Modeling What Friendship Patterns on Facebook Reveal About Personality and Social Capital

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17

In this study, we demonstrate how analysis of users' social network structure—a topic that has remained until recently inconspicuous within Human-Computer Interaction (HCI) research on social systems—can contribute to our understanding of Social Networking Services (SNS) effect on users. Despite a consensus that SNS enhance people's social capital, prior studies on SNS have provided inconsistent evidence on this process. In a multipronged study, we analyze personality, social capital, and Facebook data from a cohort of participants to model the extent to which one's SNS reflects aspects of his or personality and affects his bridging social capital. Our empirically validated model shows that empathy and conscientiousness influence the structural holes in one's social network, which in turn affects bridging social capital. These findings highlight the importance of network structure as an intermediary between one's personality and the social benefits one reaps from using SNS. Our work demonstrates how the implicit structural information embedded in users' social networks can provide key insights into users' personality and social capital.

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1. INTRODUCTION

Social Networking Services (SNS) are becoming increasingly prevalent and important instruments for users to manage their social life. For instance, Facebook is currently the second most frequently visited website on the Internet, behind Google [Alexa 2013]. As of September 2012, there are more than 1 billion monthly active members on Facebook, more than half of whom access Facebook via a mobile device [The Wall Street Journal 2012]. SNS are increasingly used to maintain, enhance, and extend people's existing social capital online through exchanging information among friends, as well as through making new friends. Consequently, it has been widely accepted that SNS are an important tool for maintaining and generating social capital in modern society. Despite this consensus, prior studies seem to offer inconsistent understanding on how social capital is enhanced through online social networking.

For instance, the research findings of Ryan and Xenos [2011] report that the time spent on Facebook is positively correlated with feelings of loneliness, and that Facebook users have significantly *higher* levels of family loneliness than nonusers. In another study, one in three participants reported feeling negative emotional outcomes, such as boredom or frustration, after visiting the site [Krasnova et al. 2013]. Yet, Facebook use was found to be positively related to bonding social capital, which refers to the benefits obtained due to emotionally close relationships, such as with family and close friends [Ellison et al. 2007]. Although many have noted that the use of online social networking (i.e., the daily length of use) enhances one's social capital (i.e., Ellison et al. [2007]; Steinfield et al. [2008]), Burke et al. [2010] analyzed the log data of time on Facebook and found that the time spent on the site has no significant relationship with bridging, bonding social capital, or loneliness. Therefore, prior studies investigating specific SNS usage (i.e., duration or frequency of service use), seem to offer inconsistent explanation on how social capital is enhanced by the use of the service.

Research has also considered how individuals' differences in terms of personality traits or skills affect how they use and benefit from these systems [Anderson et al. 2012]. One study suggests that Facebook users tend to have lower levels of conscientiousness, and that their conscientiousness is negatively correlated with time spent on Facebook per day [Ryan and Xenos 2011]. However, another study indicates conscientiousness is not a significant factor of Facebook usage [Ross et al. 2009], whereas conscientiousness has been reported to be positively associated with greater social capital in daily lives [Khodadady and Zabihi 2011]. The mixed previous findings are likely affected by differences in settings, samples, and time of study, but they also suggest that there might be some important factors that affect the interaction between social networking activities and social capital establishment that were not identified in prior studies.

Motivated by these reported inconsistencies in the social capital and SNS literature, one strategy that is being increasingly adopted by researchers is to "unbundle" the various features and the various uses of social networks [Smock et al. 2011; Burke et al. 2011]. In other words, it is important to differentiate between different uses of a social network, such as private messaging and passive browsing. Along these lines, more granular analyses have attempted to quantify Facebook usage by evaluating (i) friends whose feed stories a user clicked on, (ii) distinct profiles viewed, (iii) distinct photos viewed, and (iv) times the news feed is reloaded [Burke et al. 2010]. They found that content consumption on Facebook is associated with a deteriorative bridging social capital and a stronger level of loneliness. However, a subsequent longitudinal study found that those with lower social communication skills experience higher social capital through content consumption, while content consumption has no effect on those with higher communication skills [Burke et al. 2011]. This shows that it is important not only to differentiate uses, but also differentiate users [Burke et al. 2011] by their skills, personality traits, and other factors. Indeed, the strategy of "unbundling" entails increasingly granular analyses that differentiate to the extent possible between contexts, users, uses, and the like to probe deeper into phenomena and resolve inconsistencies in findings.

In this article, we investigate the impact of SNS on social capital by considering an aspect of SNS that Human-Computer Interaction (HCI) research on social systems has not fully adopted yet: *network structure*. Network structure refers to the patterns in which a user befriends others over time. Network structure effectively acts as a backdrop against which social network activity takes place. Social Networks Analysis (SNA) has a long history in the social sciences, and there is a body of work on network structure grounded in theories of how individuals and groups interact and affect each other (e.g., Heider [1958]; Granovetter [1983]). As a result, SNA lends itself naturally to the validation of these theories of human interaction, which makes it valuable to help us make sense of the underlying mechanisms that govern these interactions. Thus, SNA is complementary to the approach of unbundling to further our understanding of social capital and SNS.

Although a large body of work has been published on SNA and graph theory, very little work to date has attempted to use graph theory to investigate social capital in the context of SNS. Specifically, work examining network structure has either focused on predicting personality traits (e.g., Staiano et al. [2012]; Wehrli [2008]) or predicting the tie strength between two individuals based on the number of mutual friends and groups in common, how they communicate with each other on Facebook (e.g., wall posts, private messages, etc.), and how frequently [Gilbert and Karahalios 2009]. There are a number of studies that utilize basic network structure variables intuitively, such as the number of distinct friends a user communicated/initiated communication with to predict social capital [Burke et al. 2011], the number of mutual friends and groups in common to predict tie (relationship) strength [Gilbert and Karahalios 2009], or that use personality traits to predict Facebook popularity (number of contacts) [Quercia et al. 2012]. This way of using network structure remains rather descriptive in nature, and a more in-depth reflection of network structural variables is largely missing (i.e., structure holes).

