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RESEARCH ARTICLE

SHARING IS CARING: SOCIAL SUPPORT PROVISION AND COMPANIONSHIP ACTIVITIES IN HEALTHCARE VIRTUAL SUPPORT COMMUNITIES

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Appendix A

IS Studies that Adopted Social Capital Theory to Investigate the Determinants of Social Support

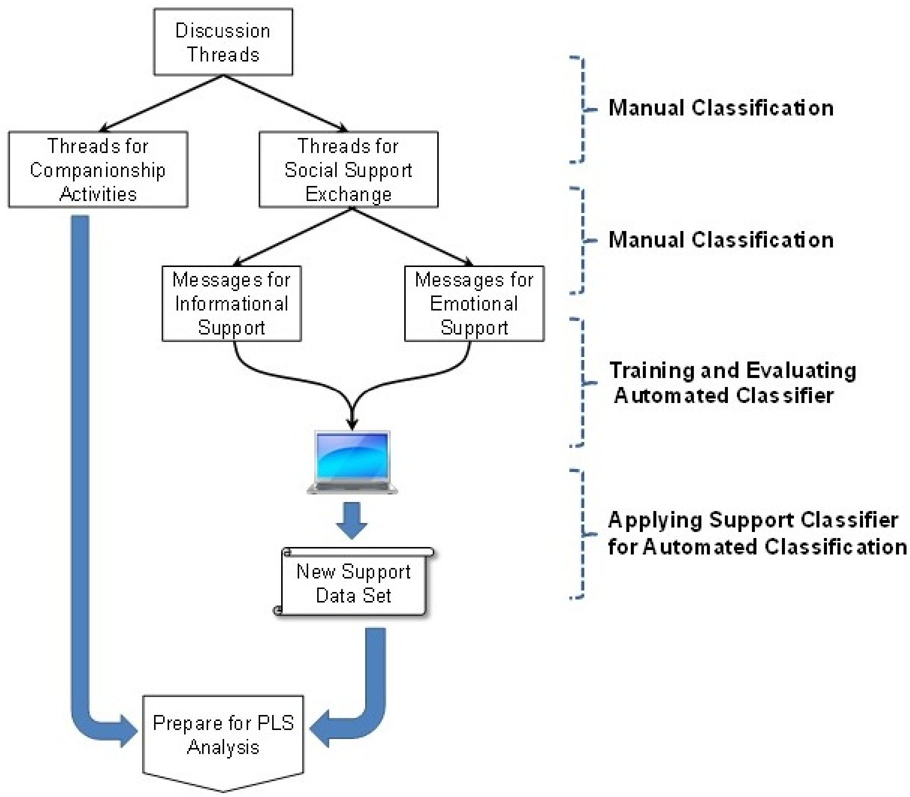
Author	Type of helping behavior (social support)	Manifested constructs	Operationalization (when measuring social capital dimensions directly)	Positively predict the provision of social support?	Major findings
Social Capital Dimensions as Predictors					
Lu and Yang 2011	Knowledge and information	Structural capital	Second order reflective construct with social interaction ties as the first order variable (reflective)	Y	• Structural capital was positively related to individual message contribution • Relational capital and cognitive capital failed to predict the message contribution behavior (hypotheses were not supported)
		Relational capital	Second order reflective construct with trust and reciprocity as first order variables (reflective)	N	
		Cognitive capital	Second order reflective construct with shared vision and shared language as first order variables (reflective)	N	

