TIE STRENGTH VS. NETWORK OVERLAP: WHY INFORMATION FROM LOVERS IS MORE VALUABLE THAN FROM CLOSE FRIENDS ON SOCIAL NETWORK SITES?

Completed Research Paper

Ksenia Koroleva
Goethe-University Frankfurt
Grüneburgplatz 1, 60323 Frankfurt-am-Main
koroleva.ksenia@gmail.com

Vid Štimac
Hertie School of Governance
Friedrichstrasse 180, 10117 Berlin
stimac@hertie-school.org

Abstract

Network structure is an important determinant of information value contained in individuals' social networks. Researchers argue whether more value is contained in strongly connected cohesive networks or the weaker ones that are rich in structural holes. In the paper we differentiate between two measures of network structure - tie strength and network overlap – and explore their impact on the value of information that users derive from Social Network Sites. We analyze the data collected trough a survey administered to 121 Facebook users via a platform application. Our findings reveal that although users prefer information from their stronger ties on the network, high overlap in their networks decreases information value.

Keywords: tie strength, network overlap, cohesion

Introduction

Social Network Sites (SNS) are becoming important tools for obtaining novel information, especially because they transmit information which was recommended by friends and is more tailored to the user's interests. On SNS users stay up to date with the information about a diversified network of their closer friends and weaker acquaintances as well as have timely access to information about their favorite artists, brands and organizations. As opposed to the earlier generations of electronic networks, which have been suitable only for exchanging quite lean and unambiguous information (Daft and Lengel 1986), SNS as a communication medium are able to transmit a lot of contextual as well as relational cues thus providing users with a new richer medium for information exchange. Considering this increasing amount and varied quality of information (Koroleva et al. 2010), users not rarely lack the necessary time and cognitive resources to process it and have to choose on which information to focus their attention. Their network structure in general and their relationships to the people in the network in particular become an important determinant of information value.

However, not all users can obtain the same amount and type of informational benefits. Those whose network is more optimally structured may enjoy higher rates of return on their informational demands and obtain more benefits of social capital. However, which configuration of the network confers significantly more informational benefits, is yet to be determined. On the one hand, networks where individuals are tightly interconnected with similar others may provide social support and promote trust, thus enabling efficient exchange of information (Coleman 1988). On the other hand, networks with weaker connections between diverse groups of individuals may provide access to non-redundant information which is not available in their immediate surroundings (Granovetter 1973). SNS allow users to construct and maintain large networks of any configuration they desire, without putting restrictions on the quality of relationship or the frequency of communication (Ellison et al. 2007). In our study we aim to determine which structure of the network brings about more informational benefits to users on SNS. As opposed to previous efforts which to some extent equated tie strength with network overlap, we want to distinguish the impact of these two dimensions of network structure on information value. Our research questions can be summarized as follows:

- *Do users prefer information from their strong or weak ties on SNS?*
- *How does network overlap impact the value of information on SNS?*

In order to answer these questions, we develop a Facebook application that simulates the user's Newsfeed and ask users to select the information they would pay attention to. Using the unique capabilities of SNS, we combine two methods of measuring network structure that effectively complement each other: on the one hand, by asking participants to identify the underlying relationships with their friends, and on the other by measuring their network size and relative network overlap. Thus, we are able to combine the subjective evaluations of users with the objective measures of network structure and determine their impact on information value. Using several regression methodologies, we report robust results that show that while strong ties are associated with information value, network overlap has a negative impact on the information benefits users derive from SNS.