Using a multipronged approach, our study explores the interdependencies among personality, bridging social capital, and SNS through investigating the structure of individuals' online social network. To achieve this, we recruited volunteers to use an application we developed to capture their whole social network information on Facebook. From these data, we were able to estimate a number of network structure metrics for each participant using graph theory, including their network degree centrality and betweenness centrality. Furthermore, standardized questionnaires were issued to all participants to collect personality and bridging social capital measures. Through the use of structural equation modeling, we verify the reliability and validity of our measurements and incorporate both reflective and formative factors into the research model to investigate their interdependencies. Our main finding is that the personality traits we investigate do not affect one's bridging social capital directly; instead, they affect individuals' online social network structure, which in turn affects bridging social capital. This finding highlights the importance of network structure, since we show that network structure acts as intermediary between one's personality and one's gains from investing time on SNS.

Methodologically, our work paves the way by demonstrating how network structure can become a valuable source of data for HCI researchers investigating SNS. Indeed, there are hundreds of social network metrics that can potentially be used. Therefore, this article is a first step in establishing a "recipe" for bridging personality and network structure metrics in analysis. Substantial follow-up work can be conducted by exploring different metrics and their nuances. For this reason, we argue that our article is really just a first step in a new direction for analysis.

2. LITERATURE REVIEW AND RESEARCH MODEL

We synthesize here prior work that provides fragmented insights into the possible relationships among personality, social capital, and network structure.

2.1. Social Capital

Social capital can be defined as the ability of actors to secure benefits by virtue of membership in social networks or other social structures [Portes 1998]. Social capital offers a diversity of various benefits. Through social capital, actors can obtain direct access to economic resources (i.e., subsidized loans), increase their cultural capital through contacts with experts or individuals of refinement, or, alternatively, they can affiliate with institutions that confer valued credentials [Portes 1998]. Young people with greater social capital are found to be more likely to engage in behaviors that bring about better health, academic success, and emotional development [Ellison et al. 2007; Morrow 1999; Steinfield et al. 2008].

Prior literature indicates that social capital consists of two distinctive components: bridging and bonding social capital [Putnam 2000]. Bridging social capital refers to the social capital created from bonds across individuals of different backgrounds. Although these ties may lack depth, they offer individuals a broader horizon and open opportunities for new resources and information. Conversely, the bonding social capital of an individual is created in bonds between individuals belonging to a closed group such as family and close friends, and these provide substantial and strong emotional support. These two types of social capital are closely related but not equivalent, and they are oblique rather than orthogonal to one another [Williams 2006].

Closely related to social capital theory, structural hole theory postulates that social capital is a function of the brokerage opportunities in a network [Burt et al. 1998; Burt 1992]. A typical feature of social networks is that they consist of dense clusters linked by occasional bridge connections between the clusters. The “holes” in the network between these dense clusters of individuals who are not interacting are referred to as *structural holes* [Burt 2004]. Individuals within a cluster are likely to be of similar background due to homophily [Burt 2004]. Therefore, structural holes are of interest to us because those who act as bridges between clusters are exposed to diverse ties.

In a social network, individuals with structural holes may bridge different unconnected communities and therefore facilitate the information and resource exchange among these micronetworks, thus acting like a bridge. People with structural holes serve an important role in the network: they help separate nonredundant sources of information from sources that are more additive than overlapping. In other words, if the nodes with structural holes are removed from the network, the whole network may collapse into a number of small and separated communities. Hence, the extent of structural holes is a measurement of an individual’s importance in his network. We argue that when an individual’s network has many structural holes, others will perceive the person to be important because they gain access to valuable information or resources through that person, therefore making the person more popular. Therefore, we propose that when an individual’s online social network contains lots of structural holes, his or her popularity in the virtual world will be promoted. Online popularity is measured via degree centrality in this study, which will be specified later. Accordingly, we hypothesize:

H1: Online structural holes positively relate to online popularity.

Although individuals with strong structural holes are regarded as being beneficial to others in the network, there is an ongoing debate about whether these individuals can actually benefit themselves from their structural holes in terms of social capital [Portes 1998; Zheng 2010]. The theoretical argument is that structural holes facilitate the establishment of social capital because dense networks tend to convey redundant information, and weaker ties can be sources of new knowledge and resources [Portes 1998; Burt 2000]. Based on structural hole theory literature, individuals who span structural holes are enabled to access resources with their large social networks, whereas social capital can be obtained by occupying "brokerage positions" within the network [Burt 1992; Wellman and Frank 2001; Fang et al. 2010; Jonas et al. 2012]. Our own work examining network structure on Facebook seems to confirm this: based on simple correlation analysis, the amount of structural holes was indeed positively associated with bridging social capital [Venkatanathan et al. 2012].

However, many social capital theorists highlight the opposite: that social capital is created by a network of strongly interconnected nodes (for a review, see Portes [1998]; Burt [2000]). Dense networks facilitate a higher quality of information transformation among peers and reduces the risk for people in the network to trust one another, which gives rise to increased social capital [Coleman 1988, 1990]. Kalish and Robins [2006] indicated that people with strong network closure and weak structural holes tend to report themselves and others in terms of group memberships. "A cohesive network conveys a clear normative order within which the individual can optimize performance, whereas a diverse, disconnected network exposes the individual to conflicting preferences and allegiances within which is much harder to optimize" [Podolny and Baron 1997: 676]. In this regard, in a cohesive online network, individuals may obtain more opportunities for collective or cooperative activities online or offline (c.f. Sobel [2002]), therefore facilitating the building of bridging social capital.

