Social Networks 38 (2014) 1–15

Contents lists available at ScienceDirect

Social Networks

journal homepage: www.elsevier.com/locate/socnet

Assessing structural correlates to social capital in Facebook ego networks

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ARTICLE INFO

Keywords:
Social capital
Facebook
Ego networks
Transitivity
Community detection

ABSTRACT

Research in computer-mediated communication has consistently asserted that Facebook use is positively correlated with social capital. This research has drawn primarily on Williams' (2006) bridging and bonding scales as well as behavioral attributes such as civic engagement. Yet, as social capital is inherently a structural construct, it is surprising that so little work has been done relating social capital to social structure as captured by social network site (SNS) Friendship networks. Facebook is particularly well-suited to support the examination of structure at the ego level since the networks articulated on Facebook tend to be large, dense, and indicative of many offline foci (e.g., coworkers, friends from high school). Assuming that each one of these foci only partially overlap, we initially present two hypotheses related to Facebook social networks and social capital: more foci are associated with perceptions of greater bridging social capital and more closure is associated with greater bonding social capital. Using a study of 235 employees at a Midwestern American university, we test these hypotheses alongside self-reported measures of activity on the site. Our results only partially confirm these hypotheses. In particular, using a widely used measure of closure (transitivity) we observe a strong and persistent negative relationship to bonding social capital. Although this finding is initially counter-intuitive it is easily explained by considering the topology of Facebook personal networks: networks with primarily closed triads tend to be networks with tightly bound foci (such as everyone from high school knowing each other) and few connections between foci. Networks with primarily open triads signify many crosscutting friendships across foci. Therefore, bonding social capital appears to be less tied to local clustering than to global cohesion.

1. Introduction

With more than one billion active users, Facebook is the most widely used social network site (SNS) in the world (Facebook, 2013). Users employ Facebook to maintain relationships with existing friends (Ellison et al., 2007; Hampton et al., 2011), reconnect with old friends (Smith, 2011), organize social engagements (Ellison et al., 2013), and seek information from their connections on the site (Lampe et al., 2012; Morris et al., 2010). To assess the potential benefits of Facebook use, researchers have regularly used the notion of social capital—a sociological framework which captures both the potential and actual resources available from an actor's network (Bourdieu, 1986; Lin, 2001; Putnam, 2000). In particular, there is an expanding body of research that employs the distinction between "bridging" and "bonding" social capital (Gittell and Vidal, 1998; Putnam, 2000) to characterize the potential benefits of Facebook engagement. This distinction was popularized by Robert Putnam, who argues that community organizations work as engines of bonding social capital by bringing together individuals for shared events and group solidarity (2000). Bridging social capital can be traced to Granovetter's (1973) articulation of how weak ties enable access to novel information (and consequently greater job search success). Since Facebook houses both dense clusters of strong ties (Gilbert and Karahalios, 2009) and large swaths of weak ties, it is plausible that Facebook can be a site for the activation of both bonding and bridging social capital.

Although social capital has its roots in structural analysis, the bulk of social capital scholarship in computer-mediated communication concerning Facebook has focused on survey scales that relate perceptions of social capital to individual-level metrics such

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http://dx.doi.org/10.1016/j.socnet.2014.01.002

as self-esteem, messages sent, and attitudes toward Facebook. In particular, many researchers have used Williams (2006) Internet Social Capital Scales (ISCS) to claim that specific characteristics of users' networks (e.g., Ellison et al., 2011; Vitak, 2012) and users' behaviors on the site (e.g., Burke et al., 2011; Ellison et al., in press) positively predict perceptions of social capital. When these studies take network composition into account they tend to use network size. On the other hand, there is a small body of research that explicitly examines ego-centric measures of network structure on Facebook. However, these studies tend to take network structure *as* social capital (Brooks et al., 2011) or examine social cohesion more broadly (Friggeri et al., 2011).

In this study we jointly consider the structural properties of Facebook networks, scales of bridging and bonding social capital, and measures of site engagement. In doing so, we wish to extend past research that has examined individual level variables, such as time on the site, while explicitly considering the potential for structural-level metrics to have an independent effect on perceptions of social capital. Consistent with Brooks et al. (2011) and Friggeri et al. (2011), we assume that dense clusters of ties have a significant bearing on the overall cohesion of the network, and therefore, the likelihood of resource provision from the network. Consistent with other work in this vein (e.g., Burke et al., 2011; Ellison et al., in press), we use a modified version of Williams' (2006) Internet Social Capital Scale (ISCS) to measure perceptions of social capital.

One of the attractions of researching Facebook ego networks is that information about virtually all alters is available programmatically. This allows us to operate at a scale in between two established strategies for capturing ego networks: name generators, which tend to focus mainly on the small number of core social ties (McPherson et al., 2006), and enumeration methods, which tend to focus on estimating total network size but forgo alter–alter connections (McCarty et al., 2000). Although Facebook networks are only approximations of offline personal networks, they nevertheless include large swaths of weak ties and the alter–alter connections between these weak ties. Further, past work has shown that the relationships on Facebook tend to be characteristic of offline relationships (Ellison et al., 2007), and that activity on Facebook is able to discriminate offline strong and weak ties (Gilbert and Karahalios, 2009; Jones et al., 2013).

As our findings suggest, one of the further advantages of using Facebook networks is that we can assess with high fidelity the consequences of linkages across social groups that may not necessarily be obvious to ego, but still felt as a form of social cohesion. In most ego network analysis studies alter–alter ties are reported by ego, and thus subject to a host of inaccuracies and biases (Bernard et al., 1984). Thus, the network that is analyzed is not a list of friendships as articulated by the friends, but a list of friendships as seen through ego's eyes. In this regard, we extend Friggeri et al. (2011), by considering the cohesion of the network as a whole, rather than the cohesion of distinct clusters within the ego network. Whereas Friggeri et al. use closed triads to signify distinct social groupings; we suggest that the presence of open triads may in fact be a better measure of global cohesion, and that the presence of many closed triads (relative to open triads) is in fact a strong indicator that the ego network is highly fragmented. Each individual cluster might be tightly knit, but the lack of open triads indicates a lack of connections *across* groups, and potentially a lack of social cohesion in the network.

This paper is organized as follows: First, we review the use of social capital in studies of computer-mediated communication and social network analysis. Second, we summarize current scholarship examining Facebook, both as a resource for social capital and as a personal network measurement tool. We then define our basic research questions and hypotheses followed by our methodological approach, variable conceptualizations, and descriptive data about our participants. We then present the results of a series of bivariate and multivariate analyses and conclude by discussing how network structure can partially influence the perception of social capital in ego networks on Facebook. In general, we assert that individual attitudes to Facebook usage remain the strongest explanatory factors for social capital, but that structural measures, particularly triadic closure, can have a strong independent effect. Perhaps most interesting, this effect of triadic closure is opposite to what would be assumed – a higher clustering coefficient is actually associated with less bonding social capital. We argue that this is the result of less open triads across groups and is experienced by ego as a network that is "fragmented" rather than globally cohesive.

2. Literature

2.1. Conceptualization of social capital

Social capital—the "aggregate of the actual or potential resources which are linked to possession of a durable network of more or less institutionalized relationships" (Bourdieu, 1986, p. 51)—has been adapted and integrated into a large number of academic fields. Scholars have explored the presence of social capital in politics, religion, education, family, and culture. In all cases, social capital tends to be a general stand-in for positive social outcomes from social interaction. The prominence (and perhaps the dilution) of the concept of social capital has led members of the social network analysis community to criticize the notion of the concept as being overly general, instrumental and artificial (Kadushin, 2004; Fischer, 2005; Fine, 2010). However, there remains a plausible need to consider how structural features and individual behaviors lead to differences in perceptions and outcomes of social resources. Facebook is not solely a site for sharing music tastes, comparing opinions on current affairs, or organizing social events. Rather, it effectively functions as a computer-mediated platform for all of the above. Thus, our operationalization of social capital emphasizes attitudinal sentiments, and any descriptions of these resources as processes that can be invested or traded are ancillary. We focus on the question of whether individuals believe they can draw upon their network for emotional and material resources (as a measure of bonding social capital) and whether individuals believe their network connects them to the wider world and provides them with new information and experiences (as a measure of bridging social capital).