Theoretical Background

Network Structure

Networks can enhance individual performance in two ways: by facilitating access to information and resources possessed by others (Granovetter 1973, Burt 1992) and by ensuring cooperative behavior (Coleman 1988). When estimating the benefits that accrue to users due to the maintenance of relationships with others, one might consider their relative network size: the bigger the network, the higher is the probability that one person in the network possesses the desired resources. More important than the size, however, is the structure of the individual social network, that determines the benefits that can be gained. Researchers study the configurations of individuals' networks on three different levels: (i) at the network level by analyzing the structure, measured by e.g. network density; (ii) at the node level of analysis by estimating the structural position of a person, with the help of e.g. a centrality measure; and (iii) at the dyad level the relationship between two people, where tie strength determines their relationship (Borgatti et al. 2009). In this paper we explore the networks of users on two levels: dyadic level by assessing the tie strength, and network level – by assessing the relative network overlap.

On the *network level* of analysis, network structure is related to the benefits users obtain from their network. A debate persists whether cohesive networks or those rich in structural holes provide more social capital benefits to their participants. On the one hand, *cohesive networks* – where most or all of the contacts are strongly tied with one another (Burt 1992, Garguglio and Benassi 2000) - provide easy access to each other's information as well as facilitate trust, norms and sanctions. Such networks are known to be more reliable communication channels, that can verify the information that is exchanged and thus facilitate trust between the members (Granovetter 1985, Coleman 1988). Most benefits of the cohesive networks come from network closure – a property when everyone is connected to everyone. By facilitating social norms and effective sanctions, such network enables cooperation between participants and diminishes the risk of opportunistic behavior (Coleman 1988). As users receive social reinforcement from multiple users in their network, behavior spreads farther and faster in such networks (Centola 2010). The disadvantage of a such a cohesive network is that everyone possesses similar or even redundant information and therefore the benefits they provide to each other are overlapping (Burt 1992).

On the other hand, a network rich in *structural holes* – bridges between otherwise disconnected groups of people – is more beneficial because the people on either side of a structural hole circulate in different flows of information and therefore the benefits they provide to each other are rather additive (Burt 1992, 2001). The benefits of such a network mainly result from the diversity of information contained in these separate clusters as well as the ability to broker the opportunities in connecting the separate clusters of a network (Burt 1992). Thus, such networks are more advantageous contacts to others that can provide access to sparse resources (Granovetter 1973), offer comparative advantages in negotiating relationships (Gargiulo and Benassi 2000), exercise control over more rewarding opportunities (Burt 1992), and be responsible for the spread of the new ideas and behaviors (Burt 1999). A network rich in structural holes has been found to be positively associated with better job placement, promotion, creativity, innovation, productivity and performance (e.g. Uzzi 1997; Hansen 1999, 2002).

On the *dyad level* of analysis, the discussion about the value of rather strong or weak ties in creating social capital persists. Some researchers propagate the value of strong ties, as these ties can transfer any kind of information and possess knowledge about who knows what and requires which information (Uzzi 1997, Hansen 1999). However, as strong relations tend to develop between people with similar social attributes (Fischer 1982), they are likely to possess the same information and provide redundant benefits (Burt, 2001). Other researchers, guided by the fact that weak ties are less likely to provide redundant information and more likely to connect people from otherwise diverse groups, are more beneficial for information exchange (Granovetter 1973). At the same time, weak ties are known to be opportunistic, functional and only selfishly cooperative (Granovetter 1973, Uzzi 1997). Therefore, whether weak or strong ties are more beneficial for information exchange still remains ambiguous.

Finally, it seems that many researchers do not distinguish between these two levels of network analysis and equate strong ties with network cohesion, whereas weak ties with the availability of structural holes. This is evidenced by the definition of cohesion as strongly interconnected ties with each other (Burt 1992) and by the similarity of arguments in the discussions above. Although tie strength and network cohesion are correlated, not distinguishing between them might lead the researchers to make inappropriate conclusions about the impact of network structure on social capital. Although strong ties are more likely to occur in cohesive networks, not all of the ties are strong in such networks. For example, neighbors exhibit cohesive networks, but their connections usually lack sufficient depth to be referred to as strong ties. At the same time, ties acting as a bridges between otherwise unconnected groups can also be characterized by a strong, and not always by a weak relationship. In fact, strong ties might be necessary to realize the value contained in structural holes, as they provide motivation to exchange the information between two otherwise distinct groups (Burt 2002). Overall, both types of ties can be beneficial for information value as the frequency of interaction between strong ties can compensate for the diversity contained in the weak relationships (Granovetter 1973). The later empirical evidence finds that both the diverse network of weak ties and a high bandwidth of communication with strong ties can provide novel information, depending on the information environment surrounding these ties (Aral and Van Alstyne 2012).

