A Social Capital Perspective to Understand Individual Contribution of Social Support in Healthcare Virtual Support Communities

Kuang-Yuan Huang
Faculty of Management
McGill University
kuangyuan.huang@mcgill.ca

InduShobha Chengalur-Smith
Department of Information Technology Management
University at Albany, SUNY
shobha@albany.edu

Abstract

Drawing from social capital theory, this study attempts to present a model that applies the structural, relational, and cognitive dimensions of social capital to theorize the determinants of the provision of informational and emotional support in healthcare virtual support communities. The results show that individual provision of emotional support is determined by his/her extent of social interaction with other community members, and his/her social identification with the community. Moreover, one's contribution of informational support can be predicted by his/her level of healthcare-related expertise.

1. Introduction

The burgeoning number of Internet users participating in healthcare virtual support communities has drawn researchers from various fields to study the online social support phenomenon (e.g., [1]). In the literature on online support studies, however, little attention has been paid to the provision of social support as a dependent variable, i.e., the discovery of the psychological, relational, or contextual determinants that predict the provision of social support [2]. Such identification is essential to the investigation support receivers' as well as providers' health outcomes [3, 4]. Additionally, for practitioners and virtual community administrators, identified determinants can also lead to appropriate healthcare intervention, and improved design of the online environment to facilitate support exchange [5]. For healthcare organizations seeking to enhance the quality of their offerings through virtual community initiatives [6], knowing the determinants of individual online helping behaviors can also lead to more effective collaboration with them. For organizations pursuing new knowledge management systems or other information systems, the identified determinants can also shed lights on employees' voluntary contribution of help [7].

This study attempts to bridge the gap in the literature on healthcare virtual support communities by examining the determinants of the provision of informational (the provision of information about the stress itself or how to deal with it, [8]) and emotional (the communication of love and caring, [8]) support, the most common types of social support exchanged online [9]. More specifically, different aspects of relationships formed among members of a virtual support community, characterized by the structural, relational, and cognitive dimensions of social capital [10], are conceptualized as the predictors of the contributions to the two types of social support.

This study makes three main contributions. First, this study represents one of the few attempts to explore the determinants of support provision, and is the first endeavor to systematically investigate this topic in online contexts. Second, this study is the first to examine the applicability of Nahapiet and Ghoshal's social capital framework [10], in which social relationships are characterized through the structural, relational, and cognitive dimensions of social capital, to online social support activities. The third contribution of this study is the use of an automated method to analyze online messages. An automated analysis method would generate more reliable results by better representing the dynamics of the target community due to its ability to analyze data spanning a long period of time [11].

This article is organized as follows. Section 2 provides the theoretical background. The proposed research model are then presented in section 3. In section 4, the method for testing the proposed model is discussed, which is followed by results (section 5), discussion (section 6) and conclusions in section 7.

2. Theoretical Background

2.1. Social support and virtual support communities

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Lakey and Cohen [12] defined social support as "aid and assistance exchanged through social relationships and interpersonal transactions" (p. 187). The social support phenomenon has been studied for decades as researchers endeavored to theorize about social support functions and to investigate the role that social relationships and social support embedded therein play in mediating individuals' life stressors. Social support has been found to have positive effects on individuals' physical and mental health [13].

In the age of the Internet the number of virtual support communities has grown exponentially [14]. Such communities are based on the premise that people who share similar difficulties or disease would be better able to empathize with one another and exchange support [15]. Features of virtual support communities such as anonymity, invisibility, and delayed reactions allow community participants to disclose information about self safely without the fear of being stigmatized, create a sense of solidarity, and enhance the feeling of personal empowerment [15].

In this study, the phenomenon of social support is studied in the context where resources are actually provided to support receivers [13] instead of one's subjective perception of being cared and supported by others [2]. Among the social support studies based on this view, the types of support that are exchanged and the function that each type of support has on individuals have been a common interest (e.g., [16]). According to recent findings [9, 17], informational support and emotional support have emerged as the most common types of support exchanged online.

