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Investigating the Reciprocal Relationships Within Health Virtual Communities

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ABSTRACT

Health virtual communities are a major channel through which health consumers share health-related knowledge and/or exchange social support with their peers. Because of the collaborative nature of health virtual communities, user participation is a critical factor for community growth and prosperity. In this study, we examine the impact of reciprocity on user participation within health virtual communities. Additionally, we investigate the impact of the homophily (similarity of user characteristics such as age, gender, and tenure) on user participation. To do so, we analyzed 1947 messages exchanged between 130 users and their peers. Our results support short-term reciprocity, but refute the positive relationship associated with long-term reciprocity. Among homophily hypotheses, our results support gender homophily, but not age homophily and tenure homophily.

Keywords

Health virtual communities, online social networks, user participation, reciprocity, homophily.

INTRODUCTION

Health virtual communities provide information, advice, and news on health topics. The Pew Internet & American life Project (Fox, 2011) recently reported that 80% of all Internet users search for health information online. This information may pertain to such areas as a specific disease or medical procedure, or more detailed information related to health care practitioners or facilities. Potential Internet sources include websites, blogs, publications, and advertisements. Healthcare discussion groups help people concentrate on a specific disease or class of health problem, find other people with a similar problem or experience, and provide a means for discussing relevant issues. WebMD.com and DailyStrength.org are among the most popular health virtual communities.

In line with the growth of health virtual communities, over 4,000 hospitals in the United States have established a social networking presence to facilitate communication of physicians, patients, and caregivers (Bennett, 2011). For example, the Mayo Clinic provides links to YouTube, Twitter, and Facebook (Mayo Clinic, 2011).

Given the emergent role of health virtual communities in both society and healthcare organizations, managers and administrators of these networks should be aware of their roles in managing the networks. Simply providing the infrastructure for social network exchange does not guarantee that people are willing to join and participate (Butler, 2001). Instead, health social network providers should explore different methods or strategies which benefit potential and current members, as well as establish the potentially productive dyad relationships. They can also shape the groups of members who are more likely to work together effectively. In this vein, they can promote member participation, support exchange relationships, and facilitate group discussions that ultimately lead to the networks' success, prosperity, and sustainability.

To achieve this, the healthcare social network providers must understand the factors that can influence member participation. These factors may include member characteristics such as demographic attributes, personality, and their interaction with other members. However, despite considerable interest in online social networks, no known study has examined the characteristics of the interactions within health virtual communities and the impact of these interactions on the individuals' participation in the networks.

The primary focus of this study is on two primary constructs that may influence user participation: reciprocity and homophily. Reciprocity is one of the most prominent drivers that motivates members of a community to share their knowledge (Chiu, Hsu, and Wang, 2006; Wasko and Faraj, 2005). Reciprocity in mutual relationships originates from the inherent tendency of people toward fairness. People may deviate from self-interested behaviors when

encountering friendly and supportive actions of others (Fehr and Gächter, 2000). Drawing upon social exchange theory, people within a social network seek mutual reciprocity in return for the time and effort made participating in the network and potentially helping others (Chiu et al., 2006).

People tend to make friends with other people who share similar characteristics such as race, education, gender, and age. (Feld, 1982; Marsden, 1988; McPherson, Smith-Lovin, and Cook, 2001). This phenomenon, called homophily (McPherson et al., 2001), is consistent with the similarity-attraction principle proposed by Monge and Contractor (2003). Similarity-attraction is an underlying reason for one's tendency to interact and self-categorize with those who are similar. People are more willing to interact with others who have much in common with them because the interactions are generally more comfortable, rewarding, and efficient (Carley, 1991).

In this study, we address two main research questions:

- How does the reciprocal interaction with other members impact one's participation in a health virtual community?
- How do member characteristics impact one's participation in a health virtual community?

THEORETICAL BACKGROUND AND HYPOTHESES

Participation in virtual communities includes posting comments, questions, pictures, videos, etc. by a user as well as viewing/reading these objects posted by other users within a community (Butler, 2001; Koh, Kim, Buttler, and Bock, 2007). Within the context of health virtual communities, individual participation refers to exchanging social support in the form of support-seeking and support-providing messages and comments. The communication mechanisms include blogs, discussion boards, private messaging services, and also chat services.