Thus, we have seemingly opposing views that structural holes facilitate bridging social capital, on the one hand, and that cohesive networks facilitate bridging capital on the other. This calls for a deeper probe into these variables, in order to tease apart their actual effects on each other. Given that online popularity is likely to be closely related to structural holes (hypothesis H1), it is possible that popularity acts as a "confounding" variable in the correlation between structural holes and bridging social capital: that is, this correlation might be explained by the effect of popularity on bridging social capital. This possibility reconciles the two views outlined earlier: an increase in structural holes through increased popularity can lead to increased bridging social. However, for a fixed popularity, higher structural holes imply dispersed connections, which can hinder collective or cooperative activities, thus potentially reducing bridging social capital. Accordingly, we hypothesize:

H2: When popularity is accounted for, online structural holes negatively relate to bridging social capital.

Finally, it has been widely argued that SNS contribute to extending people's social capital (i.e., Ellison et al. [2007]; Steinfield et al. [2008]). Therefore, consistent with prior studies, we hypothesized:

H3: Online popularity positively relates to bridging social capital.

2.2. Personality

An important aspect of personality is empathy, which in the broadest sense refers to the reactions of an individual to the observed experiences of another [Davis 1983]. Prior studies have investigated empathy mainly from two perspectives. Some researchers regard empathy as the intellectual processes of accurately perceiving others, which can therefore be considered as a cognitive phenomenon. Other researchers refer to empathy as an emotional reactivity and, for instance, study empathy in the context of helping behavior (for a review, see Davis [1983]). The ability to identify and empathize with others relies on familiarity, attraction, and a degree of homophily (see Brass et al. [1998]).

Prior studies also suggest that empathy is an important personality trait for building social capital. Preece [2004] argued that empathy, trust, and reciprocity are the building blocks for relationships that unite members and that they provide conduits for the knowledge exchange and learning needed to solve problems and achieve shared goals. Social capital can be created by an empathy for and an understanding of the other [Anderson and Jack 2002]. Brass et al. [1998] noted that empathy helps build social capital by avoiding unethical behavior. Empathy is found to be positively associated with peer acceptance and friendships [Frostad and Pijl 2007]. Therefore, it is possible that people with strong empathy would be more popular among peers and be more capable of making friends with people from different backgrounds. This effect should be applicable to both online and offline social networking environment. Hence, we hypothesize that:

H4a: Empathy positively relates to online popularity.

H4b: Empathy positively relates to bridging social capital.

H4c: Empathy positively relates to online structural holes.

A second important personality trait, conscientiousness, has been strongly associated with social capital. Conscientiousness refers to individual differences in impulse control, conformity, determination, and organization [George and Zhou 2001]. Khodadady and Zabihi [2011] found that conscientiousness is positively associated with greater social capital. People's conscientiousness is an effective predictor of their academic performance (e.g., Blickle [1996]; Busato et al. [2000]). An individual's achievements will be recognized by others thereby making the person more popular. Meanwhile, one's achievements may facilitate one to promote his social class and meet persons of diverse background, therefore building structural holes in his network. Furthermore, a study of Burt et al. [1998] indicated that people's personality is attributed to structural holes. People with conscientiousness (i.e., being in control of his or her own destiny, looking for a chance to be in a position of authority, closely following the original mandate of the group) have rich structural holes in their networks [Burt et al. 1998]. This should apply to both online and offline social networking environments. Therefore, we hypothesized that:

H5a: Conscientiousness positively relates to online structural holes.

H5b: Conscientiousness positively relates to online popularity.

H5c: Conscientiousness positively relates to bridging social capital.

The level of education has previously been closely linked to personality and social capital. Prior studies have suggested that education fosters a grasp of sophisticated cognitive skills and psychosocial resources necessary to understand the complexities of the self and the emotions of others [Eisenberg and Fabes 1990; Franks et al. 1999; Schieman and Gundy 2000]. Furthermore, education is typically associated with income. "When seen as resources, both education and income can improve the opportunities and resources that help people relate to the self and to others [Herzog and Markus 1999; Skaff 1999], and to manage various forms of emotionality [Schieman 2000]" [cited from Schieman and Gundy 2000: 153]. Schieman and Gundy [2000] found that people with

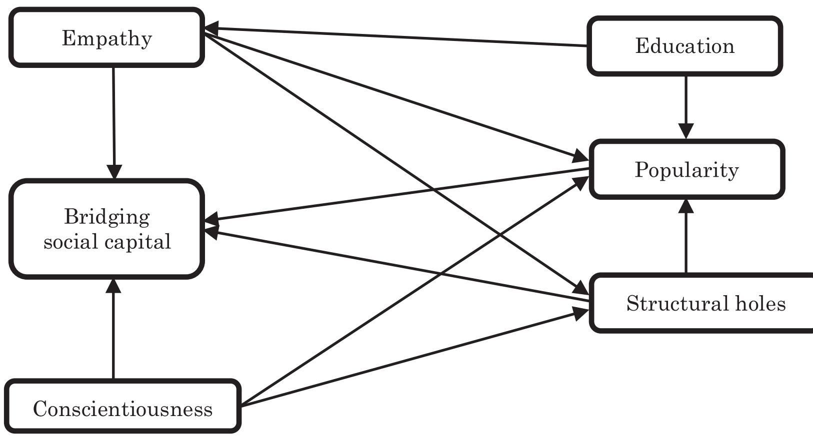

Fig. 1. Research framework.

more education and higher household income report higher empathy. Therefore, we hypothesize:

H6: Education positively relates to empathy.

Education has been regarded as the most important predictor of political and social engagement [Helliwell and Putnam 1999]. People with higher education are more likely to have a higher level of social trust [Helliwell and Putnam 1999; Alesina and Ferrara 2002], which facilitates them to build ties with others and to befriend more people. Therefore, we propose that this should apply to online social networking environment as well. Hence, it is hypothesized:

H7: Education positively relates to online popularity.

Based on these proposed hypotheses, the research model is established as shown in Figure 1. The left-hand side of the model includes aspects of social capital and personality, while on the right-hand side it includes SNS and network metrics.