Robert Putnam is widely regarded as popularizing the distinction between bridging and bonding social capital (even if the distinction is often attributed to the previously published Gittell and Vidal (1998)). In *Bowling Alone*, Putnam argued that community organizations enabled individuals to converge in shared locations and engage in activities that increase group solidarity. He asserted that these organizations were associated with a large number of positive outcomes, such as greater health and lower crime. Furthermore, he postulated that television was among a number of factors that might be responsible for the decline in voluntary activity and an associated decline in social capital. At the time of its publication, the Internet was only beginning to emerge as an object of study for social capital in everyday life and Putnam remained agnostic about its consequences for public life. Subsequently, a number of scholars explored whether the Internet impeded social capital, by taking time away from "offline" activities (cf., Nie et al., 2002) or enhanced social capital, by providing increased connectivity within the personal network (Quan-Haase and Wellman, 2004).

Williams (2006) addressed the growing popularity of CMC as a method of communication—and thereby a separate outlet through which social capital could be created and exchanged—by constructing scales of social capital and examining online and offline variants of it. Drawing on Putnam's articulation of the distinction between bridging and bonding capital (2000) and Resnick's extension toward 'sociotechnical capital' (2001), Williams (2006) developed scales to capture bonding and bridging social capital that focused on theoretical components associated with social capital as a sense of access to social resources. For bonding social capital, items assessed the extent to which participants reported having someone who could provide emotional support and advice and access to a scarce resource, such as a financial loan. For bridging social capital, items assessed the extent to which participants reported they had interactions that are consistent with access to different kinds of people or diverse worldviews. These scales do not attempt to quantify the volume of resources available; rather, they assess respondents' perceptions of the availability of resources in a specific context; in Williams' (2006) work, this was divided into "online" and "offline" contexts, while in subsequent research, local (e.g., Ellison et al., 2007) and site-specific (e.g., Ellison et al., in press) contexts have also been used when framing the items.

Subsequent research employing Williams' scales has highlighted significant relationships between both bridging and bonding social capital and a number of behavioral and attitudinal SNS-related factors such as various Facebook activities and self-esteem (Burke et al., 2010; Ellison et al., 2007; Papacharissi and Mendelson, 2011; Steinfield et al., 2008; Valenzuela et al., 2009).

2.2. Facebook and social capital

In the last decade, researchers have explored the extent to which use of SNSs—and specifically Facebook—is associated with various social capital constructs, including perceived access to informational and support-based resources (e.g., Burke et al., 2010, 2011; Ellison et al., 2007, 2011, in press) and network characteristics (e.g., Brooks et al., 2011; Friggeri et al., 2011). As detailed below, the literature reveals a complex relationship between *use* and the various operationalizations of social capital.

Much of the research looking at the relationship between social capital and SNS use has employed an adaption of Williams' (2006) perception-based social capital measure. Notably, work by Ellison and colleagues (e.g., Ellison et al., 2007, 2011, in press) has established a positive relationship between various characteristics of Facebook use and perceptions of access to bridging and bonding resources. For example, characteristics of a user's network composition, such as the number of actual friends (Ellison et al., 2011)—which was intended to capture a more meaningful measure of a user's network than total number of Facebook Friends—and how diverse they perceive that network to be (Vitak, 2012) positively predict users' perceptions of social capital, as does users engagement in communication behaviors that support relationship maintenance, such as when they respond to a request for advice or wish a Friend 'happy birthday' (Ellison et al., in press).

Moving one step beyond strictly perceptual data, research by Burke and colleagues has examined perceptions of social capital—again measured using an adapted version of Williams' (2006) scale and server-level data of Facebook use. In their initial study (Burke et al., 2010), they found that while Friend count positively correlated with both forms of social capital, one's level of directed communication—measured as the number of messages a user exchanged with another Facebook Friend—was only related to bonding social capital, such that increases in interaction with a specific Friend were associated with increased perceptions of access to bonding resources from their network, but not to bridging resources. In a follow-up longitudinal study, however, the authors (Burke et al., 2011) found no relationship between bonding social capital and directed communication over time; the authors suggested that bonding social capital may be generated through a single good friend and is thus not reliant on changes in Facebook-based communication. However, the authors did find that a more sensitive measure of directed communication that only captured inbound messages (i.e., posts, messages, and Likes sent by Friends) positively predicted bridging social capital in the longitudinal dataset. Ellison et al. (in press) argue that these more visible interactions serve to signal one's relationship, not just to the recipient, but also to the entire network, and can serve a social grooming purpose by highlighting the relationship and potentially providing the Friend with a needed resource.

At the opposite end of the spectrum, social capital may be measured not by users' perceptions of resources, but through their network structure. While still rarely used in online studies of social capital, Facebook provides an ideal environment to measure and analyze ego networks. Brooks et al. (2011) utilized Facebook's API to generate personal networks for the purposes of measuring social capital. Brooks et al. conceptualized bridging social capital based on the number of clusters within an individual's network and bonding social capital as the average degree of the network. The degree for every node in an undirected ego network can be considered the number of friends that alter shares with ego. Thus, the average degree is the mean number of mutual friendships all alters have with ego. Having many mutual friends, on average, implies many opportunities for reciprocity, closure and other structural features normally associated with bonding social capital. Findings from Brooks et al. suggest that socioeconomic status or more diverse economic resources was not associated with number of cliques, but rather a larger and more dense network. Likewise, Friggeri et al. (2011) used an online experiment employing a Facebook application called "Fellows" to present users with a visualization of their Facebook Friends network (generated using a simple greedy algorithm). The application showed users a group of Friends and asked them, "Would you say that this list of friends forms a group for you?" If participants answered yes, they were given the opportunity to name the group and save it as a "Friends list" on Facebook. Users then rated the quality of these suggested groups. When researchers compared these ratings to the cohesion of the group, they found that "cohesion is a strong indicator of users' subjective perception of the community-ness of a set of people" as indicated by the fact that more cohesive groups received higher ratings (e.g., 4 stars instead of 1 or 2). This work suggests that cohesion is a representative way to evaluate a community, at least at a correlational level. However, Friggeri et al. (2011) did not find support for typical measures of community quality such as density, clustering, or conductance. Taken together, these two papers suggest that there is some missing link between personal network measurement and the theoretical social network structure of social capital attached to the individual. Thus, this current study examines the association between the above identified two methods for conceptualizing social capital.

2.3. Facebook personal networks and structural social capital

Facebook networks represent ties from a variety of social contexts, such as school, work, church or the neighborhood. While each context may be distinguishable from another, some of the same people may exist in multiple contexts, leading to multiplex (or multistranded) ties. Past work on personal networks has found multistrandedness to be a common occurrence. For example, in Fischer (1982) Northern California study, the average number of contexts per alter was 1.6. At the same time, most ties do not occupy many contexts, since ties bridging more than two social contexts are rare. Fischer noted that on average only 2.6 alters per network were members of three or more contexts. This suggests personal networks have a structure that is characterized by high degrees of connectivity across contexts, but not necessarily a core common to all contexts. It is not the case that a core set of ties stand as a lynchpin linking all contexts, but different ties link the multitude of contexts into a cohesive personal network. This assertion is also aligned with past analysis of personal networks, such as Wellman and Wortley (1990) and McCarty (2002).

Structural properties of personal networks on SNSs have the potential to engender 'context collapse' (Binder et al., 2009; Houghton and Joinson, 2010; Marwick and Boyd, 2010; Vitak, 2012) in that social connections from different life contexts tend to be presented together in the same stream and because these sites encourage broadcasting content to one's entire network. While Facebook enables users to segment their connections into subgroups, the default settings typically reflect one's full audience and, in many cases, few users take advantage of these features; for example, in one study, just 14% of users reported using Facebook's "Friend List" feature to recreate some of the offline groups and filter content they shared (Vitak, 2012). The net effect of the collapsed contexts often present in SNSs on social capital is unclear. On the one hand, such context collapse provides an opportunity to monitor and interact with a diverse set of ties in one convenient location. This consolidation may enhance access to diverse resources and thus social capital because individuals can learn about new information across social contexts in a single sitting, rather than having to congregate with each individual cluster of ties. On the other hand, such context collapse may engender new privacy concerns, where, for example, pictures from the bowling team's bar night are accessible to church friends, or political messages meant for one's friends are made visible to work colleagues. Binder et al. (2009) found that more diverse networks on Facebook were associated with increased perceptions of tension in their social spheres whereas Houghton and Joinson (2010) documented a number of privacy violations Facebook users experienced, many resulting from private information being shared across contexts. These situations might constrain disclosures on the site, which some researchers note are a necessary requirement to accessing specific social capital resources (Ellison et al., 2011). For example, individuals may find it easier to ask for information about mundane topics like advice on a new phone or a vacation spot and harder to ask about sensitive or taboo topics like coming out, health issues, financial woes, or family problems (Newman et al., 2011).