Author	Type of helping behavior (social support)	Manifested constructs	Operationalization (when measuring social capital dimensions directly)	Positively predict the provision of social support?	Major findings
Robert et al. 2008	Knowledge and information	Structural capital	Interaction intensity and degree centrality (aggregated as a single item)	N	• Relational capital and cognitive capital both had positive impacts on knowledge integration and sharing • Structural capital failed to predict knowledge integration behavior (hypothesis was not supported) • When communicated through lean digital networks, structural and cognitive capital had stronger impacts on team members' knowledge integration and contribution
		Relational capital	Norms, social identity, trust, and obligation (reflectively)	Y	
		Cognitive capital	shared mental model	Y	
Components of Social Capital Dimensions as Predictors					
Chang and Chuang 2011	Knowledge and information	Social interaction ties (as a component of structural capital)		N	• Individual online contribution behavior was determined by social identity, norm of reciprocity, shared language, and individual altruism • Social interaction ties, trust, and perceived reputation enhancement failed to predict online contribution behavior (hypotheses were not supported) • Altruism has a stronger effect on online contribution when members have higher levels of online participation involvement
		Trust (as a component of relational capital)		N	
		Social identity (as a component of relational capital)		Y	
		Reciprocity (as a component of relational capital)		Y	
		Shared language (as a component of cognitive capital)		Y	
Chiu et al. 2006	Knowledge and information	Social interaction ties (as a component of structural capital)		Y	• Knowledge contribution behavior was predicted by social interaction ties, norm of reciprocity, social identity, shared vision (negative relationship, hypothesis was not supported), and community-related outcome expectations (e.g., help sustain the community, help enrich knowledge in the community) • Trust, shared language, and personal outcome expectations (e.g., enjoyment, reputation, making friends) failed to predict individual knowledge contribution (hypotheses were not supported)
		Trust (as a component of relational capital)		N	
		Reciprocity (as a component of relational capital)		Y	
		Social identity (as a component of relational capital)		Y	
		Shared language (as a component of cognitive capital)		N	
		Shared vision (as a component of cognitive capital)		N	

Author	Type of helping behavior (social support)	Manifested constructs	Operationalization (when measuring social capital dimensions directly)	Positively predict the provision of social support?	Major findings
He et al. 2009	Knowledge and information	Social interaction ties (as a component of structural capital)		Y	• Online knowledge contribution intention was affected by individual knowledge contribution belief (which is formed by online social relationship, enjoyment of helping, management influence, and effort required for contribution (-)) and individual knowledge contribution attitude
		Trust (as a component of relational capital)		Y	
		Shared norms (as a component of cognitive capital)		Y	
Sarker et al. 2011	Knowledge and information	Communication centrality (as a component of structural capital)		Y	• Individual knowledge sharing behavior was predicted by his/her trust centrality and interaction centrality • The level of knowledge possessed by an individual failed to predict his/her knowledge sharing activities (hypothesis was not supported)
		Trust centrality (as a component of relational capital)		Y	
Wasko and Faraj 2005	Knowledge and information	Communication centrality (as a component of structural capital)		Y	• Community members helped others due to tangible returns (e.g., access to useful knowledge), intangible returns (e.g., personal enjoyment), and community interests (e.g., norm of reciprocity)
		Reciprocity (as a component of relational capital)		N	
		Commitment (as a component of relational capital)		N	
		Tenure (as a component of cognitive capital)		Y	
		Expertise (as a component of cognitive capital)		N	
Wiertz and de Ruyter 2007	Knowledge and information	Reciprocity (as a component of relational capital)		N	• Online knowledge sharing behavior was predicted by individual online interaction propensity (which can be strengthened when norm of reciprocity increases) and individual commitment to the firm-hosted virtual community (the effect can be strengthened when one's online interaction propensity increases) • Norm of reciprocity and individual commitment to the host firm failed to predict online knowledge sharing behavior (hypotheses were not supported)
		Commitment to the community (as a component of relational capital)		Y	
		Commitment to the host firm (as a component of relational capital)		N	
Zhao et al. 2013	Knowledge and information	Trust (as a component of relational capital)		Y	• Knowledge contribution was predicted by social identity and empathy, which was determined by social identity and trust
		Social identity (as a component of relational capital)		Y	