2.2. Social capital and its dimensions

Social capital [18-20] refers to the existence of social relationships and the relational assets, such as identity, trust, and social norms that are embedded within the relationships. The emergence and maintenance of social capital allows connected partners to share benefits, such as increased accessibility to useful information [18] and increased community solidarity [19]. By providing a theoretical foundation to explore and seek explanations for various social phenomena, social capital theory seems appropriate to this study.

This study is based on Nahapiet and Ghoshal's conceptualization of social capital, wherein the properties of social relations within an organization are linked to the creation of organizational knowledge [10]. In their conceptualization, facilitated organizational knowledge exchange and combination are the benefits embedded within social relations, which are characterized by three dimensions of social capital – structural (the existence of social interaction ties and their structural patterns among social actors), relational (the assets created in social relationships such as trust, social norms and identity), and cognitive (shared knowledge, language, and mental models among connected parties) [10].

In this study the level of analysis is at the individual actor level [21]: the dimensions of social capital are operationalized and measured for each member connecting to others in the community. Figure 1 illustrates the proposed model.

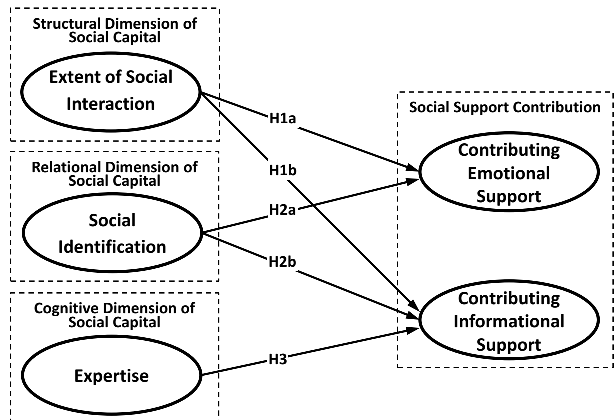

Figure 1. Proposed model of support provision in virtual support communities.

3. Hypotheses

3.1. Structural dimension of social capital and support provision

The structural dimension of social capital in this study is manifested as the extent to which one engages in social interaction with other members in message threads s/he participates in, which captures the intensity of one's social relationships.

Through regular social interactions with other group members, one has better access to these members' information and support, and thus has higher awareness of their needs [22, 23]. He or she is also more likely to be asked by these members for support [22, 23]. This results in higher opportunities for him/her to engage in supportive interactions. Barnes and Duck also suggested that frequent social interactions set up a context that fosters support exchange [24]. As virtual support community members interact through their participation in the same discussion threads, channels of support between them will also be created. Hence:

H1*. The extent to which an individual of a virtual support community interacts with other members is positively associated with his/her contribution of (a) emotional support and (b) informational support.*

3.2. Relational dimension of social capital and support provision

In this study, we consider social identification as a relational asset that is embedded in social relationships and motivates one's provision of informational and emotional support in virtual support communities.

Social identity theory [25] concerns one's psychological state by which one sees oneself as a member of, and belonging to, a social group. Research has shown that one's sense of social identity fosters his/her prosocial, citizenship behaviors toward the group s/he belongs to and its members [26]. For example, sharing of a common group identity has been found to contribute to the feelings of responsibility for the welfare of others and thus, one's helping behavior [27], even when the person who receives help is a stranger to the provider [28]. In online environments, group identity has also been found to predict virtual community members' knowledge sharing behavior [29]. As a result, when a member of a virtual support community identifies with the community, s/he is more likely to provide support to those who are in need, even if they do not know and never see each other. Hence:

H2. *An individual's degree of social identification with a given virtual support community will positively influence his/her contribution of (a) emotional support and (b) informational support to other members.*

3.3. Cognitive dimension of social capital and support provision

The cognitive dimension of social capital refers to the shared knowledge, mental models, and language that are embedded in social relationships [10]. Adler and Kwon regarded the cognitive dimension of social capital as one's "ability" to exchange social capital benefits [21]. This dimension of social capital is thus tightly related to one's expertise and the exchange of expert knowledge across social relationships [7]. Even if relationships among community members afford the opportunity and motivation to contribute useful information, contribution is not possible unless one correctly interprets the other's needs, can evaluate the context in which others need the resource, and knows what to provide [7, 21]. It has also been shown that one is less likely to contribute knowledge to other community members when one feels a lack of ability to do so [30]. Therefore, in virtual support communities, informational support – the provision of knowledge about a problem and how to solve it – is more likely to be provided by members with greater healthcare-related expertise. As a result, we hypothesize:

H3. *An individual's degree of healthcare-related expertise is positively associated with his or her contribution of informational support in the target virtual support community.*

4. Method

This study contains two stages of data analysis to study the proposed model. We first adopted manual and automated content analysis methods to analyze online message content and classify them into different categories. Based on the results of the content analysis methods, we used Structural Equation Modeling (SEM) method to test the hypotheses.

4.1. Data collection

The target virtual support community for this study is a large U.S. based virtual cancer support community that hosts discussion boards for various kinds of cancers and has more than a hundred thousand registered members posting hundreds of messages to these boards every day. Breast cancer discussion board, the most active cancer discussion board of this virtual community, was chosen as the data source from which messages were collected.

Discussion threads from the discussion board initiated within these four different time periods – the first week of May 2011, the first week of October 2011, July 1, 2012 through August 31, 2012, and September 1, 2012 through October 31, 2012 – were downloaded for investigating the research model. The collected data spanning four time periods pertains to three separate data sets used for different purposes. The information about the collected messages is listed in Table 1.

4.2. Respondents

Participants of this study were derived from the 2nd downloaded data set, i.e., participants of discussion threads initiated during the two-month period from July to August, 2012. Based on the user ID which is unique for each registrant, a total of 293 community members were identified from the collected messages. In order to have a complete record of individual online social interactions that took place across the two-month period, from July 1st to August 31st, we eliminated those who registered during this period. This resulted in 187 community members. Our aim was to study the causal relationships between the social characteristics of these 187 members in terms of their structural, relational, and cognitive dimensions of social capital, as measured during July and August, 2012 (the 2nd data set), and their subsequent provision of informational support and emotional support during September and October, 2012 (the 3rd data set).

4.3. Data analysis

Based on the three data sets, two stages of analysis were conducted. The first stage consisted of conte analyses of collected messages, first manually and then automatically, to classify them into pre-defined categories. The goal of manual classification is to generate the "training" data for the computer program to learn to classify support messages into either informational support or emotional support automatically [11].

Two coders [1] analyzed the first data set, which consists of 100 message threads, and classified it into message threads initiated either for social support exchange or for companionship activities, based on the definitions and purposes of these two types of activities (support exchange: for problem solving; companionship activities: for fun and relaxation). [2] We chose to first classify message threads into these two types of social activities since they are the two primary activities that members of virtual support communities engage in [32], and our focus is specifically on social support activity. Cohen's Kappa [33] was used to measure inter-coder reliability, resulting in the value of .86. Disagreements were resolved through discussion. This manual classification task resulted in 40 threads that were initiated for companionship purposes and 60 threads for social support exchange.

The second manual classification task focused on the 60 remaining threads (containing 795 messages) that were about support. Here the individual message posting was chosen as the basic unit of analysis. Each of these 795 messages was further manually classified into message posted for either informational or emotional support. If more than one support type was provided in a support message, the primary focus or the predominant one was coded. The resulting inter-coder reliability was .90.

After the manual classification results of informational support and emotional support messages were generated, these classified messages were then used to train the computer program coded with machine learning algorithms to classify the two types of support messages automatically. Specifically, we used the LIBSVM software library [34] to do the training and automated classification. A 10-fold cross-validation method [35] [3] was used to evaluate the "goodness" of the trained computer program (the classifier), yielding a 92.48% average classification accuracy.

The process described above was repeated using the 2nd and 3rd data sets. That is, first the total of 877 threads (containing 11,617 messages) from the two data sets were manually classified into threads for support exchange or for companionship activities. Messages from the support threads were then classified into messages for either informational support or emotional support. Due to the large amount of support messages involved (2nd data set: 3,230 support messages; 3rd data set: 3,618 support messages), manual classification would have been time consuming and error-prone. Instead, the previously trained automated support classifier was applied to classify the total of 6,848 messages into either messages for informational support or for emotional support.