We believe context collapse may be experienced differently depending on the arrangement of the various contexts that ego interacts with on Facebook. Some individuals may have networks that are highly fragmented, meaning that the default newsfeed enables a single cross-cutting view of many diverse areas and potentially incongruous social circles of one's personal network. Other individuals may have networks with a high amount of closure between social contexts. Whether individuals perceive their networks as "closed" (with many linkages across social contexts) or "open" (having content from highly differentiated social roles exist side-by-side) ought to make a difference on their perception of the site as a channel for garnering social support and social information.

The structural properties of Facebook ego networks help guide us toward reasonable social capital metrics for analysis. While a great deal of work has focused on the number of ties in a Facebook network, relating it to personality (Golbeck and Robles, 2011; Quercia et al., 2012), brain size (Kanai et al., 2011) and closeness (Gilbert and Karahalios, 2009), there has been much less analysis examining the topology of personal Facebook networks (c.f., Friggeri et al., 2011; Brooks et al., 2011). As such, we draw upon existing understandings of personal networks, intuitions from network visualizations, and past work where available. Insofar as we believe these networks consist of multiple locally dense clusters typifying the social contexts of personal life, we employ measures that capture these features. Specifically, we employ a measure to identify cohesive subgroups embedded in a personal network using the Louvain method (Blondel et al., 2008) and assess the global cohesion of the network across various clusters through average degree and transitivity. We discuss our hypotheses and research questions based on the above literature.

3. Research question and hypotheses

3.1. Bonding social capital

Research suggests that network density is strongly related to feelings of social support and social capital. For example, Lin writes, "a denser network with more intimate and reciprocal relations among members may increase the likelihood of mobilizing others. . .to defend and protect existing resources/expressive returns" (2001, p. 20). Unfortunately, density scores vary widely between networks of varying sizes, placing undue demands on larger networks to have disproportionately more ties per alter. For this reason, we opt to include average degree. Average degree in personal Facebook networks has previously been correlated with higher socioeconomic status, suggesting a baseline for higher potential social resources (Brooks et al., 2011). Alter's degree has also been correlated with traditional measures of closeness (Gilbert and Karahalios, 2009), although the latter finding did not imply that overall higher average degree meant a presence of more close ties overall. Since average degree implies more interconnections within a network, we follow Lin in proposing:

Hypothesis 1: Average degree is positively related to perceived bonding social capital.

Expanding on average degree we use a measure of the cohesion of the network rather than simply the density or average degree. In this paper, we are interested in the overall cohesion of a personal network. By including a measure of triangles over two-paths, we are measuring the presence of sites of local density. If transitivity is high, then either the network exhibits a core–periphery structure with many dense connections in the core, or a multi-core network with few linkages between said cores, but many dense connections within each core. In either case, transitivity means more linkages within a set of nodes. Thus, the dense connections, whether present in the core or multiple cores with a few ties between cores, are a measure of bonding social capital assuming these core groups represent stronger personal ties than those on the periphery.

Hypothesis 2: High transitivity is positively related to perceived bonding social capital.

Both transitivity and average degree signify greater connectivity within the network, but do so in different ways. Average degree makes fewer assumptions about how the network is connected, yet in practice, we assert that a higher average degree is likely to be present in networks characterized by pockets of high internal connectivity such as 'high school friends.' In this case, more linkages from the high school context to other contexts may actually lower transitivity as each new link between these separate contexts that is unclosed would lower transitivity.

3.2. Bridging social capital

Although it is now widely accepted that Facebook networks include multiple social contexts (Binder et al., 2009; Vitak, 2012), there are no established ways to count the number of social contexts in a network programmatically. Friggeri et al. (2011) make one attempt by using overlapping clusters drawn from a respondent's Facebook network and asked the respondent to rate the quality of these clusters. They use a novel cohesion measure based on triangles inside and outside a cluster. In that work, users tended to rate highly dense clusters as accurately signifying a group, and less dense clusters as less accurately describing a group. That said, the demands of that algorithm lead to a large number of relatively small groups in a given ego network rather than a coarse number of social contexts such as work, family and high school that would signify different arenas for the distribution of bridging social capital. Consequently, we employ a widely-used community detection algorithm (the "Louvain" method; Blondel et al., 2008) in order to capture these larger group structures that represent differing groups of social cohesion and thus different sites for the potential distribution of bridging social capital.

We believe that our approach captures the spirit of bridging social capital, as it implies the spread of information across groups or bridging between pockets of dense ties. We consider bridging social capital as a metric of access to diverse social resources and a sense of connectedness to the wider world. A technique that maximizes modularity presents a count of the number of groups where there are few connections between the groups, thus ensuring that each cluster would uniquely contribute different information, or at least information from a substantively different set of alters.

We then assume that each unique cluster within a Facebook network represents a specific context. The number of those clusters represents access to possible diverse social resources captured through the reported bridging social capital measure. Thus, using this measure we propose:

Hypothesis 3: More clusters (found using community detection) is positively related to perceived bridging social capital.

3.3. Beyond structure: mobilizing social capital

Social capital encompasses both actual and potential resources that individuals have access to through their network. In designing his scales, Williams (2006) noted that the intent of these scales is to measure sentiment as *expected outcome*. As such, none of the items in the scales measure either actual network topology or user behaviors that would lead to particular structural outcomes. This strategy of explicitly distinguishing social resources from network topology was also articulated by Van Der Gaag and Snijders (2005). This emphasis on perceived outcomes makes it possible to deploy structural, behavioral, demographic and attitudinal measures separately to assess their relationship to the scales. While our foremost emphasis in this paper is on the relationship between structural covariates and social capital, we also wish to address the relationship between the latent structure as a potential site of social capital and the behaviors actors employ to become more aware of what potential social resources are embedded in the network. Put bluntly, what good is having a network if you do not know who has what resource? Based on previously mentioned Facebook research, we pose the question, are some individuals better at paying attention to their network than others? We consider individuals' engagement with their network using two recent scales developed specifically for this purpose: Facebook Relationship Maintenance Behaviors (FRMB); Ellison et al. (in press)) and Information-Seeking Behaviors (ISB; Lampe et al., 2012).

ISB and FRMB are ways of examining individuals' engagement with their Facebook network, while Williams' (2006) social capital scales attempt to elicit perceptions of resources that network contains, as well as individuals' perceived access to those resources. As such, we hypothesize that these measures have both a direct effect on bridging and bonding social capital and a mediating effect. More formally we propose:

Hypothesis 4a: Greater FRMB will be associated with both bridging and bonding capital.
Hypothesis 4b: Greater ISB will be associated with both bridging and bonding social capital.

Furthermore, with regards to the mediating effect, we suggest that these scales will attenuate but not eliminate any positive relationship between structural measures and social capital. We suggest that given a specific network topology, those individuals who take an active interest in their network through social grooming and question-asking are likely to report higher levels of social capital.

Hypothesis 5a: FRMB will partially mediate the association between structural network properties and bridging and bonding capital.
Hypothesis 5b: ISB will partially mediate the association between structural network properties and bridging and bonding capital.

3.4. Considering Facebook activity

Based on previous work (Ellison et al., 2011), having more self-described 'actual' friends on Facebook should lead to higher levels of bridging capital, because these represent more meaningful relationships with ego (as compared to very weak, non actual Friends). We believe that there are compelling arguments for why more actual friends could lead to either higher or lower bonding capital. More friends could mean a denser set of core ties for bonding. It could also mean that individuals feel their Facebook networks represent too broad a set of ties to successfully capture the affective and intimate resources associated with bonding capital. Thus, instead of hypothesizing we consider its effect to be a research question of interest.

RQ: What is the relationship between number of actual friends on Facebook and bridging and bonding social capital?

4. Methods

The data collection for this research combined an online survey with an online Facebook API network generator. This method was unique in its technique for comparing ego network metrics and self-reported behavioral data.

The sample for this study was recruited through a large Midwestern university within the United States. An email was sent by the university to a random sample of 3149 non-faculty staff (1000 in November 2010 and 2149 in February 2011). Fall participants completed a short screener survey which was used to select participants for a more detailed lab session. Lab session participants completed the full survey in addition to other tasks not discussed herein. Spring survey participants were invited to provide their to be entered into a drawing for one of ten Amazon gift cards. The survey asked a series of questions including user demographics, Facebook use, Williams' (2006) social capital scales, privacy attitudes and behaviors, and network characteristics. The online survey included a link to a Facebook application (a modified version of NameGenWeb [Hogan, 2010]), that included study-specific instructions and a consent statement. Participants who agreed to this part of the study had to (temporarily) add the application to their Facebook account while they completed the rest of the survey. The application saved a copy of the participants' Facebook ego network to a server maintained by the second author.