Appendix B

Automated Support Classification Tasks



Appendix C

Variables Used in this Study

Independent Variables	
Second-level construct	Structural Capital
First-level construct	Frequency of Interaction
Indicator	Frequency of Interaction (FI) (Adler and Kwon 2002)
Description: Frequency of interaction is calculated as the average number of different threads in which one posted messages during the days one was present in the discussion board and posted messages (i.e., during the days one was active). This indicator represents the diversity of information received as well as the degree to which one has access to different members. Specifically, this indicator was calculated as $\frac{\text{Sum of the number of the target member's thread participation for each of his / her active day}}{\text{number of days of the target member's community participation (i.e., active days)}}$ We chose this conceptualization of structural capital over the often-used approach that relies on the degree of centrality measure as compared with pure quantitative measures, our conceptualization complements and promises a better understanding of the concept of structural capital and its manifestation in social relationships (Adler and Kwon 2002).	
Second-level construct	Structural Capital
First-level construct	Intensity of Interaction
Indicator	Intensity of Interaction (II) (Adler and Kwon 2002)
Description: Intensity of interaction was calculated as, of the threads one participated in on a day when s/he is present in the community, the average number of messages s/he posted in each thread. In other words, it represents the intensity of one's thread participation during the days one was present in the discussion board. The higher the value, the greater the depth of information exchanged (Yli-Renko et al. 2001). Specifically, this indicator was calculated as $\frac{\text{Total number of messages posted by the target member during the collection period}}{\text{Sum of the number of thread participation for each of his / her active day}}$	
Second-level construct	Structural Capital
First-level construct	Multiplexity of Interaction
Indicator	Multiplexity of Interaction (MI) (Adler and Kwon 2002)
Description: Multiplexity of interaction was measured as the degree to which one interacts with others on multiplex occasions (i.e., both for support and for companionship purposes) in the discussion board. It measures the degree to which the purpose of a community member's interactions has shifted from social support exchange to engagement in companionship activities. The higher the value, the higher the degree to which the member interacts with others not just for support purposes but also to fulfill intrinsic needs of social integration and enjoyment (Rook 1987, 1995). This highlights the diverse interactions between community members in HVSCs, representing additional channels for information exchange. Specifically, this indicator was calculated as $\frac{\text{Number of members with whom one participated in companionship threads together}}{\text{Number of members with whom one participated in social support threads together}}$	

Second-level construct	Relational Capital
First-level construct	Social Norm (reflective construct)
Indicator 1	Norm of being Supportive to New Members (NM1) (Maloney-Krichmar and Preece 2002; Wellman et al. 1996)

Description:
Norm of being supportive to new members measures the degree to which one participated in discussion threads initiated by new community members—those who registered between June and August 2012 (i.e., the second dataset)[1]—when one participated in the community (i.e., during the days when one is active in the community). That is, on average, of the number of new-user-initiated threads one is exposed to on a day when s/he is present in the community, the actual number of these threads to which one posted messages.[2] Specifically, this indicator was calculated as

$$\frac{\text{Number of the target member's message postings in threads initiated by new members}}{\begin{array}{c}\text{Sum of the number of threads initiated by new members that have message - posting activities}\\ \text{on the days when the target member is active in the community (number of thread}\\ \text{participation opportunities to help newcomers)}\end{array}}$$

Indicator 2	Norm of being Supportive to Community Members (NM2) (Maloney-Krichmar and Preece 2002; Wellman et al. 1996)

Description:
The norm of being supportive to other members is also measured as the degree to which one participated in discussion threads to support others (Wellman et al. 1996), either friends or new members. This indicator measures, on average, of the different members one has the opportunity to help (i.e., those members' threads had message-posting activities) during the days when s/he is present in the community, the actual number of their threads in which s/he posted messages. Specifically, this indicator was calculated as

$$\frac{\begin{array}{c}\text{Number of different members whose threads were joined by the target member}\\ \text{during his / her active days}\end{array}}{\begin{array}{c}\text{Sum of the number of different community members the target member}\\ \text{had the opportunity to help during his / her active days}\end{array}}$$

Second-level construct	Relational Capital
First-level construct	Trust (reflective construct)
Indicator 1	Self-Disclosure in Emotional Support Messages (TR1) (Callaghan et al. 2013; Houghton and Joinson 2012)

