words used in the corpus. Therefore, the  $ij^{th}$  entry of the matrix represents the number of times word  $i$  is used in respective document  $j$ .

For our analyses we developed a document term matrix for all root posts and a separate document-term matrix for all responses and examined the interaction between them. The root post corpus consists of the collection of individual root posts that included the term surgery. Documents in the response corpus were the collection of all response posts associated with a given root post in conversation threads. We constructed document-term matrices for each corpus using standard techniques that include word stemming (Zeimpekis and Gallopoulos, 2006).  $P$  was an  $n_1 \times k$  matrix where  $k$  is the number of root posts and  $n_1$  is the number of words in the dictionary for the root corpus and  $R$  was an  $n_2 \times k$  matrix where  $n_2$  is the number of words in the dictionary for the response corpus. For our application, we disregarded the 1,000 most common words in the English language and words that occurred fewer than five times across each corpus. Additionally in our analyses, we ignored the term “surgery” in the root posts because it was used to identify conversation threads.

To analyze the interaction between the two corpora, we generated a new matrix  $C = RP^T$ . This was an  $n_2 \times n_1$  matrix with  $C_{ij}$  equal to the number of times word  $i$  appears in the response thread when word  $j$  appears in the root post, counted across all conversation threads. From a different point of view, the matrix  $C$  describes a weighted bipartite network linking words in root posts to words in the responses. As a linear transformation,  $C$  acts on a vector which represents a weighted combination of words in the root post and returns a weighted vector of words that we expect, based on the given corpora, in the response thread.

We used singular value decomposition (SVD) of matrix  $C$  to further explore the interaction between the two document-term matrices. The SVD is a matrix factorization where matrix  $C$  is approximated by the product of three matrices:  $C = U\Sigma V^T$ .

Therefore matrix  $\Sigma$  is a diagonal  $n_2 \times n_1$  matrix that acts as a matrix scalar with entries  $\sigma_1 \geq \sigma_2 \geq \dots \geq 0$  and the columns matrix  $U$ ,  $\{u_1, \dots, u_{n_2}\}$ , are the left singular vectors of  $C$  while the columns of  $V$ ,  $\{v_1, \dots, v_{n_1}\}$ , are the right singular vectors of  $C$ . Both of the sets of singular vectors form orthonormal bases of their respective Euclidean spaces. With the SVD, we may rewrite  $C$  as follows:

$$C = \sigma_1 u_1 v_1^T + \sigma_2 u_2 v_2^T + \dots + \sigma_{n_1} u_{n_1} v_{n_1}^T. \quad (1)$$

Thus, a good low-dimensional approximation of  $C$  is given by the first term,  $\sigma_1 u_1 v_1^T$ , particularly if  $\sigma_1 \gg \sigma_2$ . Consider a vector of words in the root post,  $w$ . Since  $\{v_1, \dots, v_{n_1}\}$  form an orthonormal basis for the space of all such vectors, there are constants,  $\{a_i\}$ , so that  $w = a_1 v_1 + \dots + a_{n_1} v_{n_1}$ . Using Equation (1), we have:

$$Cw = a_1 \sigma_1 u_1 + a_2 \sigma_2 u_2 + \dots + a_{n_1} \sigma_{n_1} u_{n_1}.$$

As  $Cw \approx a_1 \sigma_1 u_1$ , we have that  $u_1$  and  $v_1$  capture most of the action of  $C$  on relatively generic vectors  $w$ . By the Perron-Fröbenius Theorem, we can assume that all entries within these vectors carry the same sign. We interpret the weights of the entries of the vectors as the primary interaction of the root post and response thread – the collection highest weighted terms in  $v_1$  describe the content of the root posts which is likely to generate responses whose content is described by the collection of highest weighted terms in  $u_1$ .

We used this approach to examine words in root posts that elicit the most response words. Fig. 2 shows the results of this analysis, showing the ten words with the highest singular vector weights for the root posts (A) corresponding to  $v_1$ , and for the responses (B) corresponding to  $u_1$ . The bars next to these terms