From the fall and spring data collection efforts, 666 participants completed a survey, with 534 reporting having an active Facebook account; of that group, 238 added the Facebook application which accessed their Facebook network data; this latter group will be used in all analyses in this paper. Among the network-only subsample, the average participant was female (66.8%), 45 years old (SD = 10.8) and a college graduate (43.7% had a bachelor's degree, 35.3% had postgraduate training). These numbers correspond closely to the demographic composition of the entire sample.

4.1. Measures

The two types of data collected for this study—self-reported perceptual measures and ego network characteristics—are detailed below. Scale items were measured on five-point Likert-type scales ranging from Strongly Disagree to Strongly Agree unless otherwise noted. All non-network variables used less than 5% missing values, which were imputed using mean replacement. Items, means, and standard deviations for each scale are presented in Appendix A. Table 1 also provides full descriptive characteristics for variables used in the study.

4.2. Survey items

Gender was a self-report item with the option of "male" or "female" with three missing values, which were excluded from analyses and descriptive reporting. ***Age*** was self-reported in years. ***Education*** was asked using an ordinal question with responses "less than high school," "high school degree," "technical, trade or vocational school after high school," "some college, no 4-year degree," "college graduate," "post-graduate training/professional school after college" and "I don't want to disclose".

Facebook bridging and bonding social capital were measured using an adapted version of Williams' bridging and bonding scales (2006). For this study, we replaced Williams' (2006) "online/offline" language with "on Facebook" and "in my social network" to distinguish between social capital perceptions associated with their Facebook Friends and perceptions associated with their full social network, which includes their Facebook Friends as well as those who are not on the site, respectively. In this paper, we only consider the Facebook-specific responses, in which participants were asked to think only about their interactions with their Facebook Friends when reporting the extent to which they felt they could access various kinds of resources.

The bonding scale (Cronbach's $\alpha = 0.88$, $M = 3.40$, SD = 0.73) includes items such as, "When I feel lonely, there are several people in my Facebook network I can talk to" and "The people I interact with in my Facebook network would share their last dollar with me." The bridging scale (Cronbach's $\alpha = 0.90$, $M = 3.47$, SD = 0.66) includes questions such as, "Interacting with people in my Facebook network makes me want to try new things" and "Interacting with people in my Facebook network reminds me that everyone in the world is connected."

Facebook Relationship Maintenance Behaviors (FRMB) measures the extent to which Facebook users engage in social grooming and attempt to respond to requests from their Facebook network, which may in turn signal that ego is paying attention to alter (Ellison et al., in press). The scale (Cronbach's $\alpha = 0.90$, $M = 3.72$, SD = 0.80) includes five items, four of which reference users' likelihood to respond to requests from other members of their network and a fifth that captures the common practice of signaling attention to a specific Friend by writing "Happy Birthday" on their Wall. Past research employing this measure found significant differences in perceptions of bridging and bonding social capital across different levels of engagement in FRMB, although measures of network structure were not considered (Lampe et al., 2012).

Information-Seeking Behaviors (ISB) examines the extent to which individuals use Facebook's communication features to seek a range of informational resources from their network (Lampe et al., 2012). This scale (Cronbach's $\alpha = 0.83$, $M = 2.34$, SD = 0.83) measures participants' use of Facebook for getting information or advice regarding purchases, health, business referrals, and other specific questions.

Self-esteem was measured using Rosenberg's (1989) seven-item validated scale (Cronbach's $\alpha = 0.86$, $M = 4.32$, SD = 0.50). Sample items include, "I feel that I have a number of good qualities" and "On the whole, I am satisfied with myself."

Actual friends was measured using a self-report question, based on Ellison et al. (2011), in which users were asked, "Approximately how many of your TOTAL Facebook Friends do you consider actual friends?" At present, Facebook Friends remain in one's Friends list until explicitly removed by one of the dyad. Thus many years later, individuals may still be friends on the site despite no contact. In offline personal networks, however, network membership is in flux and ties tend to fade over time (Suitor and Keeton, 1997)—without the ease of connection offered by social technologies such as Facebook, individuals may lose the ability to re-connect as people move away, change jobs, etc. Thus, individuals may have networks on Facebook that do not reflect their active ties, or even people they would consider friends. To address this, we follow recent approaches that ask participants to report on the number of 'actual' friends within their Facebook network as well as the time spent on the site. As noted in Table 2, actual friends is correlated with the number of Facebook Friends ($r = 0.49$, $p < 0.001$). To note,

Table 1
Sample descriptive statistics.

	Mean	Median	SD	Min	Max
Nodes	217.74	153.00	227.61	14.00	1950.00
Average degree	14.02	12.00	10.67	1.00	70.00
Transitivity	0.57	0.55	0.12	0.33	0.95
Clusters	6.54	6.00	3.45	1.00	22.00
Modularity	0.43	0.46	0.17	0.00	0.77
Giant component percentage	0.82	0.89	0.17	0.24	0.99
Gender (Female)	0.70	1.00	0.46	0.00	1.00
Age	44.21	46.00	10.73	23.00	65.00
Education (ordinal)	5.05	5.00	0.95	2.00	6.00
Self-esteem	4.32	4.29	0.50	2.57	5.00
Actual friends on Facebook	80.90	45.00	103.17	0.00	700.00
Visits per day to Facebook	2.21	2.00	1.12	1.00	5.00
Facebook engagement (FRMB)	3.73	4.00	0.79	1.00	5.00
Info-seeking on Facebook	2.35	2.25	0.83	1.00	4.75
Facebook bonding capital	3.40	3.50	0.74	1.00	5.00
Facebook bridging capital	3.47	3.60	0.66	1.00	5.00

$N = 235$.

Table 2
Bivariate correlations between variables of interest.

	Nodes	Average degree	Transitivity	Clusters	Modularity	Actual friends on Facebook	Self-esteem
Average degree	0.82**						
Transitivity	−0.40**	−0.21**					
Number of clusters	0.45**	0.31**	−0.52**				
Modularity	0.27**	0.04	−0.46**	0.40**			
Actual friends on Facebook	0.49**	0.33**	−0.38**	0.37**	0.32**		
Self-esteem	0.04	0.01	−0.04	0.02	0.03	0.13*	
Age	−0.37**	−0.37**	0.29**	−0.32**	−0.30**	−0.23**	0.06
Sex	0.08	0.00	−0.10	0.11†	0.10	0.16*	0.04
Education	0.05	0.03	0.04	0.08	0.05	0.01	0.06
Visits per day to Facebook	0.47**	0.37**	−0.38**	0.42**	0.28**	0.44**	0.06
Facebook engagement (FRMB)	0.24**	0.21**	−0.23**	0.37**	0.20**	0.32**	0.10
Info-seeking on Facebook	0.34**	0.32**	−0.28**	0.34**	0.18**	0.40**	0.04
Facebook bridging capital	0.26**	0.18**	−0.21**	0.31**	0.19**	0.32**	0.11†
Facebook bonding capital	0.20**	0.12†	−0.37**	0.30**	0.27**	0.34**	0.17*

	Age	Sex	Education	Visits per day to Facebook	FRMB	IBS	Facebook bridging capital
Sex	0.08						
Education	−0.11†	−0.09					
Visits per day to Facebook	−0.36**	0.12†	0.00				
Facebook engagement (FRMB)	−0.12†	0.25**	−0.01	0.42**			
Info-seeking on Facebook	−0.19**	0.25**	−0.15*	0.41**	0.49**		
Facebook bridging capital	−0.05	0.24**	0.01	0.35**	0.59**	0.54**	
Facebook bonding capital	−0.26**	0.10	0.00	0.27**	0.44**	0.42**	0.51**

$N = 235$.
† $p < 0.1$.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

non-parametric correlations indicate a substantially stronger relationship (Spearman's rho = 0.67, $p < 0.001$) suggesting that when we account for the few individuals with very large networks, there is a reasonably close, if not perfect, relationship between these values. Individuals report having a mean of 217.7 nodes (median 153) in their networks, but report a mean of 81 (median 45) actual friends on the site.

Visits per day to Facebook measured time spent on Facebook using a self-reported measure of visits per day. Past research (Burke et al., 2010) has indicated that visits per day was more accurately measured by participants than time spent on the site in minutes. Such a measure also accounts for instances where individuals will keep Facebook available for chatting on multiple devices. Thirty percent of our sample said they visit Facebook once a day or less and 5% said they visit Facebook five or more times per day.