User participation is an important driver for the sustainable growth of online communities (Koh et al., 2007; Ling, Beenen, Ludford, Wang, Chang, Li, Cosley, Frankowski, Terveen, and Rashid, 2005). Recent research efforts have focused on investigating user participation in online communities. Results show that needs such as social identity and social presence play a crucial role in one's contribution in online communities (e.g., Bishop, 2007; Koh et al., 2007; Nonnecke, Andrews, and Preece, 2006). Other research has focused on structural characteristics of the community, such as community size (Butler, 2001; Koh et al., 2007), or on relational dimensions, such as trust, that influence participation in virtual communities (Chiu et al., 2006; Lin, 2008) and social ties (Chai and Kim, 2011; Chiu et al., 2006).

Because the viability of any community relies on the viability of the ties between users, we believe that more attention should be dedicated to investigating the impact of reciprocity on one's contribution behaviors within virtual communities. Moreover, similarity between the characteristics of two individuals who interact can influence their willingness to initiate and continue their interaction (McPherson et al., 2001). Nonetheless, few studies have researched whether individual characteristic similarity influences peer communication and support. Our study aims to fill this void.

Reciprocity

Reciprocity can be realized at different levels of communication, such as with individuals or to an entire group (Monge and Contractor, 2003; Wasko and Faraj, 2005). Some members join social support networks because they enjoy helping others and realize their intrinsic motivation by doing so (Wasko and Faraj, 2005). Other members may only provide assistance if they feel that others provide them with similar help (Nahapiet and Ghoshal, 1998). Network members consider this reciprocal support as a "personal reward" that serves as an incentive for them to contribute more actively to the community (Von Hippel and Von Krogh, 2003). Equity Theory (Adams, 1966) suggests that people compare the social support they receive with that they provide to others in the network. If they perceive equality, they are motivated to contribute in the future; otherwise, they may reduce their support. Wasko and Faraj (2000) argue that the exchange of knowledge and support within a community is facilitated if members perceive such exchange to be fair and reciprocal. These arguments are consistent with expectation theory (Blau, 1986; Monge and Contractor, 2003), which contends that the expectation of receiving value in terms of respect, status, reputation (Wasko and Faraj, 2005) as well as support from others (Chiu et al., 2006; Shumaker and Brownell, 1984) plays a crucial role in the amount which members contribute to a social support network.

Health virtual communities are a form of social support network. Users within these networks may seek reciprocity in their direct or one-to-one relationships with others. We call this one-to-one reciprocity, which we define as the mutual exchange of social support (in the form of supportive messages) between a user in a social network and the

user's friends in the network. One-to-one reciprocity can be a driver for participation of members in health virtual communities at the individual level. Users in a network tend to make their social support relationships reciprocal by providing more support for other users who have provided them with a high level of social support. We hypothesize:

H1 (*One-to-One Reciprocity*): *In health virtual communities, there is a positive relationship in the exchange of messages between individual group members.*

Homophily

McPherson et al. (2001) studied key homophily factors of friends. They found that ethnicity is the highest ranked friendship factor, followed by age, religion, educational level, occupation, and gender. Although friendship homophily of offline participants has been studied extensively, little research has been conducted on social network homophily. Thelwall (2009) studied homophily of friends on MySpace and found significant relationships among characteristics such as ethnicity, religion, and age, but not for gender homophily.

Gender homophily

Various researchers have discussed gender homophily and the impact of this phenomenon on the membership and participation of members within networks and communities specifically in the organizational or task-specific context. Ruef, Aldrich, and Carter (2003) found that business discussion networks dominated by male members are more willing to admit men rather than women and such homophily also positively affects the formation of organizational founding teams. Gender homophily also plays a crucial role in shaping the friendship relationships of young children and their playmates (McPherson et al., 2001; Ridgeway and Smith-Lovin, 1999). Within the context of discussion networks, there is a high level of gender homophily in political discussion networks (Huckfeldt and Sprague, 1995).