Network Structure and Information Value on SNS

SNS are effective tools that make the exchange of information much easier than it was possible in previous IT-enabled networks. Previous generations of CMC were accused of the lack of non-verbal cues and contextual information, which made it possible only for the transmission of lean and less ambiguous information (Daft and Lengel 1986). SNS by design are tailored at transmitting relational and contextual information. Any piece of information that is exchanged on SNS, is accompanied by at least three social context cues: i) information about the sender (gender, name, number of friends, mutual friends, etc.); ii) history of communication both publicly (by commenting and liking) and privately (through messages and chat) between sender and receiver; iii) social information from others through ratings and comments. These features allow users to process information more easily and give the impression of the presence of other users during the interaction on the platform. Therefore, in our paper we explore the impact of underlying tie strength, network overlap as well as ratings and comments on the informational benefits users derive on SNS.

Informational benefits of a network are centered around more broad access and faster timing of information (Burt 1992), which can be enhanced by the unique features of SNS. Access refers to receiving a valuable piece of information and knowing who can use it. The information contained in the profiles as well as revealed through communication on SNS allows to determine who possesses the desired information and to whom this information can be useful. Although the Newsfeed does not have perfect algorithms for information filtering, users do not have to actively search for information, thus decreasing the costs of information access. Moreover, timing allows people to receive information from personal contacts earlier. Although this information may sometimes be subjective and incomplete, users can act on it, if they need it, either by learning more or passing it on to other contacts (Burt 2001).

Findings on the value of SNS for information exchange are quite scarce, but the insights point that a broad and diversified network structure usually leads to the benefits of social capital (Koroleva et al. 2011). Most researchers equate the weak ties with the bridging, whereas strong ties with bonding social capital benefits (Ellison et al. 2007). Overall, rather a ‘bridging role’ has been attributed to SNS, as the costs of maintaining relationships with a diverse network of others are quite low (Ellison et al. 2007). One of the dimensions of the bridging social capital scale recognized by Williams (2006) is horizon broadening – which capitalizes on the new and unexpected information that people can obtain from their network. Although bonding social capital has been initially found to result from SNS usage, the later findings disproved its potential (Vitak et al. 2011). At the same time, the increasing amount of information exchanged on SNS, induces users to prefer information coming from their strong rather than weak ties on SNS (Koroleva et al. 2011). Recent empirical evidence sheds some light on these conflicting findings: strong ties are better for the transfer of information on SNS, whereas weak ties transmit information that one is unlikely to be exposed to otherwise (Bakshy et al. 2012). We set out to explore the impact of network structure on the informational benefits users derive from their network.

A unique feature of SNS is easy visualization and therefore measurement of the networks of users with a better precision. Previously researchers used surveys to elicit the subjective impressions of users about their network in general or tie strength with specific people in particular. SNS allow to measure the network as a whole, as well as to assess the underlying relationships between specific people. We assume that the relationship between network structure and information value will not only be determined by the tie strength between users, but also by the relative overlap in the users’ networks. We propose to exploit the unique possibilities of SNS and to measure the networks on the dyad level of analysis, that is for each pair of users, by the strength of their underlying relationship and tapping into the network level of analysis, by their relative network overlap. Although previous studies have explored the impact of tie strength on information value (Koroleva et al. 2011), no study so far has studied the impact of network overlap on informational benefits users derive. Moreover, we operationalize tie strength not only as the people with whom users already maintain an existing relationship, but also those weak ties that the users want to develop in the future and those with whom users frequently communicate on the network.