At the second stage of the analysis, independent and dependent variables used for testing the hypotheses were prepared, and the proposed model was tested. As noted earlier, the variables in this study were generated from objective data such as online message content. The use of objective data for analysis avoids some potential biases associated with other widely used research methods such as survey questionnaires [36]. It also provides a different perspective on the phenomenon of online support exchange. Table 2 summarizes the variables used in this study. As indicated above, the unit of analysis for hypothesis testing was each individual community member.

4.3.1. Independent variables.

Structural dimension of social capital: In order to measure the extent of social interaction construct, three indicators were used: *post-thread ratio*, *exchanged post-thread ratio*, and *average exchanged*

[1] Since the themes to be identified through content analysis are prevalent in healthcare virtual support communities [31], two independent coders are sufficient to analyze the data.

[2] For classifying message threads into social support and companionship activities, only the first message of each message thread was considered. This strategy was undertaken due to the nature of online threaded discussion in which the first message of a thread sets up a discussion topic and the conversation that follows is supposed to revolve around this topic.

[3] The procedure of conducting 10-fold cross-validation to evaluate the automated support classifier is available upon request.

posts with an alter per thread. These indicators are expected to measure the average activity of a member within a given thread, the average interactivity of each thread a member participates in, and the average pairwise interactivity of each thread a member participates in, respectively.

The *post-thread ratio* is expected to measure, on average, the degree to which a community member engages in discussion threads s/he participates in. The higher the value, on average the more messages s/he posts when involved in a thread. In addition to this indicator, we also consider messages posted by others in threads a given member participated in. The *exchanged post-thread ratio* for a community member is intended to capture the average number of messages posted by all the posters of the threads a given member participated in. Put in other words, it measures the average amount of information a given member is exposed to when s/he participate in a discussion thread.

The *average exchanged posts with an alter per thread* indicator is about information exchanged between pairs of community members. We consider that information is exchanged between community members when they post messages in the same thread. For a given member, this indicator measures the average number of messages exchanged between him/her and each of those who had ever participated in a thread together with him/her (i.e., an alter). More specifically, this is done by measuring the average number of messages posted both by the given member and an alter, for all the threads they both participate in together. Such a calculation was carried out for all those who had ever participated in thread(s) together with the given member. This indicator is intended to measure the average amount of information exchanged between a member and an alter when they co-participate in a thread.

Relational dimension of social capital: The social identification construct of the relational dimension of social capital can be assessed by three indicators: The ratio between individual use of *we-words* (e.g., "we," "our") and *I-words* ("I," "my") in his/her messages, the *number of reciprocal friends* one possesses, and one's *tenure in the virtual support community*.

To calculate community members' use of we-words and I-words, we used the Linguistic Inquiry and Word Count (LIWC) [37] to analyze collected messages. The LIWC is a research tool used to search text documents and count the frequencies of the occurrence of words belonging to each of the 68 pre-defined word categories. In this study the "first person plural" pronouns (we-words) and the "first person singular" pronouns (I-words) categories were used to measure one's level of social identification, as researchers have suggested that the use of we-words and its comparison to I-words usage in texts are a marker of shared social identity in online environments (e.g., [38]).

In the target cancer support community, each member can explicitly designate other members to be his/her friends. This friendship assignment is not necessarily reciprocal, which means a member A can assign another member B as friend without B's assignment of A as friend. As a result, when two community members assign each other as friends, it can be seen as that the two members recognize each other as friends, forming close social bonds. Hogg and Abrams [25] argued that a sense of group identification begets liking between members of the same group. In other words, the more reciprocal friends one has, the more one identifies with the target virtual support community.

In addition, we also consider an individual's tenure in the target virtual support community as an indicator of social identification. As an individual's tenure in a virtual community increases, due to his/her history of interaction with other members, it is likely that his/her feeling of attachment and sense of belonging, and the perceived similarities between the individual and other members also increases, leading the individual to identify more with the community [39, 40].