3. RESEARCH METHODOLOGY

3.1. Reflective Variables: Questionnaire Measurement and Samples

Each participant in our study installed an application we developed that gave us access to their list of friends and the friendships between these friends on Facebook. From these data, we were able to reconstruct each participant's social network and calculate a number of structural metrics regarding his position in his own network. In addition to providing us access to their Facebook social graph, each participant responded to standardized questionnaires of bridging social capital [Williams 2006], empathy [Loewen et al. 2009], and conscientiousness [Rammstedt and John 2007]. The questionnaire items utilized are shown in Table I.

3.2. Formative Variables: Degree Centrality and Structural Holes

Based on the criteria proposed by Coltman et al. [2008], online popularity (quantified by degree centrality) and structural holes (quantified by betweenness centrality) are defined as formative variables.

Degree centrality refers to the number of connections of the ego. This, in other words, refers to the number of friends that each participant has on Facebook. Because the data from Facebook, unlike Twitter, is undirected, every single friendship tie is counted

Table I. Reliability and Validity of Questionnaire Measurement

Constructs and items	α	CR	AVE	FL	T-values
Empathy	.65	.81	.59		
I am good at predicting how someone will feel.				.70	7.568
I am quick to spot when someone in a group is feeling awkward or uncomfortable.				.73	7.523
Other people tell me I am good at understanding how they are feeling and what they are.				.87	21.215
Bridging social capital	.66	.80	.57		
I come in contact with new people all the time.				.80	8.440
Interacting with people reminds me that everyone in the world is connected.				.81	6.755
I am willing to spend time to support general community activities.				.66	4.441
Conscientiousness	.67	.85	.75		
I see myself as someone who tends to be lazy. (reverse coded)				.90	5.682
I see myself as someone who does a thorough job.				.83	6.326

FL: Factor loading. α: Cronbach's alpha. CR: Composite Reliability. AVE: Average Extracted Variance.

toward degree centrality. We use degree centrality [Freeman 1979] to directly measure online popularity because degree centrality has been closely associated with the importance of an actor in his network, prestige, and popularity [Faust and Wasserman 1992]. Because we rely on Structural Equation Modeling (SEM), we have the ability to use proxy variables that indirectly reflect a latent construct. Our use of degree centrality is used as a proxy for online popularity because degree centrality is shaped by direct and explicit user actions ("add new friend") over time.

Structural holes are quantified through the *betweenness centrality* metrics. Betweenness centrality captures the relative importance of an ego in the quick transmission of information within the ego network. Proposed by Freeman [1977], it measures the extent to which a person brokers indirect connections between all other people in the network. As both the online popularity and structural hole are measured via the use of log data, they are formative variables to our research model. The betweenness centrality of an individual node "v" in a network is defined by the following formula:

$$\sum_{s,t} (\sigma_{st}(v)/\sigma_{st}),\ s \neq v \neq t,$$

where σ_{st} is the total number of shortest paths from node s to node t and $\sigma_{st}\ (v)$ is the number of those paths that pass through v. A high betweenness centrality suggests the existence of more structural holes.

4. RESULTS

A total of 93 volunteers (57 male; average age = 28.2, SD = 5.1) were recruited through online announcements on a Portuguese university's email lists and on Facebook aimed at English speakers. A lottery of four Amazon.com gift vouchers worth US$25 each were offered as an incentive for participation.

4.1. Network Analysis

The 93 participants were found to come from 11 different countries, of which the biggest group is Portuguese (N = 36). The participants had on average 314.6 friends (SD = 172.0, max = 875, min = 50), meaning our analysis considered our 93 participants and their more than 2,9000 friends. For each participant, we constructed an "ego" network as shown in Figure 2. This is a network that reflects all the friendships of each participant and all the friendships among the friends of each participant. These

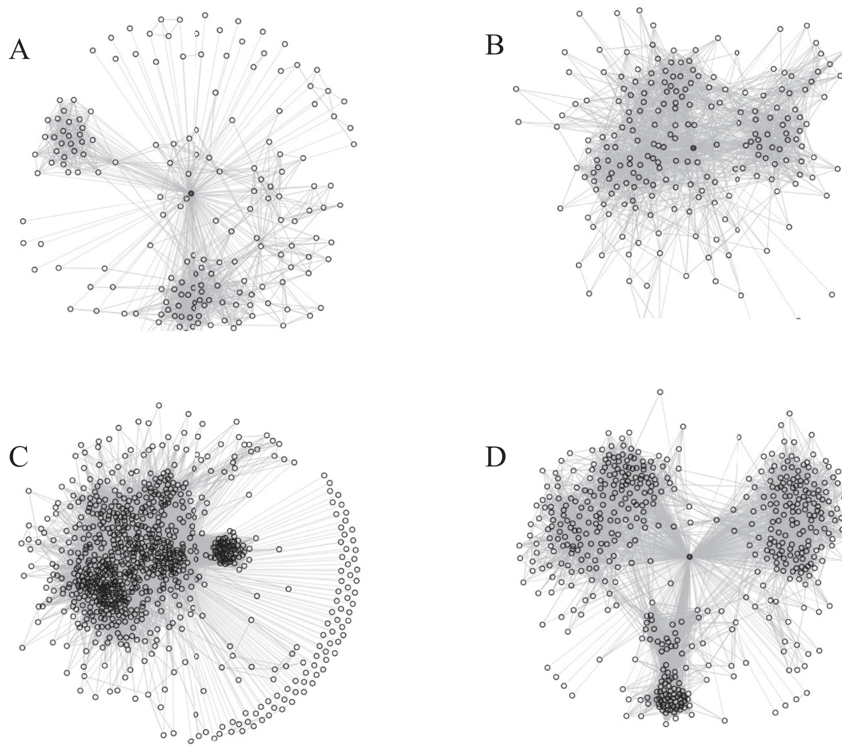

Fig. 2. The social networks of four participants. Each network consists of the ego (i.e., the participant) shown in the center of the graph in red and captures all the friends of each participant and all the friendship ties between those friends. Indicative statistics for each participant. Participant A: degree 178, betweenness 12,314, social capital 2.33. Participant B: degree 213, betweenness 12,195, social capital 3. Participant C: degree 875, betweenness 226,522, social capital 4. Participant D: degree 516, betweenness 100,892, social capital 4.33.

networks are effectively graph structures that allow us to calculate a large number of metrics using theoretically grounded algorithms and measures. We then proceeded to calculate for each ego network two metrics: (1) popularity of the ego and (2) betweenness of the ego. We show a histogram for each calculated metric in Figure 3.