4.3. Personal Facebook networks

The personal networks of participants were collected using a custom-built Facebook application accessed through a hyperlink in the survey. The algorithm for this application was based on code from Hogan's (2010) "NameGenWeb," a public-facing application for downloading one's friendship relations in a network format, such as GraphML (Brandes et al., 2002). In order to download the network, respondents had to approve the application from within their Facebook accounts. Data downloaded from this project was cached while user statistics were calculated.

The networks used in this study were larger than the average network on Facebook, as reported by the site. According to the site's statistics, the average network contains approximately 130 nodes (Facebook, 2011), although this number varies widely by country. The mean number of nodes in our survey was 217, but was heavily skewed by the presence of a few individuals with very large networks (the size of the five largest networks were 843, 1026, 1050, 1367 and 1950). The median network size was 153, which is closer to the global average of 130. These networks were also very dense, with an average degree of 14 and an average transitivity of 0.57.[1] That is to say, over half of all potential triads are closed and on average each alter in the network is connected to at least 14 other alters.

Facebook personal networks in our sample tended to be well connected overall, in that the giant component for any given network comprised most of the network. The median percentage of nodes in the giant component was 89 and the mean was 82. The remaining nodes tended to be isolates or isolated dyads. A median of 99% (mean of 93%) of all nodes was either part of the giant component, an isolate, or a dyad. Thus, while it is likely that many social groups coexist in one's Facebook network, these groups are not separate social islands. Rather, they are zones of either greater or lesser connectivity where some alters will be highly connected to multiple social groups while others will be primarily tied to specific clusters. This also reinforces the use of modularity maximization techniques for partitioning rather than simply counting the number of components. Fig. 1 is characteristic of the networks we saw when visualizing Facebook personal networks.[2]

Transitivity in a network can be measured in a multitude of ways, but two conventional measures stand out. The first is three times the count of triangles in the graph divided by the count of all two paths (Davis, 1967; Holland and Leinhardt, 1971). The second is the global clustering coefficient, which measures transitivity around each node in the network and takes the average of these results (Watts and Strogatz, 1998). Also, these calculations

[1] All network metrics were calculated using iGraph 0.6 (Csárdi and Nepusz, 2006) and Python 2.7.

[2] This figure does not come from the study, but was created by one of the authors, with clusters detected using the same algorithms as done for participants.

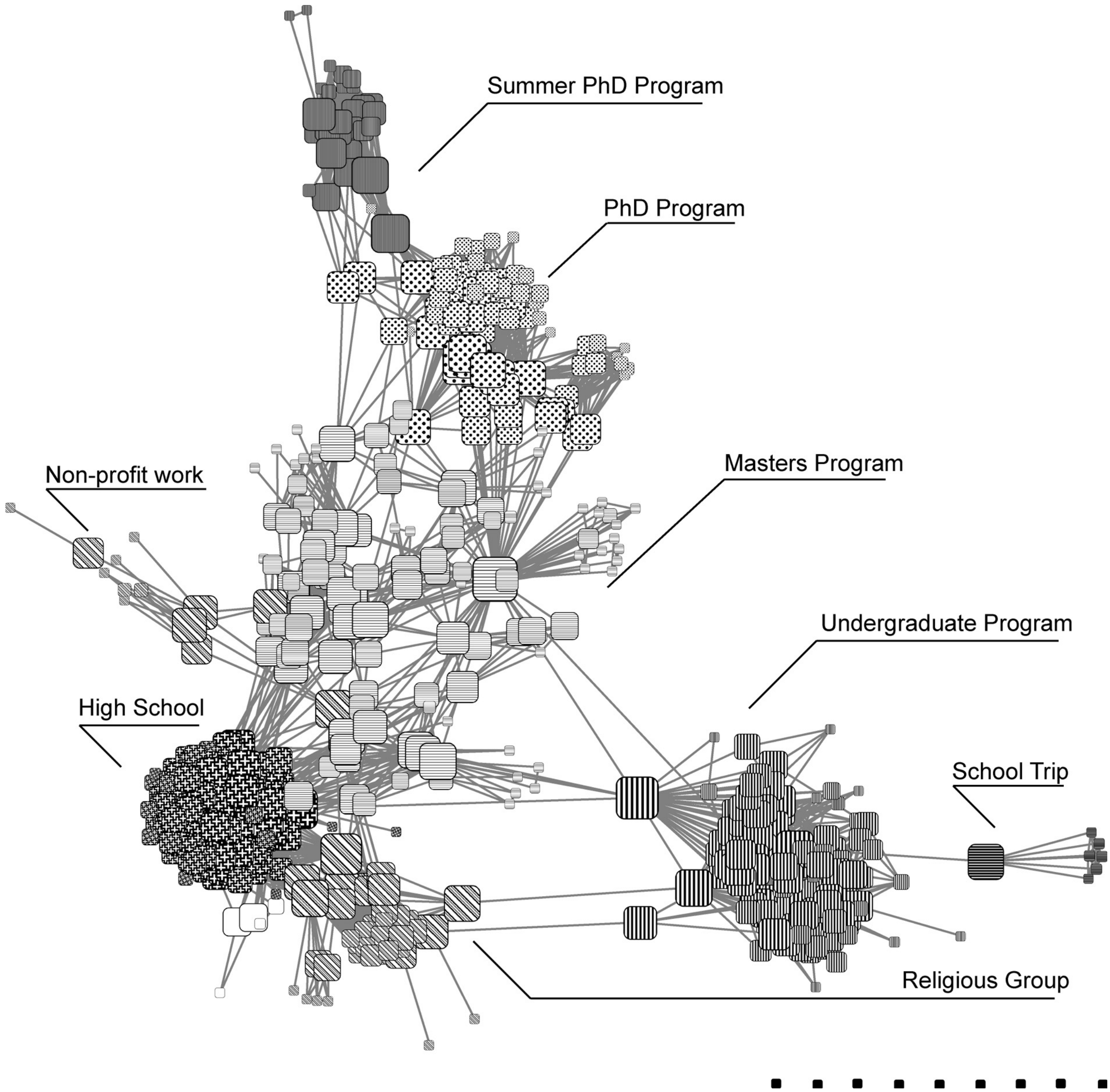

Fig. 1. Facebook network with clusters found through multilevel community detection (the "Louvain method"). Node size corresponds to a log scale of betweenness. Network owner has labeled the clusters and verified their accuracy as distinct subgroups. Network captured using NameGenWeb and rendered using GUESS 1.04 (Adar, 2006). Different swatches denote separate subgroup membership.

exclude ego, so in the complete graph, triangles actually represent 4-cliques, as ego is connected to all three alters. However, our interest here is in the network that ego perceives as an external object, and so ego is excluded from calculations. The other reason for excluding ego is that it simplifies calculations dealing with isolates, who would otherwise extremely skew any transitivity score.

Clusters were measured using an automated "community detection" algorithm. We loosely consider these clusters to represent distinct social groups or contexts. Specifically, we used the "Louvain method," a highly efficient technique for decomposing a network into mutually exclusive clusters that seek to maximize modularity (Blondel et al., 2008). We acknowledge that in a network that is not completely disconnected some individuals link across contexts, and ego may consider this individual as belonging to both contexts. We opt for the Louvain method rather than alternate methods for its efficiency and its capacity to maximize modularity relative to other methods, such as Girvan-Newman (Girvan and Newman, 2002), Greedy community detection (Clauset et al., 2004) and spectral partitioning (Newman, 2006). The groups are identified using a greedy optimization technique that seeks out local clusters of high density. This iterative process continues until it reaches the highest modularity values, thereby ensuring that each cluster has the fewest number of links between each group, the most within each group, relative to a null model and every node is assigned a group. We only calculate clusters within the giant component. We use the standard configuration null model that fixes the degree distribution while randomizing edges. While Fortunato (2010) suggests that in some cases the configuration model may be unrealistic as a benchmark since it assumes the potential for any node to connect to any other node. We believe connections between any two nodes is actually a legitimate assumption within Facebook personal networks since all alters have at least one friend in common—ego. Along with the number of groups, we include the modularity (or quality) score as a supplementary measure of the distinctiveness of the groups.

5. Models and analyses

The correlation matrix of our variables of interest indicates a multitude of strong relationships. Results in Table 2 suggest that many of the measures discussed above can at least partially explain variations in bridging and bonding social capital, given the many correlations over 0.2. We first review some of the most notable correlations and then proceed to discuss nested OLS regression and multiple mediation models.