Cognitive dimension of social capital: To assess an individual's level of healthcare-related expertise, two indicators were used: the *average number of the Unified Medical Language System (UMLS) terms* used in each informational support message one posted, and the *number of non-reciprocal incoming friendship* assignments one has.

UMLS [41] is an online meta-thesaurus of controlled vocabularies of biomedical terminologies, which was developed by the U.S. National Library of Medicine (NLM). Each term in the UMLS belongs to one or more of the total 135 semantic types such as "Disease or Syndrome" (e.g., infection, lymphedema), "Mental or Behavioral Dysfunction" (e.g., depression, addiction), or "Therapeutic or Preventive Procedure" (e.g., chemo, reconstruction). We used MetaMap, a software tool that applies the UMLS for identifying biomedical terms in texts, to analyze collected messages and map word occurrences to UMLS semantic types [42]. Here we measured the average number of UMLS terms used in each informational support message one posted, which represents one's ability to apply his/her knowledge in the provision of informational support.

Social comparison theory [43] suggests that people under anxiety conditions are likely to affiliate and seek information from those who adjust better than themselves [44]. This tendency of "upward affiliations" allows individuals to simultaneously acquire guidance from these experts for coping with the stressors, and treat experts as role models to provide hope and inspiration for themselves [44]. It can thus be inferred that members of virtual support communities who have a high degree of non-reciprocal, incoming friendship assignments from other community members are expected to have "either overcome their threatening circumstances or adjusted well" [44] (p. 571) and thus have higher expertise.

4.3.2. Dependent variables. Individual provision of informational support and emotional support are the two dependent variables in this study. To assess the two constructs, we measured the quantity and effort aspects of support provision as indicators. In other words, for each community member, the number of informational and emotional support messages s/he posts, and the average number of words in his/her provision of informational support and emotional support message, i.e., the effort s/he took to provide support, were calculated.

5. Results

To test the proposed hypotheses, we chose Partial Least Squares (PLS) analysis, a component-based approach to SEM, for model validation and structural model testing. The SmartPLS 2.0 software package [45] was used for data analysis in this study.[4]

5.1. Measurement model validation

We assessed the indicator reliability, convergent validity, internal consistency reliability, and discriminant validity of the measurement model [46, 47]. As can be seen in Table 3, the factor loadings for the indicators are 0.6 or higher, suggesting indicator reliability.[5] In addition, the values of the average variance extracted (AVE) and composite reliability (CR), as shown in Table 4, are greater than 0.5 and 0.7, respectively, suggesting convergent validity and internal consistency reliability of the measurement model. Lastly, Table 4 shows that all the square roots of AVE (diagonal elements) exceed the corresponding inter-construct correlations (off-diagonal elements), providing evidence of discriminant validity.

5.2. Structural model testing

Figure 2 illustrates the results of the structural model test. As seen in the figure, around 13% of the variance in the emotional support contribution and around 10% of the variance in the informational support contribution could be explained by the proposed dimensions of social capital constructs.

As for the proposed hypotheses, an individual member's extent of social interactions with other members in a thread is positively related to his/her contribution of emotional support (H1a, $\beta = 0.18$, $p < 0.01$), as is his/her social identification with the community (H2a, $\beta = 0.30$, $p < 0.01$). However, an individual's extent of social interaction and his/her level of social identification failed to predict the provision of informational support, rejecting hypotheses 1b and 2b. As predicted, an individual's level of healthcare-related expertise significantly and positively predicted his/her informational support contribution (H3, $\beta = 0.32$, $p < 0.01$).

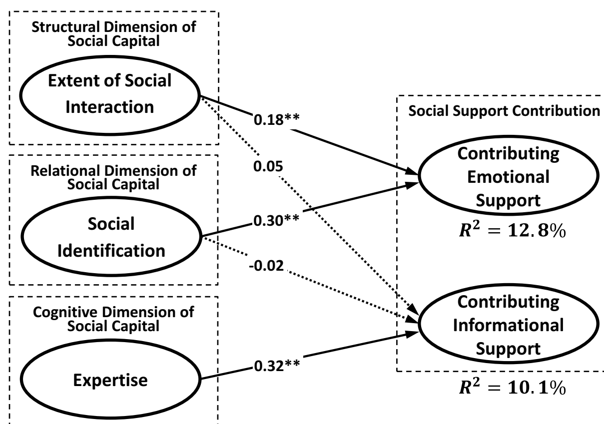

Figure 2. Results of PLS analysis.