Description:
Self-disclosure represents one's willingness to trust and take risks in disclosing personal and sensitive information (Grabner-Kräuter 2009). It also signals that the discloser trusts and values the receiver's opinion (Jiang et al. 2011). Self-disclosure in this study was objectively measured by applying the Linguistic Inquiry and Word Count (LIWC) software package (Pennebaker et al. 2007) to analyze online message content. 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. Following previous studies using LIWC to assess the degree of self-disclosure (e.g., Callaghan et al. 2013; Houghton and Joinson 2012), LIWC categories including first-person singular pronoun (e.g., I, my), first-person plural pronoun (e.g., we, our), family (e.g., husband, mom), friend (e.g., neighbor, roommate), positive emotion (e.g., love, happy), and negative emotion (e.g., hurt, insult), were used to identify self-disclosure words in online messages. Two reflective indicators were generated for measuring trust based on these LIWC categories. The first indicator is the ratio of self-disclosure words in emotional support messages posted by an individual, to the total number of words in these messages. Specifically, this indicator was calculated as

$$\frac{\begin{array}{c}\text{Total number of self disclosure words (identified via LIWC)}\\ \text{in emotional support messages posted by the target member}\end{array}}{\begin{array}{c}\text{Length of all the emotional support messages (as number of words)}\\ \text{posted by the member}\end{array}}$$

[1]While we took into account the threads posted by members registered during the second dataset period in calculating and generating this variable, these new members, as indicated above, were not considered as the sample of this study.

[2]In the target discussion boards, discussion threads are listed in a reverse chronological order based on the date and time they were last responded. In this study we used the number of threads that had message-posting activities during the day the target member also posted messages as a proxy of the number of threads s/he was exposed to on that day.

<table>
<tr><td>Indicator 2</td><td>Self-Disclosure in Informational Support Messages (TR2) (Callaghan et al. 2013; Houghton and Joinson 2012)</td></tr>
<tr><td colspan="2">Description:
The second indicator of the Trust construct is the ratio of self-disclosure words in informational support messages posted by an individual, to the total number of words in these messages. Specifically, this indicator was calculated as

$$\frac{\text{Total number of self disclosure words (identified via LIWC) in informational support messages posted by the target member}}{\text{Length of all the informational support messages (as number of words) posted by the member}}$$</td></tr>
<tr><td>Second-level construct</td><td>Relational Capital</td></tr>
<tr><td>First-level construct</td><td>Social Identity (formative construct)</td></tr>
<tr><td>Indicator 1</td><td>In-Group Liking (SI1)</td></tr>
<tr><td colspan="2">Description:
In-group liking results from one’s identification of group members in terms of their embodiment of the group prototype (Bergami and Bagozzi 2000; Hogg and Terry 2000). Hogg and Terry (2000) called it “social attraction,” by which one intends to friend others due to shared group membership (Bergami and Bagozzi 2000). According to the SIDE model (Postmes et al. 2005; Spears and Lea 1994), such a group-based liking tends to take place in virtual settings. Recognizing that in the target HVSC, members can set each other as friends, we measured in-group liking as the number of friend assignments made by community members.[3] As a measurement capturing the degree to which a community member feels a sense of liking for, and an interest in socializing with, other members, this indicator represents the degree to which one (affectively) identifies with the community. Specifically, this indicator was calculated as

Total number of community-friends the target member has in the target discussion board</td></tr>
<tr><td>Indicator 2</td><td>Favorable In-Group Evaluation (SI2) (Cassell and Tversky 2006)</td></tr>
<tr><td colspan="2">Description:
Favorable in-group evaluation represents the “evaluative” component of social identity, concerning a positive value connotation of being a group member (Bergami and Bagozzi 2000; Ellemers et al. 1999). Motivated by an intrinsic need for self-esteem, this aspect of social identity reflects one’s selective evaluation in favor of the group one identifies with when comparing in-group and out-group memberships (Hogg and Adams 1988). According to Brewer and Gardner (1996), and Perdue et al. (1990), such an evaluative bias toward the group is evoked automatically as group members use words referring to in-group categorization (e.g., we, our). As suggested by previous research (e.g., Cassell and Tversky 2006), we used the ratios between individuals’ uses of pronouns in messages that connote in-group favoritism, that is, we-words (e.g., we, our) and their uses of I-words (e.g., I, me) in social support messages to measure one’s positive evaluation toward the HVSC. LIWC was applied to identify we-words and I-words in messages. Specifically, this indicator was calculated as

$$\frac{\text{Number of "We" words used in the member's social support messages}}{\text{Number of "We" words + "I" words used in the member's social support messages}}$$</td></tr>
</table>

[3]Similar to the feature of social networking communities, in the target HVSCs a member can friend other community members (either the member accepted friend assignments from others or got accepted as a friend by others). The list of community “friends” a member has is open to all registered members.