Finally, for each participant, we recorded the number of memberships he or she has with educational institutions. This refers to the number of diplomas and universities that they indicated on Facebook they have attended. For instance, if a participant had indicated a bachelor's degree and master's degree from the same institution, that would count as 2 memberships. The reason for counting these separately is because they indicate an increasing possibility for participants to join a new group of friends or acquaintances, which in turn provides increasing opportunities for obtaining social capital. We show a histogram of the education data for our participants Figure 4. Regarding frequency of Facebook usage, most participants accessed Facebook many times a week (N = 55) or about once a day (N = 24). Thirteen participants accessed

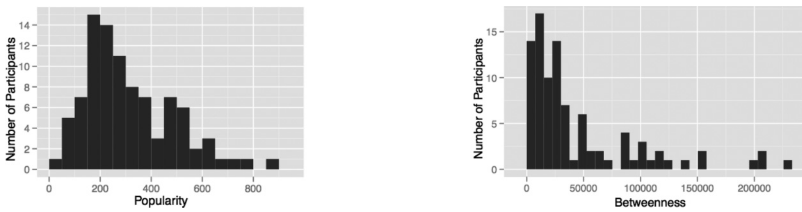

Fig. 3. Histograms for each of the two metrics we calculated for all the ego networks we captured: popularity and betweenness.

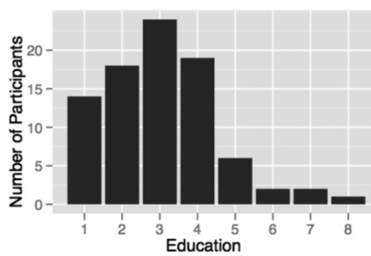

Fig. 4. Histogram of the number of diplomas and universities our participants have indicated on Facebook.

Table II. Square Roots of Average Variance Extracted (on the Diagonal) and Correlations among Reflective Latent Variables

Construct	Empathy	Bridging social capital	Conscientiousness
Empathy	**.77**		
Bridging social capital	.19	**.75**	
Conscientiousness	.10	−.14	**.87**

Facebook about once a week, whereas one participant who has only 50 Facebook friends reported using Facebook rarely. In the study, it is necessary to include this infrequent Facebook user in order to examine whether Facebook usage mediates the relationship between personality and overall bridging social capital. No significant correlations were found among usage frequency, age, and education. However, frequency of Facebook use is found to significantly correlate with online popularity (correlation = 0.283, $p < 0.01$). Furthermore, age is found to insignificantly correlate with personality traits of empathy and conscientiousness, as well as with online popularity.

As shown in Figure 2, participants A and B have similar levels of structural holes, but B has stronger online popularity than A, and, accordingly, a stronger bridging social capital. For participants C and D, even if C has many more online friends than D (69.5%), the bridging social capital of C is weaker than of D. As shown in Figure 2, we can see the much stronger values of structural holes of C and D.

4.2. Questionnaire Results

SEM is employed to evaluate the research model through the use of SmartPLS 2.0. The reliability and validity analysis of the questionnaire constructs are shown in Table I. All Factor Loading (FL) values were found to be above the threshold of 0.6, whereas the Cronbach's alpha values (α) of three reflective variables were over the threshold of .6. Furthermore, we calculated the Composite Reliability (CR) values and Average Extracted Variance (AVE) of all the constructs, and they are shown to satisfy the recommended level of .8 and .5, respectively, thereby indicating good internal consistency. As shown in Table II, the square root of AVE of all constructs is greater than the

Table III. Rotated Component Matrix, Showing No Substantial Cross Loadings on the Reflective Factors

	Component		
Conscientiousness 1	−.031	.011	**.835**
Conscientiousness 2	−.107	.086	**.804**
Empathy 1	−.024	**.737**	.249
Empathy 2	.150	**.705**	−.075
Empathy 3	.076	**.883**	−.012
Bridging social capital 1	**.713**	.073	−.262
Bridging social capital 2	**.805**	.042	−.013
Bridging social capital 3	**.815**	.097	.046

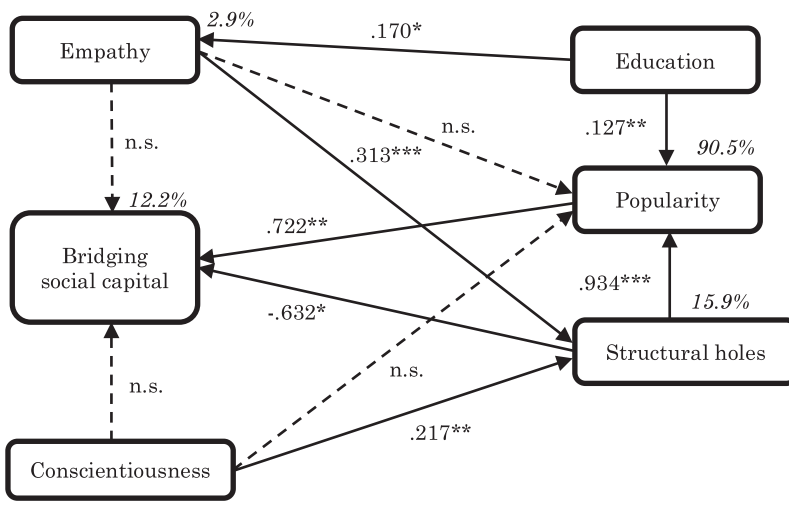

Fig. 5. Result of model evaluation. Solid lines indicate significant findings, dashed lines indicate nonsignificant findings (*: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.001$; n.s.: not significant).

correlation estimate with the other constructs. This suggests that each construct is more closely related to its own measures than to those of other constructs, and discriminant validity is therefore supported.