6. Discussion

This article attempts to answer the question of what leads to individual contributions of social support in healthcare virtual support communities. The results suggest that, although both the extent of social interaction and social identification (H1a and H2a, the structural and relational capital) are positively and significantly associated with one's provision of emotional support, they fail to significantly predict the provision of informational

[4] A bootstrapping procedure (500 resamples) in SmartPLS 2.0 was used to assess the significance level of the hypothesized paths.

[5] A general rule of thumb for indicator reliability is that the factor loadings for the indicators should be 0.7 or higher. However, as indicated by some researchers (e.g., [46]), for exploratory research design with newly developed indicators, as is the case for the proposed model, factors loadings of 0.5 or 0.6 may be acceptable.

support (H1b and H2b). A possible reason that H1b and H2b were not supported may be due to the fact that even if one has the opportunity to share information (the structural capital), and is motivated to share information (the relational capital), one may still be reluctant to contribute if s/he lacks the ability to help (the cognitive capital) [21]. When a community member asks for information about a medication and its side effects, symptoms of a disease, a healthcare provider, or an insurance plan, other members may not be able to help if they do not have the knowledge to do so. As hypothesized, an individual's healthcare related expertise (H3, the cognitive capital) significantly predicted his/her provision of informational support.

The implication, for website designers as well as healthcare organizations aiming to facilitate individual participation in virtual support communities, is to identify experts in the community and work with them to encourage the provision of informational support. By examining individual use of biomedical terms in supportive messages, experts in the community can be discovered. Furthermore, people can analyze community members' uses of personal pronouns, friendship status, or their tenure in this community to locate those who are more identified with the community. Through the collaboration with those experts and/or committed members to build a virtual community conducive to social interactions, the community will have greater longevity, healthcare intervention through virtual support communities will be more effective, and healthcare organizations can also co-create value with community participants from the facilitated exchange of support [6].

We should note some limitations. First, an inevitable limitation of conducting automated content analysis is that it introduces certain classification errors. To solve this problem, future studies should employ parallel research methods such as survey questionnaires to triangulate the research findings. This can also lead to a more meaningful analysis of the dynamics of the virtual support community.

Because the target virtual support community of this study is U.S.-based, the generalizability of the findings to virtual support communities located in different countries could be limited. However, because anyone in the world can register and participate in the target virtual support community, we believe this limitation is alleviated to some extent. Still, replication and comparison of this study to see if virtual support communities of different countries exhibit similar dynamics is worth performing.

Third, this study intentionally classified online user activities into companionship activities, informational support, and emotional support. Such an exclusive and exhaustive classification may underestimate the "messy" real world situations in which a message may be posted by an individual to serve multiple purposes. More insights into the complexities of online relationships and their impact on social support provision require future research to reflect the nature of social activities.

Lastly, in this study indicators for measuring the "extent of social interaction" construct (i.e., the structural dimension of social capital) were used for the first time in the literature. As a result, the validity of these indicators needs to be further examined. Future study should assess the suitability of these indicators in capturing this aspect of social capital.

7. Conclusion

This study aims to conceptualize the relationships between social capital and the provision of social support in virtual support communities. The structural dimension of social capital, manifested as the extent of social interaction, was hypothesized to provide opportunities for community members to provide social support. The relational dimension, manifested as social identification, was hypothesized to motivate individuals to provide help. The cognitive dimension, manifested as individual healthcare-related expertise, was hypothesized to capacitate individual to share knowledge with other members. This study not only provides insights into the design and administration of virtual support communities, but it could also be the basis of future endeavors for improving the social and health outcomes of participation in such communities.