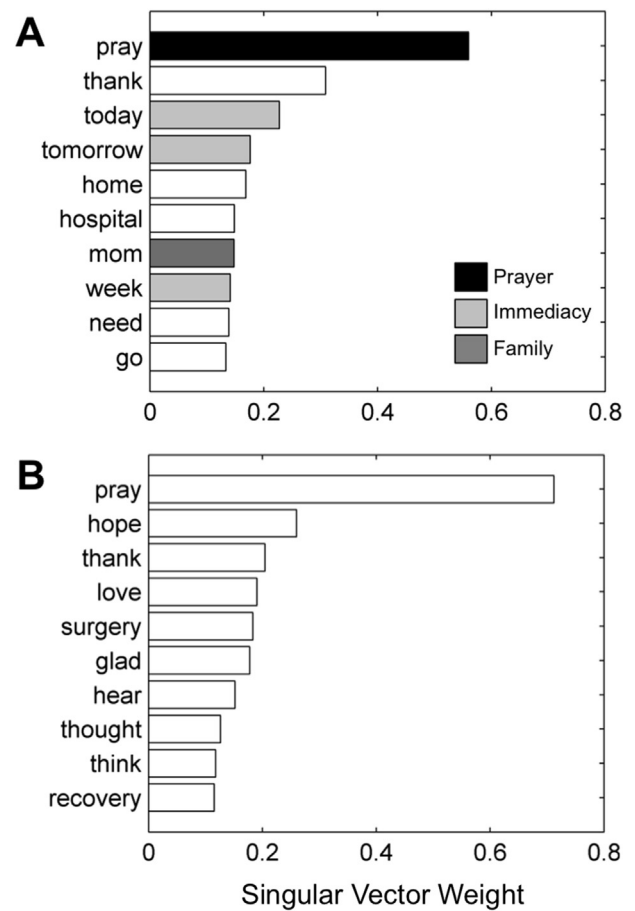


Fig. 2. The top ten words with the highest singular vector weights for the root posts (A) corresponding to  $v_1$ , and for the responses (B) corresponding to  $u_1$ . The size of the bars correspond to the entries of the singular vectors associated with the words.

indicate the weight associated to the term in the singular vector. Recall that the 1,000 most common words have been removed from both vectors, as has the term “surgery” from all root posts (since it is in all root posts). The dominance of the term “pray” (and its grammatical variations – prays, praying, prayer, etc.), shaded in black, indicates that the notion of prayer is the most common word in root posts (Fig. 2A). Second, several terms, shaded in light gray, had temporal aspects pertaining to the immediacy of the surgery – today, tomorrow, week – which suggests the importance of temporal immediacy in the root post. Third, the presence of the term “mom,” shaded in medium gray in the top ten root post words (Fig. 2A), indicates the potential importance of family terminology.

Based on these observations, we created thematic categories of words based on family, immediacy of the surgery, and prayer. The selection of terms in the first two categories is informed by examination of the 50 words with highest weight in the vector  $v_1$ . As the only two family related terms in this list are “mom” and “dad,” we restricted the family category to members of the immediate family. For the immediacy category, we selected all terms in this list reflecting temporal conditions of immediacy. The prayer category is the simplest, containing only terms with the root “pray” (e.g. pray(s), prayer(s), praying). Table 1 shows the lists of words included in each of the thematic categories. In our sample of Facebook conversation threads, 32.5%, 39.5%, and 50.7% of root posts were classified as using prayer, immediacy, and family terminology respectively (Table 3).

Because many Facebook users had more than one conversation thread that used the term “surgery” in our sample (range from 1 to 82), we used mixed-effects regression models to determine if specific characteristics of Facebook users and the terminology used in the root post predicted the likelihood of response – as measured as the total number of response posts. We assumed a Poisson distribution (a log link function) for the dependent variable (total number of response posts) and models were fit allowing each study participant to have a random intercept. Therefore, fixed effects in our models included the characteristics of the Facebook user (e.g. age, sex, network size) and terminology used in the root posts (i.e. using prayer, immediacy, and family terminology as indicator variables). Fewer than 10% of covariates were missing and we assumed missing values to be missing completely at random. Therefore, all analyses were based on complete case analysis. We performed univariate analyses for each independent variable in a mixed model with a random intercept for each study participant, and multivariate analysis in a model that included all the independent variables including both Facebook user characteristics and indicator variables for the terminology used in the root post. We used MATLAB version 2013a for analytic software (Natick, Massachusetts) for natural language processing and matrix operations and Stata version 12.1 statistical software (College Station, Texas) for all regression models.

### 3. Results

Using a novel variant of LSA, we examined the corpus of words in the initial posts, which we call root posts, to determine the combinations of words represented by the singular vector associated to the largest singular value of an interaction matrix. From these, we generated thematic categories of words based on family, immediacy of the surgery, and prayer (see Table 3).