Health virtual communities are discussion-based networks within which users exchange supportive comments and discuss specific health-related topics. Although Thelwall (2009) found no support for gender homophily on MySpace, we propose that people may feel more comfortable discussing health issues with other people of the same gender. We therefore hypothesize:

H2: *In a health virtual community, members tend to communicate with other members of the same gender.*

Age homophily

Age homophily, or age similarity, has been shown as a predictor of friendship ties (Feld, 1982; McPherson et al., 2001; Thelwall, 2009). However, the importance of age homophily varies among different types of relationships. In close friendships, age is the strongest dimension of homophily (McPherson et al., 2001). Until recently, most studies on age homophily concentrated on face-to-face or offline relationships. With the emergence of online social networks, researchers have begun investigating the role of this type of homophily in online social ties. For example, Thelwall (2009) researched friendships among MySpace users. His study showed a high level of age homophily among people up to age 40 who exchanged messages with each other. Although his results did not indicate age homophily among older users, he argued that this might be due to the dominance of younger users in the dataset.

We argue that age homophily may also be present in health virtual communities, where it plays an influential role in the social ties among network members and in their participation in supportive relationships. We hypothesize:

H3: *In a health virtual community, members tend to communicate with other members of similar age.*

Tenure homophily

Tenure homophily may also impact the participation level of users in health virtual communities. Tenure is the period of time in which a user has been a member of an online health social network. Unlike ascribed characteristics such as age and gender, tenure is attributed to each individual in a particular network (McPherson et al., 2001). Members of a variety of social networks would have different tenure homophily, dependent upon when they joined a given social network.

Pahor, Škerlavaj, and Dimovski (2008) found a significant influence of tenure homophily on the formation of social ties among people within the organizational context. In a study of online game interactions, Huang, Shen, Williams, and Contractor (2009) found that online gamers were more willing to interact and play with others who had similar tenure in terms of their experience in playing the game.

We argue that tenure homophily may also be present in health virtual communities. We expect members more willing to provide their support to other members with a similar level of tenure. We hypothesize:

H4: *In an online health social network, members tend to communicate with other members of similar tenure.*

The above hypotheses are summarized in Figure 1.

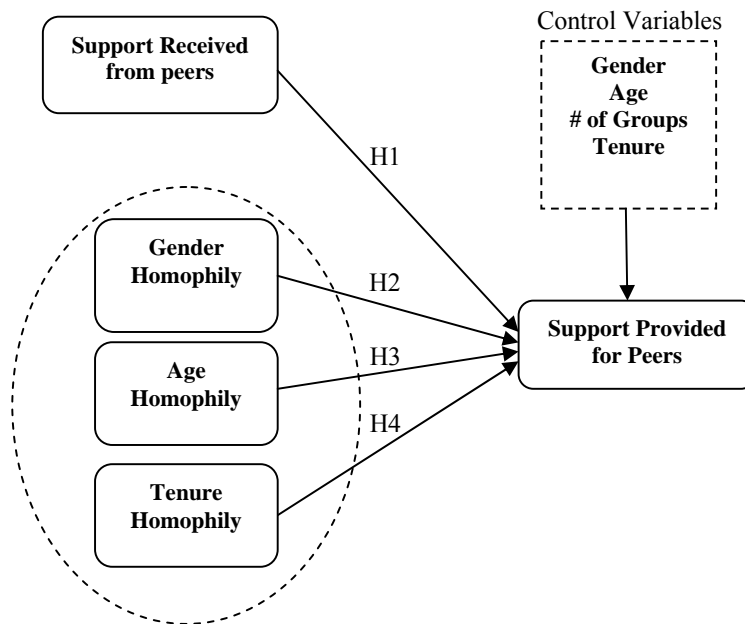


Figure 1. Research Framework

DATA AND MEASURES

DailyStrength.org was our data collection site. It is a popular health virtual community, with more than 500,000 registered members who can subscribe to approximately 500 support groups dedicated to different health-related topics (e.g., cancer, diabetes, depression). Members can seek, obtain or exchange support through initiating or responding to discussion threads posted in various support groups. The number of members subscribed to each support group varies from less than 100 to more than 48,000. Membership and subscription to individual support groups are free, and there is no restriction on the number of support groups to which a member can subscribe. Registered members have a profile page that displays their demographic information such as age, gender, location, the date they became a member, and the support groups to which they subscribe.