5.1. Correlations

Bivariate correlations reinforce our earlier characterization of the topology of Facebook ego networks: larger networks are associated with higher average degree, less transitivity, more clusters and a higher modularity score. The network metrics also significantly (where $p < 0.05$) relate to the demographic and engagement variables. Most notably, networks with more nodes strongly correlate with more actual friends as well as more visits to Facebook. Also, information-seeking is strongly related to the number of clusters. This suggests individuals who consider Facebook as an information source tend to have more social contexts from which to draw, providing a preliminary validation of hypothesis 4b above. We will explore this relationship further in a multivariate model below.

Average degree is (weakly) positively related to bonding social capital as hypothesized. More clusters and higher modularity are both (weakly) related to bridging social capital as hypothesized. Transitivity actually shows a significant negative relationship to both forms of social capital. This goes against the basic hypothesis that more connectivity in the network would be associated with greater perception of inclusiveness as suggested by a traditional social capital approach. This finding will be explored in the models below and the subsequent discussion.

Only one correlation is high enough to suggest potential multicollinearity issues: average degree and nodes ($r = 0.82$, $p < 0.001$). In our subsequent regressions we check for multicollinearity using VIF and Tolerance parameters within SPSS version 19. No models showed VIF scores above 10 or Tolerance scores below 0.20. Apart from concerns with multicollinearity, this correlation in itself is interesting—as nodes come into the network, the average degree increases. It would suggest that when people add new alters, these alters are likely to share friends in common with ego. We will return to this finding in the discussion as it helps to explain how transitivity and bonding social capital can be negatively related.

5.2. Multivariate analysis

Although we wish to test for the independent effects of our key structural metrics, we first consider these metrics in a standard OLS regression framework. For bonding and bridging social capital we include two models each. These are standard nested models where the second model includes all variables from the first as well as additional social engagement variables. The smaller models [Models 1 and 3 in Table 3] include five structural metrics: number of nodes, average degree, modularity, number of clusters and transitivity. These models also include controls based on previous work: age, education (ordinal), gender and self-esteem. The expanded models [Models 2 and 4 in Table 3] append four Facebook engagement metrics: visits per day to Facebook, actual Facebook Friends, FRMB, and ISB.[3]

When controlling for other structural variables, the effects of average degree, modularity and number of nodes is rendered non-significant. Using only node or average degree (not shown) instead of both does not change this outcome. Thus, we have evidence to reject Hypothesis 1. In line with the earlier correlations, transitivity is negatively related to both perceived bridging and bonding capital. However, it is only significant where bonding social capital is used as the dependent variable. This significance persists with the inclusion of engagement variables (model 2).

In Model 3 (bridging social capital), number of clusters is the only significant variable, although this relationship is rendered non-significant by the inclusion of engagement variables (Model 4). We will explore this further in a mediation model to help clarify the relationship between number of clusters (i.e., social contexts), engagement and bridging social capital.

In model 1, Hypothesis 1 is not supported; average degree has no significant effect, which was expected based on the weak correlation. Hypothesis 2 was also not supported as transitivity persisted in having a negative effect on bonding social capital. Thus, while all network measures were significantly correlated with the bridging and bonding scores in the bivariate correlations, only the number of clusters emerges as a significant predictor for bridging and only transitivity was a significant predictor for bonding when the measures are modeled jointly. Gender is also a significant predictor, with women reporting greater bridging social capital than men. The resulting Model 1 has a moderate fit, with an adjusted R^2 of 0.17. Model 2 has an adjusted R^2 of 0.32.

Models 2 and 4 indicate support for Hypotheses 4a and 4b, namely that FRMB and ISB positively predict bridging and bonding social capital while leading to substantial increases in explained variance. These variables also alter the relationship between the structural variables and social capital. The precise nature of this effect cannot be determined in the current OLS models. Consequently, we turn to mediation models.

5.3. Mediation modeling of structural effects

To explore the relationship between network structure, engagement and social capital, we employ multiple mediation models (MML; Preacher and Hayes, 2008), as an extension to classical mediation models (Baron and Kenny, 1986). These models operate in a manner similar to structural equation models in that they determine which part of a variable's effect on a dependent variable is explained by an intermediary variable. That said, they provide an overall model R^2 and employ bootstrapping to assess the significance of the effect of the mediators. Such models are useful when seeking to disentangle the effect of individual perception or behavior on the relationship between some objectively measured value and some outcome variable. For example, Vanbrabant et al. (2012) employed mediation models in personal networks to assess how verbal aggression was mediated by status and subjective sense of power. For this study, we are interested in the extent to which measures of engagement mediate the effects of network structure on reported social capital.

Based on the regression models described in Table 3, we focus specifically on disentangling the relationship between transitivity and bonding social capital (Model 5) and number of clusters and bridging social capital (Model 6). In addition to FRMB and ISB, we include visits per day to Facebook and number of actual friends as potential mediators since these latter variables indicate ego's potential to activate social capital.

Multiple mediation models articulate three paths from the variable of interest, rather than one single path from all variables to the dependent variable (Fig. 2): the *a* path, showing the independent variable to the mediators; the *b* path, showing the mediators to the dependent variable; and the *c*' path, showing the residual effect of the independent variable accounting for the mediators. We also report the *c* path, which is the total effect of the independent

[3] Despite the high correlation between nodes and average degree, the exclusion of either does little to change the model fit or the significance of the variables.

Table 3
OLS regression predicting to the Williams scale of bonding and bridging capital.

	DV: Bonding social capital		DV: Bridging social capital	
	Model 1: Network variables	Model 2: Network + engagement variables	Model 3: Network variables	Model 4: Network + engagement variables
Demographics				
Gender (Women)	0.06	−0.05	0.19**	0.05
Age	−0.17*	−0.17**	0.08	0.10
Education	−0.02	0.02	0.00	0.06
Self-esteem	0.16**	0.12*	0.08	0.04
Network variables				
Nodes	−0.02	−0.03	0.11	0.12
Average degree	−0.01	−0.10	0.05	−0.09
Modularity	0.07	0.03	0.07	0.03
Number of clusters	0.10	−0.03	0.20**	0.02
Transitivity	−0.24**	−0.22**	−0.02	0.01
Engagement variables				
Actual friends on Facebook		0.11		0.01
Visits per day on Facebook		−0.08		0.04
ISB		0.22***		0.33***
FRMB		0.29***		0.38***
Constant (unstandardized)	3.50***	2.55***	2.21***	0.79
	$F(225) = 6.46^{***}$	$F(221) = 9.50^{***}$	$F(225) = 5.07^{***}$	$F(221) = 14.04$
Adjusted R^2	0.17	0.32	0.14	0.42

Standardized coefficients are reported for all numbers unless otherwise noted.
$N = 235$.
* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

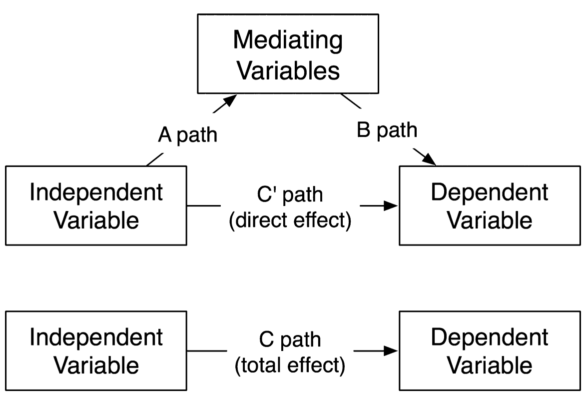

Fig. 2. Example mediation model schema denoting specific paths for independent and mediating variables. Control variables are not shown.

variable on the dependent variable. If this *c* path is non-significant, there is no meaningful relationship to test in the first place.[4] If this *c* path is significant, we can consider the mediating paths.

Model 5 examines the relationship between bonding social capital and transitivity (Table 4). The significant *c* path suggests that transitivity has an effect. The significant *c*' path suggests that transitivity has a direct effect independent of the mediators. The FRMB and ISB *b* paths to bonding social capital are significant ($p < 0.001$), but the *a* paths from transitivity to FRMB and ISB are not significant at the $p < 0.05$ level. However, given that their significance values are close to the critical value ($p \sim 0.06$), we believe that we can neither reject nor accept Hypotheses 5a and 5b for bonding social capital. Most importantly, the fact that *c*' is significant suggests that transitivity has an independent effect and therefore network structure can play a significant independent role in the perceived experience of bonding social capital. The coefficient for transitivity remains negative. We consider this further in the discussion section.