All results of the univariate (column 1) and multivariable mixed-effects (column 2) regression models are summarized in Table 4. As expected, we found moderate positive associations between our measure of emotional social support (number of response posts) and some socio-demographic characteristics. That is, married status, some college education, and having greater than \$75,000 annual income were related to a greater number of responses by 12–13 percent against relevant baselines in univariate analyses. In multivariate analyses, being married (versus single) was associated with 8 percent more response posts, and earning > \$75,000 per year (versus < \$35,000) was associated with 10% more responses. Facebook user's age, gender, and race/ethnicity were not significantly associated with response posts in either the univariate or adjusted models. Users' network size was positively and significantly associated with the number of response posts in the univariate model but not in the adjusted model. That is, after controlling for other user characteristics, having a greater number

**Table 4**

Rate ratios for the association between characteristics of Facebook user and terminology used in root post and total number of response posts.

	Univariate models		Adjusted model <sup>a</sup>	
	RR (95% CI)	p-value	RR (95% CI)	p-value
<b>Characteristics of root post (n = 8,343)</b>				
<i>Family terminology used</i>				
No	1.00 (reference)		1.00 (reference)	
Yes	1.64 (1.61, 1.67)	<0.01	1.40 (1.37, 1.43)	<0.01
<i>Immediacy terminology used</i>				
No	1.00 (reference)		1.00 (reference)	
Yes	0.97 (0.95, 0.99)	0.01	0.99 (0.97, 1.02)	0.58
<i>Prayer terminology used</i>				
No	1.00 (reference)		1.00 (reference)	
Yes	2.25 (2.20, 2.30)	<0.01	2.07 (2.02, 2.12)	<0.01
<b>Characteristics of study participant</b>				
Natural logarithm of network size	1.04 (1.01, 1.07)	<0.01	1.03 (1.00, 1.06)	0.06
Age, years	1.00 (1.00, 1.00)	0.17	1.01 (1.00, 1.02)	0.21
Age <sup>2</sup> , years <sup>2</sup>	1.00 (1.00, 1.00)	0.08	1.00 (1.00, 1.00)	0.13
<b>Sex</b>				
Male	1.00 (reference)		1.00 (reference)	
Female	1.05 (0.98, 1.11)	0.15	1.02 (0.96, 1.08)	0.58
<b>Race/ethnicity</b>				
Non-Hispanic White	1.00 (reference)		1.00 (reference)	
Other/multiple races	0.95 (0.88, 1.02)	0.18	0.97 (0.89, 1.05)	0.49
<b>Marital status</b>				
Single, never married	1.00 (reference)		1.00 (reference)	
Married/with partner	1.13 (1.06, 1.20)	<0.01	1.08 (1.01, 1.15)	0.02
Divorced/separated	1.00 (0.91, 1.09)	0.93	1.07 (0.98, 1.17)	0.12
<b>Education</b>				
Less than high school	1.00 (reference)		1.00 (reference)	
High school	1.03 (0.96, 1.11)	0.39	1.02 (0.95, 1.10)	0.58
Some college	1.12 (1.04, 1.22)	<0.01	1.09 (1.01, 1.18)	0.38
College or more	1.04 (0.96, 1.13)	0.30	1.08 (0.99, 1.18)	0.07
<b>Annual income, US dollars</b>				
<35,000	1.00 (reference)		1.00 (reference)	
35,000 to 75,000	1.05 (0.99, 1.12)	0.07	1.06 (1.00, 1.13)	0.06
>75,000	1.12 (1.05, 1.19)	<0.01	1.10 (1.03, 1.19)	0.01

Abbreviations: RR, rate ratio.

<sup>a</sup> Adjusted for all other factors in table.

of Facebook friends was not associated with receiving more emotional support to a post about surgery.

In both models, use of terminology from our thematic categories pertaining to family and prayer were significantly associated with a higher number of response posts. In the adjusted model, the number of response posts was approximately 40 percent higher in conversation threads with family terminology used in the root post. Use of prayer terminology in the root post had the strongest effect and was associated with nearly doubling the number of response posts. The category of immediacy terms did not have a significant effect on response. In separate analyses, we examined interactions among each pair of the terminology variables and found a statistically significant interaction between family and immediacy terminology that significantly reduced the likelihood of response posts [rate ratio 0.92 (95% confidence interval 0.88, 0.96)] (data not shown), indicating that when a post mentioned a family term and a term indicating immediate timing, the post received fewer responses. Although we cannot determine why this surprising result occurs, we speculate that a post announcing an imminent surgery of a family member may result in greater direct contact and thus less response through Facebook.