The key variables of interest in this study are the support provided and received at the individual level. On DailyStrength.org, this is best represented by the number of messages exchanged between any two members.¹ Members seeking help or support usually do so by initiating a discussion thread that describes the problem, and other members typically provide help or support by responding to these discussion threads with an answer or encouraging words. Based on the dynamics observed on DailyStrength.org and other health virtual communities, we define *support received* as the number of responses a member receives in the threads initiated, and *support provided* is the number of replies a member posts in the threads initiated by other members. To ensure a representative yet random sample, we randomly selected 130 members² from the largest support group, the "Depression" group, and followed their messages (initiated or responded to) posted in the discussion threads. We also gathered the demographic information of the other members who participated in these threads. We call these initial 130 members the "focal users" as they served as focal points in our data collection process. We call the members the focal users

¹ Another way to measure support is to analyze each individual message and convert qualitative data to quantitative measures. However, given the number of messages in our dataset, this approach demands huge amounts of time and resources and a sophisticated coding scheme to capture the highly context-dependent information embedded in messages. Hence we adopt the simplified but more consistent numeric measure.

² We started by randomly selecting 1% of the total number of members in the "Depression" support group. After removing users who are not active (does not have any interaction with other users) or have missing data on our key variables such as gender, age, tenure, etc., we ended up with an initial focal user set with 130 users.

interacted with the “non-focal users”. In other words, a non-focal user is a registered member who has either responded to a thread initiated by a focal user or received a response from one or more focal users in an initiated thread.³

We ran software scripts to parse data from all discussion threads that involve a focal user. The data we gathered included thread title, username of the thread initiator and each respondent, date and time of each message sent, and the discussion group where the message was posted. We also parsed focal and non-focal user profile pages to obtain their demographic data such as age, gender, tenure (length of membership), and the support groups to which they subscribed. DailyStrength.org keeps a full record of all discussion threads since the launching of the website. Therefore, we collected data on a full history of the interactions between focal and non-focal users that spans a period of 4 years and 2 months, and consists of a total of 1,947 messages that involve 130 focal users and their peers (focal and non-focal users).

Since we are interested in examining the reciprocal relationship at the individual level, we constructed our dataset based on the interactions between a focal user and either a focal or non-focal user. The longitudinal nature of the dataset allowed us to identify the sequence of any reciprocal interaction. The following scenario describes our data collection mechanism.

Suppose that during our sample period, a focal user A sent a total of eight messages to discussion thread(s) initiated by user B and user B sent a total of three messages to discussion thread(s) initiated by user A. For these two users we can divide the sample period into shorter interaction periods so that each interaction period consists of only either user (A or B) sending message to the discussion thread(s) initiated by the other user.

Period 1: Three messages from A to B.

Period 2: Two messages from B to A.

Period 3: Five messages from A to B.

Period 4: One message from B to A.

Accordingly, a total of 11 messages exchanged between user A and user B were recorded and converted to four data points in our dataset. Specifically, we defined an ordered pair (X_i, Y_i) for each interaction period; where:

X_i : Total number of comments user A has sent to discussion threads initiated by user B over the i^{th} interaction period.

Y_i : Total number of comments user B has sent to discussion threads initiated by user A over the i^{th} interaction period.

$X_i, Y_i \geq 0$; $X_i * Y_i = 0$ and $X_i + Y_i > 0$;

$0 < i \leq$ total number of interaction periods occurred between any two users A and B

Using the notations, in the above scenario the ordered pairs (X_i, Y_i) are (3, 0), (0, 2), (5, 0), and (0, 1) for $0 < i \leq 4$, respectively.