Furthermore, a principal component analysis on the reflective factors was conducted. As shown in Table III, no substantial cross loadings were reported, which supports the validity of our measurements. In addition, a Harmon's one-factor test was applied to test common method bias in the study [Podsakoff and Organ 1986]. No single factor was found to account for the majority of the covariance in the variables.

Note that reliability (i.e., internal consistency) and construct validity (i.e., convergent and discriminant validity) are not meaningful for formative constructs [Bollen and Lennox 1991; Diamantopoulos and Winklhofer 2001], whereas validity for formative constructs is concerned with the significance and strength of the path from the indicator to the construct [MacKenzie et al. 2005; Freeze and Raschke 2007]. Online popularity is measured through the use of one formative indicator of degree centrality, whereas structural holes are measured by the use of one formative indicator of betweenness centrality, therefore there is no necessity to evaluate their weight loading.

4.3. Validation of the Model

As shown in Figure 5, empathy is found to have a significant influence on structural holes ($\beta = .313$, $p < .001$) but has no significant influence on bridging social

Table IV. Summary of Our Hypotheses, Our Modeling Analysis, and the Significance Outcome

Hypotheses	Direction	Path coefficient	Significance level	Validity
H1	Online structural holes → online popularity	.934	$p < .001$	Supported
H2	Online structural holes → bridging social capital	−.632	$p < .01$	Supported
H3	Online popularity → bridging social capital	.722	$p < .05$	Supported
H4a	Empathy → online popularity		n.s.	Not supported
H4b	Empathy → bridging social capital		n.s.	Not supported
H4c	Empathy → online structural holes	.313	$p < .001$	Supported
H5a	Conscientiousness → online structural hole	.217	$p < .01$	Supported
H5b	Conscientiousness → online popularity.		n.s.	Not supported
H5c	Conscientiousness → bridging social capital.		n.s.	Not supported
H6	Education → empathy	.170	$p < .05$	Supported
H7	Education → online popularity	.127	$p < .01$	Supported

capital and online popularity. In a similar way, conscientiousness has a significant impact on structural holes ($\beta = .217, p < .01$) but has no significant relationship with bridging social capital. Online structural holes have a positive influence on popularity ($\beta = .934, p < .001$) but a negative influence on bridging social capital ($\beta = -.632, p < .05$). Online popularity significantly affects bridging social capital ($\beta = .722, p < .01$). Education significantly associates with online popularity ($\beta = .127, p < .01$) and empathy ($\beta = .170, p < .05$). We also calculate the total effect of structural holes on bridging social capital by including the indirect effect mediated by online popularity. However, the total effect is insignificant. The model interprets 90.5% of the variance of online popularity, 15.9% of the variance of structural holes, 2.9% of the variance of empathy, and 12.2% of the variance of bridging social capital. A summary of all the hypotheses and their validity is shown in Table IV.

We performed a test to detect whether multicollinearity exists in our model. The results show that the maximal Variance Inflation Factor (VIF) values obtained is 9.3, which less than the threshold of 10 [Kennedy 1992], while the maximal condition index is 19.9, well below Belsley et al.'s [1980] benchmark of 30. Note that all the path direction and significance levels remain even if we normalize betweenness centrality.

5. DISCUSSION

When considering the impact of SNS use on social capital, prior studies have typically adopted an analytical framework that considers personality metrics, SNS usage metrics, and social capital metrics. However, inconsistent results have been reported, and a wide range of SNS usage behavior, such as length and frequency of SNS use, seem to be unreliable predictors.

In our study, we consider a rather implicit but crucial aspect of SNS use: *network structure*. Our analysis paves the way toward considering network structure as a new factor mediating the possible effects between personality and social capital in social computing systems. Whereas prior studies have explored the interaction between personality and network structure, this study, to our best knowledge, is the first effort to connect personality, network structure, and social capital. A second contribution of the study is that while most prior studies have relied on correlation analysis, which does not imply cause–effect relationship between variables, our study employed SEM technologies to evaluate the hypothesized structural research model.

5.1. Network Structure and Social Capital

Our results indicate a strong influence of online social network structure on social capital. Specifically, structural holes have a strong negative influence on bridging social capital, whereas online popularity has a strong positive impact. In other words, individuals who are popular within their social network are more likely to obtain more bridging social capital in daily life. However, when an individual's online social networking is saturated with separated contacts, bridging social capital is very likely to suffer. This scenario is realized when, for example, an individual repeatedly befriends contacts who are strangers to the individual's existing friendship circle. For instance, this is the result of applications/systems that may attempt to befriend so-called familiar strangers [Paulos and Goodman 2004].

By associating the results with various types of online friend-making activities, a number of insights can be drawn. Our results indicate that befriending complete strangers is not an effective strategy to strengthening one's overall bridging social capital. Specifically, although adding a complete stranger to the network increases the degree centrality (online popularity) by 1, the value of structural holes will grow at a faster rate. Instead, befriending someone who already knows many other friends in one's network will enhance one's social capital without substantially increasing structural holes. Our results show a clear benefit in terms of SNS' functions to maintain and enhance *existing* offline social capital in an online environment [Kostakos and Venkatanathan 2010]. On the other hand, SNS' functions for making *new friends* should prioritize friends of existing friends because this approach increases online popularity without greatly increasing structural holes and therefore can provide an overall increase to bonding social capital. Although this potential benefit has been noted by previous work [Gilbert and Karahalios 2009], our work provides evidence on why this results in positive outcomes.

The negative effect of structural holes on bridging social capital identified through in our analysis suggests a complex and unexpected relationship between these variables. First, we note that these two variables, looked at pairwise, show a positive correlation with each other: overall, larger structural holes are indeed associated with higher bridging social capital. However, when the number of friends is also taken into account, we see a negative relationship between structural holes and bridging social capital. This provides an interesting perspective when considering the question "*Ceteris paribus*, what kind of network structure is best for the ego in terms of bridging social capital?" Structural hole theory [Burt et al. 1998; Burt 1992] would suggest a star network: a network in which all friends are linked to the ego, but no two friends are directly linked to each other. This provides the ego maximum brokerage opportunities. However, our results suggest that it is actually beneficial for the ego when some of the friends are in turn directly connected to each other, too, thus reducing the structural holes in the ego network.