Model 6 examines the relationship between bridging social capital and number of clusters found using community detection. The significant *c* path suggests that the number of clusters has an effect. However, the non-significant *c*' path indicates that this relationship is indirect. Since there are significant *a* paths from number of clusters to FRMB and ISB and significant *b* paths from FRMB and ISB to bridging social capital we consider this to be an indirect, fully mediated, path. If the *a* paths were not significant we would have considered this relationship to be spurious rather than fully mediated. Consequently, we accept Hypotheses 5a and 5b for bridging social capital.

In both models 5 and 6 there are significant *a* paths to number of "actual friends" and daily number of visits to Facebook, although there is no evidence to support the notion that these variables significantly predict perceived social capital in these models.

6. Discussion

Results from the analyses demonstrate that the perception of social capital is related to both social structure and patterns of engagement in complex ways. The fact that FRMB was the strongest predictor in most models, both bridging and bonding, reinforces recent findings in this area (Burke et al., 2010, 2011; Ellison et al., 2011, in press; Vitak, 2012). In particular, these results indicate that Facebook use in itself is not a guaranteed path to perceptions of more social capital, but that specific attitudes and strategies for maintaining relationships (FRMB) play a large part as well. This is also reinforced by the consistently significant results for ISB. This later scale describes the extent to which individuals perceive Facebook as a site for information seeking needs. Those who consider Facebook as a site for information seeking also tend to report it as a site for more general social capital, both the emotional and inclusive bonding capital and the more instrumental and broad bridging social capital. It is important to note that in this study it is not possible to posit a causal direction. As such, we cannot tell if attitudes

[4] We employ the INDIRECT algorithm (version 4.1) written by Hayes in SPSS 18.

Table 4
Mediation models for bonding and bridging social capital.

	Model 5			Model 6		
	Bonding (IV: Transitivity)			Bridging (IV: Clusters)		
	Coefficient	SE	p	Coefficient	SE	p
IV to mediators (a paths)						
Actual friends on Facebook	−177.22	52.91	0.00	5.06	1.91	0.01
Visits per day on Facebook	−1.74	0.57	0.00	0.07	0.02	0.00
Info-seeking on Facebook	−0.86	0.45	0.06	0.05	0.02	0.00
Facebook engagement (FRMB)	−0.83	0.45	0.07	0.07	0.02	0.00
Direct effects of mediators on DV (b paths)						
Actual friends on Facebook	0.00	0.00	0.07	0.00	0.00	0.67
Visits per day on Facebook	−0.05	0.05	0.24	0.02	0.04	0.53
Info-seeking on Facebook	0.19	0.06	0.00	0.25	0.05	0.00
Facebook engagement (FRMB)	0.27	0.06	0.00	0.32	0.05	0.00
Total effect of IV on DV (c path)						
Transitivity/number of clusters	−1.87	0.41	0.00	0.04	0.01	0.00
Direct effect of IV on DV (c' path)						
Transitivity/number of clusters	−1.42	0.38	0.00	0.01	0.01	0.58
Partial effect of control variables on DV						
Gender (women)	−0.07	0.09	0.46	0.07	0.08	0.32
Age	−0.01	0.00	0.01	0.01	0.00	0.08
Education	0.02	0.04	0.72	0.05	0.04	0.20
Self-esteem	0.18	0.08	0.03	0.05	0.07	0.47
Nodes	0.00	0.00	0.08	0.00	0.00	0.53

Bonding: $N = 235$, Adjusted $R^2 = (0.325)$, $F(224) = 12.29^{***}$; bridging: $N = 235$, Adjusted $R^2 = (0.424)$, $F(224) = 18.23^{***}$.

lead to behaviors that reinforce the perceptions of social capital or the accrual of social capital changes attitudes and behaviors.

While we fully expected structural measures to have a mediated effect on FRMB and ISB, we found no mediation for number of clusters. This may be due to the ways in which people interact on Facebook, but it is likely the result of a finding within Burke et al. (2011), who find that it is direct person-to-person communication that leads to an increase in bridging social capital. Thus, in the case of bridging social capital, it is more important for an individual to know of an available job or someone who can link them to a resource. Further, we agree with Burke et al. in that bonding social capital generation and maintenance on Facebook is most likely due to individuals utilizing other methods for maintaining close relationships. Our findings suggest that those individuals from networks with low transitivity will be able to experience more bonding social capital on Facebook because they are communicating with fewer contexts and do not have to limit the exposure of their mass communication to the least close relationship.

The relationship between attitudes, behaviors and social capital has face validity. People who consider Facebook a site for information seeking and a site for small symbolic practices tend to be people who consider Facebook a place for the positive social resources found in the social capital scales. That is, people reap what they sow. However, a focus on individual attitudes and behaviors alone may potentially be reductionist. Facebook ego networks are structured in significantly different ways. Some of these networks show a clear pattern of dense pockets of ties from separate contexts with a mere handful that link the network together. For example, consider a network with separate friendship groups from high school, university, a full time job and a neighborhood association. There may still be a small number of people who link these groups together, such as one's significant other or best friend, but the groups remain distinct clusters. Transitivity would be high because most triangles are closed, but there are few links between the dense clusters of closed triangles. Other networks are very diffuse with many ties overlapping between multiple clusters. This might be the case if one went to a local college alongside many people from high school then got a job in the same town while living a few blocks down from one's parents. In such a case, it is plausible that many people from high school who know one's college friends, family members and co-workers. While the entire network would be very cohesive, there would be fewer closed triangles. The co-workers might know a few people from high school, but not all. The family members might know a few friends from college, but not all.

The irony of these two kinds of networks is that by measuring local closure, transitivity could be evidence of a lack of global cohesion. In the first case, transitivity would be high because most people in each of the separate groups knows each other while there are few open paths between the separate groups. In the second case, transitivity might be lower because the overlapping social circles mean more open two paths between different groups. So while local closure is lower, this is due to the fact that there are simply more two paths to account for since there are so many ties overlapping between the groups. We initially hypothesized a relationship between transitivity and bonding social capital since we considered more closed paths to be indicative of dense pockets of reciprocal relationships. It is an assumption that is long held in social network analysis (Feld, 1981; Louch, 2000). However, this relationship between dense reciprocal relationships and social capital may be based on an untenable assumption in Facebook ego networks—a network comprised primarily of a single cohesive group. By contrast, Facebook networks are almost always characterized by the inclusion of multiple social groups that only ever partially overlap.

Networks with lower transitivity mean more open two paths within the network. This is evidence that people from separate groups know each other. Networks with higher transitivity (especially large networks) tend to have groups that are very distinct. This suggests that people from separate groups do not know each other. When people do not know each other, it suggests that a Facebook user can be torn between multiple social worlds, each with its own demands and expectations. It may be like an awkward party where separate groups unknown to each other stay on opposite sides of the room. In such a case, it is plausible that despite having as many nodes and edges as a graph with more open two paths the graph "feels" different concerning the perception of bonding social capital. Thus, somewhat surprisingly we suggest that bridging ties within a Facebook ego network are associated with greater bonding social capital by making the overall graph more cohesive even if local network structures are less dense. Similarly to Binder et al. (2009), we suspect individual's will feel less 'context collapse' because their network is still relatively well connected and therefore fewer distinct subgroups, whereas those individuals with high transitivity will experience lower amounts of trust and engagement because of the lack of privacy (Houghton and Joinson, 2010).

Interpreting these results requires us to make assumptions about the sort of relationships that comprise a group (or a cluster found using community detection). In general, we maintain that clusters in Facebook ego networks represent broad assemblages based on life course stages and shared activities. This characterization of groups also helps to explain the full mediation of number of clusters on bridging social capital. More groups should mean a greater sense of connectivity to the wider world and the diverse information resources. Yet this sense of connectedness does not emerge necessarily. Those individuals who actively attend to these groups report that they draw novel information from them. Those who have a Facebook network but remain indifferent to it (i.e. do not consider it a site of information seeking or site for small relational maintenance practices) do not report as high a perception of bridging social capital.

There is a present turn toward considering the quality of relationships rather than mere structure (Aral and Alstyne, 2011) as well as a renewed focus on individual traits that can give rise to certain network structures (Burt, 2010, 2012). What we can conclude from this analysis is that this focus on individual and dyadic relationships makes sense in some arenas. Like Aral and Alsytne's focus on bandwidth over diversity, our mediation models demonstrate that greater engagement (i.e., bandwidth) plays a larger role in bridging social capital than multiple social groups (i.e., diversity). However, not all structural factors can be reduced to individual or dyadic level covariates. Lower transitivity, as evidence of greater overlap between groups and thus greater global cohesion, has an effect independent of how individuals approach their networks.