EMPIRICAL ANALYSIS AND RESULTS

To test the first hypothesis, we ran an OLS regression using the following model:

$$\begin{aligned} Last_sent = & \beta_0 + \beta_1.Last_received + \beta_2.Received_so_far + \beta_3.Diff_sent_received \\ & + \beta_4.Respondent_groups + \beta_5.Respondent_gender + \beta_6.Respondent_age \\ & + \beta_7.Respondent_tenure \end{aligned}$$

where:

³ Note that the dataset captures all of the focal user activities but not all non-focal users' activities. For example, we did not capture non-focal user activities in threads that did not involve the focal users in our sample. This was deemed unnecessary and technically infeasible.

If $X_i > 0$ then

(1) $Last_sent = X_i$;

(2) $Last_received = Y_{i-1}$;

(3) $Sent_so_far = \sum_{j=1}^{i-2} X_j$ (if $i \geq 3$); otherwise = 0;

(4) $Received_so_far = \sum_{j=1}^{i-2} Y_j$ (if $i \geq 3$); otherwise = 0;

(5) $Diff_sent_received = (3) - (4)$;

If $Y_i > 0$ then

(6) $Last_sent = Y_i$;

(7) $Last_received = X_{i-1}$;

(8) $Sent_so_far = \sum_{j=1}^{i-2} Y_j$ (if $i \geq 3$); otherwise = 0;

(9) $Received_so_far = \sum_{j=1}^{i-2} X_j$ (if $i \geq 3$); otherwise = 0;

(10) $Diff_sent_received = (8) - (9)$;

The dependent variable (*Last_sent*) represents the operationalization of the construct *support provided for peers*. *Last_sent* denotes the number of "consecutive" comments user A has sent to user B over the last interaction period. Similarly, three independent variables are defined as "Last_received", "Received_so_far", and "Diff_sent_received" where for the *i*th ($i > 1$) interaction period occurred between two users A and B. The above scenario, for instance, results in the following three data points (see Table 1).

Data point #	Last_sent	Last_received	Received_so_far	Diff_sent_received
1	2	3	0	0
2	5	2	0	3
3	1	5	3	-1

Table 1. Variables and values associated with the scenario on the previous page

Our final data set contains a total of 445 data points associated with 445 interaction periods between the focal users in our sample and their peers.

Based on the reciprocity principle, we expect that *Last_sent* to be positively associated with *Last_received*. In addition, we also expect that *Last_sent* to be positively associated with *Received_so_far*, which represents the history of the support provided by user B to user A⁴ since their first interaction until their ($i-2$)th interaction period. We believe that the cumulative support received in the past may also affect user A's decision to provide support to user B.

The independent variable *Diff_sent_received* represents the difference between *Sent_so_far* and *Received_so_far*. We expect that a greater *Diff_sent_received* will lead to a reduced level of willingness in user A to send messages to user B.

The control variables in our model are *Respondent_groups*, *Respondent_gender*, *Respondent_age*, and *Respondent_tenure*, which refers to the number of groups a respondent subscribed to, the respondent's gender, age, length of membership (in days), respectively.

Table 2 presents a summary of the regression results. The results indicate that *Last_received* ($\beta=.210, p\text{-value}<.001$) significantly influences *Last_sent*, supporting the reciprocity phenomenon predicted in H1. *Received_so_far* ($\beta = -.015, p\text{-value}<.05$), however, does not significantly impact *Last_sent* implying that the cumulative number of comments a user receives from another user does not influence the number of comments the user sends to the other user. What is surprising is that *Diff_sent_received* ($\beta=.224, p\text{-value}<.001$) significantly and positively influences *Last_received*. This result is in contrast to the reciprocity phenomenon; the greater the difference between the number of comments user A sends to user B, versus the number of comments user B send to user A, the more likely A will continue to send comments to user B. These contradictory results indicate that reciprocity only occurred on a short-term basis, partially supporting H1.

Table 2 also shows that two of the four control variables have a significant impact on *Last_sent*. *Respondent_groups* ($\beta=-.047, p\text{-value}<.001$) and *Respondent_age* ($\beta=-.025, p\text{-value}<.001$) negatively influence *Last_received*. In other words, the greater the number of groups a user has subscribed to and the older a user is, the

⁴ If $Y_i > 0$ then B is the respondent over their *i*th interaction period and consequently A and B in all the statements in this paragraph as well as the next paragraph should be swapped.

less likely that user sends messages to other users. *Respondent_gender* ($\beta=-.297$, p -value =.172) and *Respondent_tenure* ($\beta=4.332E-5$, p -value = .856), however, do not significantly influence *Last_sent*.