Introducing each of the terminology indicator variables individually while controlling for characteristics of the Facebook users (data not shown), the RRs of family, immediacy, and prayer terminology use were 1.64 (95% CI 1.60, 1.68), 0.99 (95% CI 0.97, 1.02), and 2.24 (95% CI 2.17, 2.28) respectively, similar to those reported for the fully adjusted model shown in Table 4.

**Table 3**

Terms used to identify referencing family, immediacy of surgery, and prayer in Facebook posts.

Thematic Category	Terms
Family	Husband, wife, father, dad, mother, mom, daughter, son, sister, brother, sibling, twin
Immediacy	Tomorrow, ASAP, afternoon, tonight, soon, early, minute, current, today, morning, night, early, fast, hour, later, minute, yesterday, soon, week
Prayer	Pray, prayer, praying

Regular expression was used to account for variations in spelling and other forms of the words.

Abbreviations: ASAP, as soon as possible.

#### 4. Discussion

Social media have become an integral part of the public health landscape (Centola, 2013). While previous studies have explored support in established disease support groups within SNSs (Coulson et al., 2007; Moorhead et al., 2013), this is one of the first studies, to our knowledge, to directly examine conversations related to social support on Facebook for a major medical event. Our study empirically supports the claim by the Pew Internet & American Life Project that individuals seek support for health-related issues on SNSs outside patient support groups (Chou et al., 2009; Fox, 2011).

The literature on social support in offline settings indicates that people with certain social and demographic characteristics related to age, socioeconomic status (Heller, 1979; House, 1987), marital status (Heller, 1979; House, 1987; Waite and Gallagher, 2000), and gender (Antonucci and Akiyama, 1987; Ross and Mirowsky, 1989; Thoits, 1995) receive greater or lesser social support. As expected by the literature on social support and health, we found that people who are married received greater support (in our study measured by more response posts) to an initial post about surgery on Facebook compared to single people. We also found that those in the highest income category received a greater number of responses compared to those in the lowest category, all else equal.

While the findings on the sociodemographic variables are consistent with research on patterns of social support, they indicate a worrisome pattern of inequality online which echoes that of the offline world. In this case, resources in the offline world associated with greater social support, as well as other positive health benefits, including higher income and being married, appear to translate into greater resources online – here, more social support – that may affect health over time. This pattern is consistent with the so-called “second-level digital divide” (Hargittai and Hsieh, 2013) in which not only does access to information technology vary between groups (the first level digital divide), but the knowledge and behavior benefits resulting from information technology use may also (come to) be distributed unequally (Viswanath, 2006). These findings also reinforce arguments about the social determinants of health in which socioeconomic status leads to both differential exposure to health risks, and also to differential access to resources that can either buffer or exacerbate risks (Link and Phelan, 1995).

If inequality in the offline world translates into differential resources online that affect health over time, new technologies like SNSs will sustain, and could even exacerbate health disparities across groups, consistent with theories about the diffusion of innovations that sustain the fundamental social causes of health (Link and Phelan, 1995). Though the National Healthy People 2020 objectives recommend using “health information technology to improve population health outcomes and health care quality, and to achieve health equity” (US Department of Health and Human Services (2014)), our findings suggest such outcomes may depend on purposeful interventions and policies to ensure that new technologies do not create new “digital divides”.

Despite some support for the effects of sociodemographic factors, our main findings suggest that for emotional social support on Facebook in response to a post about surgery, it matters only somewhat who you are, but it matters a great deal more what you say. Posts about family members, or ones that reference prayer, receive significantly greater response than posts that do not contain such terms. Our findings regarding prayer terminology link to the large literature on religion and health in which religiosity is associated with positive health behaviors and outcomes and social support is found to be a key mechanism producing this relationship (Krause, 2008; Krause et al., 2002; Siegel et al., 2001).

Although such a large response to prayer words may be due to

factors associated with religiosity, it might also have to do with the situational patterns of conversation in which a request demands a response (Schegloff, 2007). In our sample, it was not uncommon for root posts to request prayers for an upcoming surgery, resulting in members of the user's social network offering prayers in response (e.g., Fig. 1). Whereas studies of conversation analysis have focused primarily on face-to-face and/or synchronous interaction, new social media provide a fertile ground for considering “conversations” taking place asynchronously and among groups much larger than the dyad, including one's entire online social network (Goffman, 1959), as in the conversations studied here. Indeed, the transparency of one's own and others' networks is a key affordance of SNS (boyd and Ellison, 2008; Ellison and boyd 2013; Kane et al., 2014). Considering conversation in view of one's social network suggests that social dynamics related to impression management by both users and responders may influence social support online (boyd and Ellison, 2008; Donath, 2008; Gibson, 2009). Kane and colleagues (Kane et al., 2014) extend boyd and Ellison's (Ellison et al., 2007) conceptualization of the capabilities of social media platforms by developing the points of intersection with social network analysis such that network transparency on SNSs may affect both user behavior and user outcomes. Future research about online social support for health should consider both social and network dynamics.