One explanation for our finding is that when the ego's friends are also connected to each other, they can begin to act as a collective community rather than simply as transacting individuals, thus enabling possibilities for greater social capital. Another interpretation of our findings is from the perspective of cognitive dissonance theory [Granovetter 1973]. This suggests that when the ego has two friends with whom she spends a lot of time, it is convenient and beneficial for her to introduce them to each other so that she can be with them at the same time and not have to spend time with each of them in a mutually exclusive manner.

These insights have interesting implications for friend recommendation features. Although Facebook already has a “People you might know” feature, our results suggest that social networking sites such as Facebook might also consider features that suggest “Friends you might like to introduce” because this can potentially benefit all, including the ego.

5.2. Network Structure as a Mediator

We note that, concerning the interaction between personality and social capital, our study highlights network structure as a mediated effect between personality and social capital. Unexpectedly, both empathy and conscientiousness are found to have no direct influence on bridging social capital, unlike in previously published results [Anderson and Jack 2002; Khodadady and Zabihi 2011]. Instead, a mediation effect of social network structure between personality and bridging social capital was found. In other words, personality contributes to enhancing the bridging social capital by altering people’s social networking structure, which in turn affects social capital.

This finding goes a long way to explain the inconsistent findings reported previously on how personality and social capital interact in the context of SNS. Our findings highlight that network structure is in fact a mediating force. What is also characteristic of network structure is its implicit nature. Unlike the time spent on Facebook or the number of photographs uploaded, network structure remains rather implicit to the user, although some applications are increasingly attempting to make this information explicit for users [Shi et al. 2012]. Its implicit nature suggests that it can be hard for users, or indeed employers, to explicitly moderate social network structure, unlike their desire to moderate what they perceive as “usage” potentially leading to “addiction” [Andreassen et al. 2012].

The implicit nature of network structure has two important implications. First, it can be a reliable measure because users are unlikely to attempt to moderate it explicitly. Second, it is an aggregate measure, which means that at any given time it reflects the culmination of a user’s behavior up to that point. Day-to-day usage, and metrics that reflect it, may fluctuate due to a number of factors [Andreassen et al. 2012], including one’s free time, networking availability, and newly adopted responsibilities. On the other hand, network structure is less likely to fluctuate on a daily basis and more likely to reflect one’s innate socialization behavior. At the same time, to the extent that network structure captures over time one’s joining of various organizations and social groups, it also reflects the opportunities an individual experiences for social capital. Although network structure is indeed a static snapshot whenever it is observed, the time at which different edges and nodes were added to it varies considerable. The structure has evolved over time, much like cities do. For instance, changing jobs, changing universities, or moving to a new place are all events that have a major impact on network structure. All these events appear as distinct clusters in one’s network of friends.

For these reasons, we argue that network structure is a key concept in investigating SNS, and next we discuss how this can be done in the context of HCI. Even abrupt changes, like moving to another country or changing jobs, will not have an instant effect on one’s network structure but a gradual one.

5.3. Methodological Adoption of Social Network Structure within HCI

Network science and its associated techniques is becoming a popular methodology that spans multiple scientific fields. In this article, we wish to highlight that network science has a lot to offer to HCI, and we do so by conceptualizing social networks as a source of data for HCI researchers. Many studies investigating the effects of Facebook or other SNS conduct their analysis using two primary sources of data: data collected from *users* (such as questionnaire, attitude, and behavioral data) and data collected from *user interface* mechanisms (such as usage logs and content analysis). We argue that a third important source of data exists: *network structure*, which reflects the patterns with which users befriend each other on these systems.

The first important source of data is users themselves, and researchers have focused on user perceptions and explicit user behavior to study broad aspects of the impact of SNS on communities of users. A number of techniques have been used to collect data from users, including questionnaires, interviews, focus groups, and diaries, to mention just a few. When relying on this type of data, researchers typically attempt to measure the effect of SNS by considering user adoption (or other self-reported measures) in relation to social capital and personality.

The second important source of data has been the user interface, by which we refer to studies that have investigated particular user interface mechanisms on SNS to identify the impact that design decisions can have on users. A variety of actual data can be derived from this data source, including usage logs of when, how, and how often people use the particular system. This may also include granular identification of the various mechanisms one uses, what type of content one has uploaded, or perhaps how often one has exhibited some particular usage behavior.

Furthermore, the combination of these two data sources and the type of data they provide has proven rather fruitful. For instance, recent studies have linked aggregate behavioral patterns, such as the set of pages that a user has liked on Facebook, to behavioral characteristics such as one's sexual orientation and even intelligence [Kosinksi et al. 2013].

Our work demonstrates how a third important source of data, network structure, can be utilized in analysis. Specifically, we show how network structure analysis can be coupled with questionnaire and survey data, as well as with usage data. Thus, we advocate the triangulation of data sources, looking at the user, the network, and the interface when analyzing SNS, as was also demonstrated in our own earlier work [Kostakos et al. 2011]. Conceptually, we consider analyses of these data sources as highly complementary. Using questionnaire, survey, and interview data, individual users can be queried and questioned and detailed understanding of individual's perceptions can be constructed. Considering the structure of ego networks, an individual's immediate network is considered in analysis. Finally, the availability of data logs from user interface mechanisms makes it practical to conduct community-level analyses and easily identify large-scale patterns in users' behavior.