Second-level construct	Cognitive Capital
First-level construct	Shared Language (reflective construct)
Indicator 1	Prototypical Language Similarity (SL1) (Baeza-Yates 1999)
Description: This indicator was generated by applying an approach commonly used in the Information retrieval and natural language processing disciplines to analyze online messages. Specifically, we applied the vector-space model (VSM) and the term-frequency-inverse-document-frequency (*tf-idf*) weighting approach (Baeza-Yates 1999) to generate a prototypical message that represents the common language shared by community members. The basic idea of a prototypical message is that the words that appear frequently in messages of one community but not other communities should represent the shared language used by members of that community.[4] Based on the prototypical message, we compared the similarities (based on cosine similarity) between it and each community member's messages. The closer a member's messages to the prototypical message, the more the member used community-specific language in his/her messages. Specifically, this indicator was calculated as Cosine similarity between the messages posted by the target member (represented as a vector of *tf-idf*-weighted terms) and the prototypical message of the target discussion board (the mean of all the message vectors of the discussion board)	
Indicator 2	LDA Topic Diversity (SL2) (Wu 2013)
Description: This indicator measures the extent to which a community member's word uses covered different discussion themes of the community, which was calculated as a two-stage process. At the first stage, we applied Latent Dirichlet Allocation (LDA), the most commonly used approach for topic modeling—machine learning techniques applied to infer the themes or patterns of word-use that characterize the observed collection of documents (Blei 2012)—to analyze the collected messages. LDA inferred a set of topics (e.g., treatment, medication, healthcare provider) statistically from the words used in discussion messages of the cancer discussion boards (messages from the three discussion boards were analyzed separately). These topics, represented in a vector space, can be regarded as the content areas of the respective boards. Following a similar approach to measure information diversity using LDA in the IS literature (Wu 2013), community members' levels of using community-specific language were then calculated at the second stage. At this stage, each member's words collection in his/her messages were converted into the topic vector space using LDA, and its vector similarity against the content vector of the whole discussion board was measured. The higher the similarity value, the more the community topics one's word uses span. Similar to the first indicator, this indicator captured the degree to which one's word uses in one's messages resembled the (topic) vector representing a given discussion board. Specifically, this indicator was calculated as Cosine similarity between the topic vector derived via LDA based on message discussions in the target discussion board and the topic vector derived via LDA that capture the target member's message postings.	

[4]Through the VSM approach, each message posting j was converted into a vector of weighted index terms ($w_{1,j}$, $w_{2,j}$,…, $w_{t,j}$), in which index terms *1* through t are words occurring in the message collection and the weight of each index term with regard to a given message represents the importance of the index term for describing that message. In the *tf-idf* approach, the *term frequency* of each index term i with regard to a given message j, f_{ij}, is calculated as $f_{ij} = freq_{ij}/max\ freq_i$, where $freq_{ij}$ is the number of times the term i occurs in the message and $max\ freq_j$ is the maximum frequency occurrence across all the terms appearing in message j. If an index term does not appear in the message, $f_{ij} = 0$. The *inverse document frequency* for an index term i across the message collection is calculated as $idf_i = log(N/n_i)$, where N is the total number of messages in the collection, and n_i is the number of messages in which the index term i appears. The weight of an index term i with regard to a given message j, w_{ij}, therefore is calculated as $w_{if} = tf_{ij} \times idf_i$. In this study the conversion of each message into its vector representation is based on all the messages of colorectal cancer, prostate cancer, brain cancer, ovarian cancer, and lymphoma discussion boards. In the generation of the prototypical messages for the three target discussion boards of this study, we calculated the means of all the message vectors of the corresponding message boards.