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Table 1. Information about messages collected for this study

Data Set	Purpose	Description	Num. of Messages
1st weeks of May 2011 and Oct. 2011	Training data for automated support classification	The collection of data spanning two different time periods (May and Oct., 2011) allowed us to account for possible behavioral differences across different seasons [48].	1,274 (100 threads)
Jul. 2012 through Aug. 2012	Generating independent variables	As with [49] and [7], data collected for testing the proposed model was separated into two time periods to address the mutual-dependence issue between the independent and dependent variables. In more specific, the messages used for generating independent variables were those that were posted two months prior to the messages used for generating dependent variables. This helps ensure the causal direction to be tested in our model.	5,491 (426 threads)
Sep. 2012 through Oct. 2012	Generating dependent variables		6,226 (453 threads)

Table 2. Variables used in this study

Construct	Indicator	Definition
Extent of Social Interaction (structural dimension)	Post-thread ratio	$\frac{\text{Total \# of msgs posted by the member}}{\text{Total \# of threads to which the member posted msgs}}$
	Exchanged post-thread ratio	$\frac{\text{Total \# of msgs in threads to which the member posted msgs}}{\text{Total \# of threads to which the member posted msgs}}$
	Average exchanged posts with an alter per thread	$\frac{\sum_{\substack{\text{each}\\ \text{alter}}} \frac{\text{\#of msgs posted by a given member and an alter in all threads that they participated in together}}{\text{\# of threads that they participated in together}}}{\text{\# of distinct alters in all threads to which the member posted msgs}}$
Social Identification (relational dimension)	“We” to “We”+“I” ratio	$\frac{\text{\# of We words occur in the member's msgs}}{\text{\# of We words + I words occur in the member's msgs}}$
	Number of reciprocal friends	# of reciprocal friendship designations made by other members and the member
	Tenure in the community	# of months since the member’s registration in the virtual support community
Healthcare-related Expertise (cognitive dimension)	Average UMLS terms per message	$\frac{\text{\# of UMLS terms used in the member's informational support messages}}{\text{\# of informational support messages posted by the member}}$
	Num. of non-reciprocal incoming friends	# of friendship designations made by other members to the member without reciprocal friendship assignments
Informational Support (Dep. var.)	Quantity of informational support	# of informational support messages posted by the member
	Effort of providing informational support	$\frac{\text{Word count in all the informational support msgs posted by the member}}{\text{\# of informational support msgs posted by the member}}$
Emotional Support (Dep. var.)	Quantity of emotional support	# of emotional support messages posted by the member
	Effort of providing emotional support	$\frac{\text{Word count in all the emotional support msgs posted by the member}}{\text{\# of emotional support msgs posted by the member}}$

Table 3. Factor Loadings and Cross-Loadings

	Ext. of Social Interaction	Social Identification	Expertise	Informational Support	Emotional Support
Post-thread ratio	0.82	-0.03	-0.02	0.07	0.12
Exchanged post-thread ratio	0.85	0.08	0.01	0.03	0.21
Average exchanged posts with an alter per thread	0.73	0.01	-0.01	0.02	0.07
“We” to “We”+ “I” ratio	0.15	0.63	0.06	0.07	0.18
Num. of reciprocal friends	0.01	0.88	0.17	0.03	0.30
Tenure in the community	-0.07	0.72	0.28	0.04	0.18
Average UMLS terms per message	-0.03	-0.11	0.69	0.21	0.03
Num. of non-reciprocal incoming friends	0.02	0.40	0.79	0.25	0.34
Quantity of informational support	0.05	0.06	0.31	0.99	0.48
Effort of providing informational Support	0.04	0.05	0.31	0.99	0.38
Quantity of emotional support	0.21	0.32	0.22	0.38	0.99
Effort of providing emotional Support	0.16	0.29	0.32	0.49	0.99

Table 4. Descriptive Statistics, AVE, CR, and Correlations

		AVE	CR	1	2	3	4	5
1	Extent of Social Interaction	0.65	0.84	**0.80**[a]				
2	Social Identification	0.56	0.79	0.04	**0.75**			
3	Expertise	0.55	0.71	0.00	0.22	**0.74**		
4	Informational Support	0.98	0.99	0.05	0.06	0.31	**0.99**	
5	Emotional Support	0.97	0.99	0.19	0.31	0.27	0.43	**0.99**

[a] The diagonal elements are the square root of the AVE