In this article, we wish to highlight the potential of our approach and analytical framework within HCI. Although an increasing number of HCI researchers use network analysis in their research, here we wish to conceptualize network structure as an additional source of data for researchers and highlight its potential benefits. A great strength of network structure analysis is that a whole arsenal of theoretically founded and empirically derived metrics exists for analyzing network structure. Ranging from social science [Macy 1991] and physics [Barabasi and Albert 1999] to biology [Strogatz 2001] and urban architecture [Hillier and Hanson 1984], various disciplines are constantly identifying novel metrics for analyzing network structure. This offers a very rich toolset to any HCI researcher who wishes to incorporate network analysis in his or her work. As in our study, network structure can be used to derive a number of concrete measures per participant. There are potentially numerous ways to subsequently analyze these metrics in conjunction with other collected data. In our case, we have adopted SEM because it allows for theoretical modeling and simultaneous analysis of multiple factors. However, other approaches are possible to analyze such metrics in conjunction with questionnaire or performance data. For instance, network metrics can be used in ANOVA, chi-square, and t-tests, but can also be fed into machine learning classifiers as features (as can survey responses). Because network structure metrics can be effectively considered as variables that have a single value associated with each participant, most types of analyses that HCI researchers conduct are likely to be able to easily incorporate network structure metrics. For instance, any of the potential thousands of network structure metrics can be studied in conjunction with gender, age, social status, time spent on Facebook, or number of photos uploaded to Facebook, just to name a few possibilities.

Despite the methodological benefits of using network science metrics in analysis, it is not clear *why* this approach should be introduced to social systems research in HCI. There exist numerous methods across all fields of science: why should network science be brought into HCI research on social systems? After all, HCI has typically focused on user needs and behavior, while network science conceptually reduces humans to nodes on a graph. Our answer to this pertinent question of *why* relies on two points. First, this article's research findings highlight the importance of network structure because we show that network structure acts as intermediary between one's personality and one's gains from investing time on SNS. Therefore, network structure is relevant to the study of human behavior in the context of SNS, whether we choose to investigate it in HCI or not.

Second and more crucially, network science offers a solid and validated theoretical basis for studying relationships between humans (and other entities), which arguably reflects human behavior and action. HCI's focus on user needs in SNS has traditionally relied on methodologies that emphasize the collection of qualitative data (even when running a tightly controlled experiment users are given preference questionnaires) and analyses that are expected to result into implications for design (even when the findings shed light on a not previously understood behavior or aspect). This has made it hard to achieve reproducibility in studies, results, and findings, to the extent that the SIGCHI flagship conference recently established a "RepliCHI" award for encouraging reproducible work. On the other hand, network science offers a theoretical basis for analyzing networks of people, places, and technology [Kostakos 2011], concepts that are fast becoming increasingly relevant to HCI. Network science provides theoretical rigor and methodological flexibility to investigate phenomena relating to people and their use of technology. For instance, a study could aim to identify a new and improved metric for reflecting some aspect of human technology use, with no need for developing "implications for design," thus encouraging reproducibility and even the revisiting of prior work. Also, qualitative data can, to a certain extent, be coupled with network science as we described here; thus, we do not have to reduce humans to plain nodes on a graph, but rather depict them as nodes with multiple characteristics and properties. We do not argue that network science can replace interviewing participants, but instead it can help us identify structure in their collective behavior.

5.4. Limitations

A methodological drawback of the study is that participants were self-selected because they responded to an online survey call posted on university mail lists. This might have led to a possible nonresponse bias in our sample, whereby the sample Facebook users who chose not to respond to our announcements for the study might have shown an overall difference from our participants in network structure, personality, or social capital. Also, it is possible that more popular people are more likely to get our survey call from their friends, which probably causes a bias in the result. In addition, the participants were mostly between 23 and 33 years old, and users of other age groups were largely ignored. Moreover, it is important to recognize that techniques to gather information on individual characteristics such as personality and empathy have inherent limitations. Particularly for this study, there are limitations in self-report because it involves subjective assessment.

For example, one of the ways in which subjectivity can affect the ratings is by self-presentation bias: participants might attempt to portray themselves in a positive manner. Although standard scales, such as the personality and empathy scales used in this paper, typically attempt to minimize this to the extent that it is possible through the wording of the questions, it is difficult to completely rule out self-presentation bias. An alternative approach could be to use a second-person assessment [Mercer et al. 2004], but this does not eliminate the issue of subjectivity: the assessment is still a subjective judgment from the viewpoint of a second person observing the participant and is therefore subject to bias.

In addition, such approaches have other logistics and validity issues, such as the issue of identifying appropriate individuals to perform the second-person assessment for each of the participants in the study. On the other hand, while more objective tests, such as tests of the ability to recognize facial expressions [Keltner et al. 2003] or even brain activity [Carr et al. 2003] can be considered, they do not directly measure empathy or personality itself, but rather certain underlying mechanisms related to these constructs. Ultimately, all approaches in drawing information directly from the participant have their strengths and limitations. Although the approach we adopted was most feasible and appropriate for this work, future work can consider different or multiple approaches to measuring personality and empathy.

A further limitation of the study is that only two personality traits of conscientiousness and empathy were examined. Therefore, it might be interesting if future studies can involve more personality traits to study individual network structure.

Finally, our approach of using ego-centric networks will always result in "unobserved" parts of the network when considering the whole Facebook network. However, we are not interested in analyzing the whole Facebook network but only those parts of the network for which we have collected detailed personality data using surveys or other means. This is a distinction between using global or local measures in network analysis, and, for practical reasons, we opt to use local measures in our analysis.

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6. CONCLUSION

Our study investigated the interdependencies among personality, social capital, and SNS through investigating the structure of individuals' online social networks. Our main finding is that the personality traits we investigated do not affect one's social capital directly; instead, they affect individuals' online social network structure, which in turn affects social capital. Reflecting on our analysis and findings, we argue that network structure is an important mediator of social capital, and, consequently, network structure is an important data source for HCI researchers in social systems. Our study demonstrates one way in which network structure can be incorporated in analysis of SNS and their usage and, furthermore, how it can be coupled with standardized questionnaire scales. We discuss the potential of this approach and describe how the numerous metrics developed for network structure may be used within HCI to enrich data collected from users and user interfaces in social systems research. We believe this approach has great and unexplored potential in further understanding users' behavior.

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