Second-level construct	Cognitive Capital
First-level construct	Healthcare-Related Expertise
Indicator	UMLS concept count (HRE)
Description: The level of healthcare-related expertise was measured by calculating community members' uses of Unified Medical Language System (UMLS) in their messages. UMLS (Bodenreider 2004) is an online meta-thesaurus of controlled vocabularies of biomedical terminologies developed by the U.S. National Library of Medicine (NLM). Each term in the UMLS belongs to one or more of the total of 135 semantic types such as "Disease or Syndrome" (e.g., infection, lymphedema), or "Therapeutic or Preventive Procedure" (e.g., chemo, reconstruction).[5] To generate the desired variable, we measured the total number of different UMLS semantic types identified in one's informational and emotional support messages. This indicator captures the degree to which a community member expresses his/her healthcare-related knowledge when interacting with other members. Specifically, this indicator was calculated as Number of distinct UMLS semantic types identified in the target member's social support messages	
Dependent Variables	
Construct	Informational Support (reflective construct)
Indicator 1	Informational Support Count
Description: This indicator measures the number of informational support messages one posted in the discussion board. Specifically, this indicator was calculated as Number of informational support messages posted by a member	
Indicator 2	Informational Support Length
Description: This indicator measures the amount of support one provides in one's informational support messages. Specifically, this indicator was calculated as Word count in all the informational support messages posted by the target member	
Construct	Emotional Support (reflective construct)
Indicator 1	Emotional Support Count
Description: This indicator measures the number of emotional support messages one posted in the discussion board. Specifically, this indicator was calculated as Number of emotional support messages posted by a member	
Indicator 2	Emotional Support Length
Description: This indicator measures the amount of support one provides in one's emotional support messages. Specifically, this indicator was calculated as Word count in all the emotional support messages posted by the target member	

[5] MetaMap, a software tool that applies the UMLS for identifying biomedical concepts in texts, was used to analyze collected messages and map word occurrences to UMLS semantic types (Aronson 2001).

<table>
<tr><th>Construct</th><th>Companionship Activities (reflective construct)</th></tr>
<tr><td>Indicator 1</td><td>Companionship Activities Count</td></tr>
<tr><td colspan="2">Description:
This indicator measures the number of messages one posted to companionship activity threads in the discussion board. Specifically, this indicator was calculated as

Number of messages posted by a member to the companionship activity threads</td></tr>
<tr><td>Indicator 2</td><td>Companionship Activities Length</td></tr>
<tr><td colspan="2">Description:
This indicator measures the amount of companionship activities one participated in in the discussion board. Specifically, this indicator was calculated as

Word count in all the companionship activity messages posted by the target member</td></tr>
</table>

Appendix D

Results of Mediation Analysis

The associations among the social capital dimensions in our proposed model called for a test of mediation effects. We applied a bootstrapping approach to estimate standard errors and to test the significance of the mediating effects (Henseler et al. 2009). Bootstrapping is a preferred approach for testing mediation effects over the widely used Sobel test (Sobel 1982), as it does not impose strict sample size and distribution requirements (Hayes 2009; Preacher and Hayes 2008). The results indicate that cognitive capital significantly mediated the effects of structural capital on emotional support ($\beta = 0.20$, $P < 0.01$) and informational support ($\beta = 0.51$, $P < 0.01$). Additionally, while relational capital did not mediate structural capital's impacts on the provision of informational support, it significantly mediated the impact of structural capital on emotional support provision ($\beta = 0.12$, $P < 0.01$). Furthermore, relational capital significantly mediated the effects of structural capital on companionship activities ($\beta = 0.12$, $P < 0.05$).

We also applied Baron and Kenny's (1986) method to compare mediated and unmediated models linking structural capital to social support provision. By changing from a model without cognitive capital and its components to a full mediation model (our research model), the direct effect of structural capital on informational support changed from significant to nonsignificant ($\beta = 0.37$, $P < 0.01 \rightarrow \beta = -0.08$, $P > 0.05$), and its direct effect on emotional support also substantially decreased ($\beta = 0.48$, $P < 0.01 \rightarrow \beta = 0.27$, $P < 0.01$). This confirms that cognitive capital fully mediated the impact of structural capital on informational support, and a partially mediated structural capital's effect on emotional support. The same procedure was applied to examine the mediation effect of relational capital, and the result shows that relational capital partially mediated the effects of structural capital on emotional support ($\beta = 0.38$, $P < 0.01 \rightarrow \beta = 0.27$, $P < 0.01$) and companionship activities ($\beta = 0.61$, $P < 0.01 \rightarrow \beta = 0.49$, $P < 0.01$).

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