We have also demonstrated that new insights about social capital can be gleaned from Facebook ego networks compared to ego networks captured using traditional respondent driven techniques such as name generators or enumeration methods. Our findings about transitivity would not have been discovered in the very small networks traditionally employed in core discussion network research as it is not an insight about the most closely connected individuals to ego, but about how these individuals are situated in the wider networks of personal affiliation. Similarly, it could not be discovered by merely articulating which individuals belong to which social groups since it is about how these groups connect to each other rather than how many individuals exist in which group. Granted, the use of Facebook as a social network is not in itself novel. For example, very large scale analysis has indicated how the mean path of Facebook is approximately 3.74, much lower than Milgram's oft-cited six degrees (Backström et al., 2012). The Taste, Ties and Time dataset has indicated how students reinforce patterns of racial homophily (Wimmer and Lewis, 2010). The Facebook 100 data set has revealed how community structure at the university-level reinforces existing networking patterns such as homophily by major, cohort or dorm depending on the school (Traud et al., 2011). However, this work highlights how Facebook ego networks can have themselves substantial explanatory power. Thus, it is possible to study Facebook as "a network of networks", considering nodes (individuals), their connections on the site, and how these connections and the groups they represent are connected. Given that access to the total Facebook graph is both extremely limited, ethically challenging and technically formidable, we believe that analysis of sampled ego-centered networks can be a germane and practical alternative in some circumstances.

7. Limitations

Facebook personal networks offer a remarkable view into an individual's personal network, but it is neither a complete view of the personal network, nor a network that necessarily matches ego's biases, since some ties may exist between alters without ego's knowledge. We assert that bonding is related to a sense of the network as being globally cohesive or fragmented. It is possible that ego may not perceive this cohesion. We consider this plausible but unlikely. Nevertheless, future research should compare Facebook networks (like those drawn from NameGenWeb, or similar programs such as NetVizz) to personal network name generators to ascertain how sociocognitive networks on Facebook differ from these publicly articulated networks. Conversely, ego may know about ties that exist in the Facebook network, but were not captured by our Facebook app. This is because Facebook offers individuals the ability to place friends on "limited profile," meaning ego cannot see alter's details, but is still alter's friend. In this case, alter will not be included in the Facebook network as downloaded. We believe this is not common practice, and thus does not significantly bias our findings.

Concerning our methods, we acknowledge several criticisms of community detection methods. Two in particular stand out: The first is the resolution limits of modularity-oriented community detection methods (Fortunato and Barthélemy, 2007). The second is the recent demonstration that most community detection methods experience degeneracy near optimal solutions (including the Louvain method, cf., Good et al., 2010). These concerns would be more corrosive if this analysis hinged on the correct assignment of liminal nodes to clusters. However, we were interested in a count of clusters, without concern for whether certain brokers were assigned to one group or the other (when in reality ego may consider such brokers as members of both groups). Moreover, the resolution limit may even work in our favor by not presenting many tiny (arguably trivial) clusters in our larger networks. Given the explanatory power of the Louvain method in this paper it is plausible that other slower but potentially more precise methods may provide a better fit as well as more explanatory power by providing more accurate results. No method we tested performed better, but new methods for partitioning are continually emerging.

Beyond this, we acknowledge the limitations of our sample as working adults and university employees from the American Midwest. There may be cultural norms within this population and within this geographical area that do not generalize to larger populations. Nevertheless, much of the current work on social network sites and social capital employs undergraduate samples. Our study confirms earlier findings that greater Facebook use is associated with higher levels of social capital and expands this to a population with a wider range of ages and life histories than represented by undergraduate students. We believe this enables us to present a fuller picture of how Facebook operates in the population at large. Further, the non-student sample is valuable, but only having a U.S. sample poses limitations on the work (Henrich et al., 2010).

Finally, we encourage longitudinal work that can disentangle how evolving networks would lead to differences in social capital, or whether persistent demographic and personality factors drive both network structure and the sentiments associated with social capital. Our work points toward future research that would attempt to disentangle this research, but does not implicitly inform the relationship between the works of Burke et al. (2010, 2011) and Steinfield et al. (2008).

Acknowledgements

We acknowledge the advice of Rebecca Gray and Joshua Melville. This work was supported in part by the National Science Foundation (HCC 0916019).

Appendix A. Scales

The scales presented in Tables A1 and A2 below are a modification of William's final scales, as pruned from a larger question bank. As in the original paper and subsequent applications, the scales have a tolerable Cronbach's alpha above 0.8. Readers familiar with the development of social capital within sociological and social network literatures may find the inclusion of job information in the bonding social capital scale as somewhat surprising, since job information is presumed to be accessed through weak ties. It inclusion in bonding social capital is based on a principal components analysis in Williams (2006). The means refer to a Likert scale from strongly disagree (1) to strongly agree (5). Items were standardized before inclusion in the scale, but not weighted by factor loadings.

Tables A3 and A4 are the engagement scales discussed.

The final Table A5 below represents the self-esteem scale discussed.

Table A1
Facebook specific bridging social capital scale.

Items	Mean	SD
Interacting with people in my Facebook network makes me interested in things that happen outside of my town.	3.75	0.82
Interacting with people in my Facebook network makes me want to try new things.	3.59	0.83
Interacting with people in my Facebook network makes me interested in what people unlike me are thinking.	3.58	0.79
Talking with people in my Facebook network makes me curious about other places in the world.	3.71	0.86
Interacting with people in my Facebook network makes me feel like part of a larger community.	3.68	0.98
Interacting with people in my Facebook network makes me feel connected to the bigger picture.	3.54	0.89
Interacting with people in my Facebook network reminds me that everyone in the world is connected.	3.71	0.91
I am willing to spend time to support general Facebook community activities.	3.02	0.92
Interacting with people in my Facebook network gives me new people to talk to.	3.17	1.01
Through my Facebook network, I come in contact with new people all the time.	2.96	1.03

Adapted from).
Full scale: $M = 3.47$, $SD = 0.66$ ($\alpha = 0.90$).

Table A2
Facebook specific bonding social capital scale.

Items	Mean	SD
There are several people in my Facebook network I trust to help solve my problems.	3.30	1.15
There is someone in my Facebook network I can turn to for advice about making very important decisions.	3.49	1.07
When I feel lonely, there are several people in my Facebook network I can talk to.	3.52	0.95
If I needed an emergency loan of $500, I know someone in my Facebook network I can turn to	3.35	1.16
The people I interact with in my Facebook network would put their reputation on the line for me.	3.38	0.94
The people I interact with in my Facebook network would be good job references for me.	3.41	0.97
The people I interact with in my Facebook network would share their last dollar with me.	3.08	0.94
The people I interact with in my Facebook network would help me fight an injustice.	3.70	0.84

Adapted from).
Full scale: $M = 3.40$, $SD = 0.73$ ($\alpha = 0.88$).

Table A3
Facebook Relationship Maintenance Behavior scale (Ellison et al., in press).

Items	Mean	SD
When I see a friend or acquaintance sharing good news on Facebook, I try to respond.	3.87	0.90
When I see a friend or acquaintance sharing bad news on Facebook, I try to respond.	3.65	0.95
When I see someone asking for advice on Facebook, I try to respond.	3.42	0.95
When a Facebook friend has a birthday, I try to post something on their wall.	3.87	1.06
When I see someone asking a question on Facebook that I know the answer to, I try to respond.	3.82	0.85

Full scale: $M = 3.72$, $SD = 0.80$ ($\alpha = 0.90$).

Table A4
Information-seeking behavior scale (Lampe et al., 2012).

Items	Mean	SD
I use Facebook to get advice about something I want to buy.	2.42	1.02
I use Facebook to get business referrals.	2.16	0.98
I use Facebook to get answers to specific questions.	2.73	1.14
I use Facebook to ask questions about health issues.	2.04	0.93

Full scale: $M = 2.34$, $SD = 0.83$ ($\alpha = 0.83$).

Table A5
Self-esteem scale.

Items	Mean	SD
I feel that I'm a person of worth, at least on an equal plane with others.	4.50	0.60
I feel that I have a number of good qualities.	4.50	0.63
All in all, I am inclined to feel that I am a failure (reversed).	4.47	0.67
I am able to do things as well as most other people.	4.22	0.65
I feel I do not have much to be proud of (reversed).	4.44	0.72
I take a positive attitude toward myself.	4.08	0.75
On the whole, I am satisfied with myself.	4.04	0.76

Adapted from Rosenberg (1989).
Full scale: $M = 4.32$, $SD = 0.50$ ($\alpha = 0.86$).

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