The contrast between the small effects of the socio-demographic variables and the large effects of choice of language suggests a distinction between online and offline social settings – SNSs provide people the opportunity to seek and receive social support irrespective of their socio-demographic categorizations. While the latter constrain the amount and effectiveness of social support in offline settings, our results suggest that these constraints are significantly weaker in the context of social network platforms.

Finally, recent work (Oh et al., 2014) shows that the *quality* of the social interaction is a substantial factor in the effectiveness of online social support. While we cannot precisely determine this factor, the association of stronger social response and the content of the root posts are consistent with this framework – Facebook users reaching out to their network for support using specific language are more likely to receive the type of support they desire. This is a natural topic for continued investigation based on this initial study.

#### 5. Limitations

There are several limitations of our study that must be acknowledged. First, the study sample was a self-selective group of participants from the HRLP; therefore, selection bias cannot be ruled out and our study may not be generalizable to all the general Facebook population. When compared to general users of Facebook, our study population (i.e., users who posted about surgery) differed in a number of ways (Duggen and Brenner, 2013); our study population was older, predominately female, less racially diverse, and overall more educated. Although we can only speculate, these differences could be explained simply by older adults being more likely to undergo surgery or perhaps even due to issues related to healthcare access (i.e., those of racial/ethnic minorities). Nevertheless, the overwhelming amount of women in our sample may suggest women are more likely to use SNSs for social support.

Second, while we found modest associations between some socio-demographic characteristics the amount of response in Facebook conversations, we do not account for all individual characteristics in our analyses. For instance, the strong association between using “prayer” in the initial post and response could be a surrogate for the fact that a person is religious and/or part of a religious community, which may have implications for the amount of response.

Third, we examined social support for surgical interventions only – thus social support may differ for other types of medical events. Fourth, the HRLP does not collect information regarding the structure of user's networks. Given that social support is related to both relational structure and processes (House et al., 1988a,b), further exploration into how the structure of user's online networks is related to social support undoubtedly would lead to additional insights (e.g., Moorhead et al., 2013). Fifth, our sample lacks both a control population and additional annotation regarding the individuals' offline sources of social support as well as their attitudes towards and perceptions of all sources of social support.

Lastly, our measure of emotional social support via the number of response posts captures only one of many aspects of the concept of social support. Future studies will want to expand the measures of additional aspects of social support in order to examine and untangle the potentially different forms of support offered on SNSs. Specific refinements in the literature include findings (Oh et al., 2014; Rainie and Wellman, 2012) that online social support is most effective when it generates positive response from the recipient of the support and is coupled with offline supportive action.

## 6. Conclusion

Over the past two decades in the US, some evidence suggests that personal social networks appear to have shrunk (McPherson et al., 2006, 2008; Fischer, 2009), while virtual social interaction has dramatically increased (Hampton et al., 2011). Despite some widespread concerns that social interaction and relationships are weakening because of Internet use (Turkle, 2011), other evidence suggests that people who engage in virtual social networks have as many or more close social relationships as those who don't (Boase et al., 2006; Hampton et al., 2011).

Whether or not the findings reported here, that words in the post more so than social characteristics, indicate a weakening of the powerful effects of social attributes in online interaction must be a question for future and ongoing research. However, our findings may indicate support for what we might call the Steiner axiom (Steiner, 1993), "On the Internet, nobody knows you're a dog." Here, we see evidence that in virtual social spaces, the social categories that may drive social support in the offline world have weaker effects, heightening the impact of the communication itself.

As described in a review by Gibson, decades of research on conversation (in the offline world) show two important, yet distinct findings (Gibson, 2009). First, conversation is greatly determined by the specific situational constraints in which it occurs. Second, conversation is significantly affected by the social attributes and relationships between the parties engaged in conversation. The world of online "conversation" such as what occurs on Facebook Walls, as described here, offers a new and possibly unique environment to explore questions of social structure versus situational logics on conversation.

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