Model	Coefficient	Std. error	P-Values
(Constant)	3.296***	0.358	0.000
Last_received	0.210***	0.041	0.000
Received_so_far	-0.015	0.009	0.085
Diff_sent_received	0.224***	0.018	0.000
Respondent_groups	-0.047***	0.012	0.000
Respondent_gender	-0.297	0.217	0.172
Respondent_age	-0.025***	0.007	0.001
Respondent_tenure	4.332E-5	0.000	0.856
F-Value: 26.583 (0.000)*** R ² = 0.308; Adjusted-R ² =0.296			

*p<.05; **p<.01; ***p<.001 (two tailed tests)

Table 2. Model summary results and coefficient estimates (estimated using SPSS 18.0)

To test the homophily hypotheses (H2, H3, and H4), we performed different ANOVA models. The results of the first model, shown in Table 3, demonstrate a significant difference between the level of support a user provides for users with the same gender compared to users with opposite gender (F=7.707, P<.01). Thus, the findings support H2.

Source of variance	Degree of Freedom	Mean Square	F-value	p-value
Between Groups	1	23.797	7.707	0.006
Within Groups	424	3.088		
Total	425			

Table 3. ANOVA results for gender homophily

To test age homophily (H3), we first attempted to set a cut-off point for contrasting similar and dissimilar ages of any pair of users. We used different cut-off points from age difference of less than 5 years to age difference of less than 9 years, and conducted ANOVA in each case. The results show that the F-values of the models vary between cut-off points (see Table 4). However, none of the models shows a significant relationship between age similarity and member participation. Therefore, the age homophily hypothesis (H3) was not supported.

Cut-off point	F-value	P-value
Age difference < 5	2.088	.149
Age difference < 6	2.314	.129
Age difference < 7	3.252	.072
Age difference < 8	1.614	.205
Age difference < 9	1.119	.291

Table 4. ANOVA results of age homophily for different cut-off points

To test tenure homophily (H4), we first defined a specific set of tenure difference that could be regarded as the border between similarity and dissimilarity of users' tenure. To do so, we considered three alternative cut-off points

and conducted ANOVA in each case to assess the behavior of the F-values. The results show that in none of the three cases significant relationship exists between participation and tenure similarity (see Table 5).

Cut-off point	F-value	P-value
Tenure difference < 61 days	2.485	.116
Tenure difference < 101 days	2.793	.095
Tenure difference < 121 days	1.390	.239

Table 5. ANOVA results of tenure homophily for different cut-off points

In summary, our results provide support for H2 (gender homophily), while H3 (age homophily) and H4 (tenure homophily) were not supported. Another interesting finding is that H1 is only supported when reciprocity is considered on a short-term basis.

CONCLUSION

In general, reciprocity has only short term impact and homophily has little impact on communication between members of health virtual communities. Members appear far more concerned with the subject matter (healthcare) than the characteristics of the people with whom they are communicating. However, please note that although users examined in this study are all members of the same social network, they are not necessarily “friends”. They just happen to have, or are close to someone who has, a healthcare concern similar those with whom they are communicating. We can only surmise whether results would have been different if we were able to monitor communication among member friends versus those not classified as friends. One potential reason for the lack of support of some of our hypotheses could be that more detailed participation is conducted with member friends rather than all members of a given support group. We suggest that this requires further study.

In future studies, researchers can utilize other methods, data collection, and analysis techniques such as content analysis, survey, and interview with community members to determine the factors that influence their participation and their support provision behaviors. Moreover, the constructs in this study can be operationalized in different ways by using other measures in order to assess reciprocity and homophily phenomena within the health virtual communities. The role of other potentially influential variables such as structural characteristics of community as well as cognitive and personality traits of the members can also be assessed in future studies.

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