We can categorize the ties on SNS along the two dimensions - tie strength and network overlap – which although correlated, do not necessarily coincide with each other (Table 1). We need not provide examples of people who have high (low) network overlap and are characterized by a strong (weak) relationship. The interesting cases are located in the lower right and upper left corners of the Table 1, that illustrate that high network overlap does not necessarily occur between individuals connected by a strong tie. On the one hand, it is possible to imagine highly overlapping networks of two users, who are connected by a weak relationship, such as for example, school classmates. On the other hand, one can be quite close with someone, but the networks may not necessarily overlap, for example two people who live in different cities or belong to different social circles, but had a period of intensive communication at one stage of their lives, such as lovers. In our study, we aim to explore the impact of each of these two dimensions of network structure on the value of information users obtain on SNS. We propose that tie strength and network overlap can have different impact on the value of information on SNS. On the one hand, if the tie is weak, there is low interest in information coming from that person and therefore no motivation to process such information. On the other hand, a high network overlap might result in redundant information and the ability to obtain the same information also from someone else in the network. Therefore, a combination of high tie strength and low network overlap might promise the highest benefits to the users: the diversity of the network allows to get access to the resources that one does not possess oneself, whereas the strong relationship allow to easily obtain those resources if needed.

Table 1. Categorization of Ties on SNS with Examples

Network overlap	**high**	E.g. classmates	E.g. good friends
	low	E.g. recent acquaintances	E.g. lovers
		weak	**strong**
		Tie strength	

Derivation of Hypotheses

Dependent Variable

The dependent variable of our study is the attention of users towards the information that is shared by their friends on SNS. That is, only the information that attracts user's attention in the overall information flow is the only valuable information that the user can effectively use. Attention has several meanings, the most common of which is selective processing, defined as differential processing of sources of information (Johnston and Dark 1986). It is necessary to distinguish between bottom-up and top-down processing. The bottom-up approach, also known as systematic processing, involves extensive evaluation of information and requires a significant amount of motivation, ability and cognitive resources. In contrast, the top-down approach, referred to as heuristic processing, involves reliance on cognitive heuristics – mental shortcuts that allow people to form opinions without extensively analysing the contents, internally based on certain stimuli (Ajzen and Sexton 1999, Johnston and Dark, 1986). On SNS users will process information heuristically and increasingly react to certain stimuli – for example, the relationship with the person who posted or the rating the information has received. Some stimuli can be explicit, such as the number of ratings or comments the information has received, whereas others can be more implicit, for example the underlying relationship or the interconnectedness of the users' networks. This will occur due to several reasons. First of all, as users are overloaded with the information they receive (Koroleva et al. 2010), they are unable to attend to each piece of information carefully. Second, people usually prefer less effort to more effort, and reliance on certain stimuli helps to easily process incoming information (Bohner et al. 1995). Third, the information on SNS is rich in different stimuli, such as the "sender" of the post, the number of comments and likes it receives, etc. that attract user's attention. In our study we want to determine which cues attract user's attention on SNS and how they impact the information value.

Independent Variables

Measures of Tie Strength

Tie strength is defined as a combination of the amount of time, the emotional intensity, the intimacy and the reciprocal services which characterize the tie (Granovetter 1973; Mardsen and Campbell 1984). In the absence of a unified measure of tie strength, authors have been approximating it by the frequency and duration of contact (Granovetter 1973), social homogeneity and level of attraction (Reagans, 2005), as well as overlap in organizational memberships and social circles (Alba and Kadushin 1976). Tie strength has been found to possess two main dimensions: time spent in a relationship proxied by duration and frequency of interaction and depth of the relationship indicated by, for example, intimacy of communication and emotional support (Mardsen and Campbell 1984). On Social Network Sites tie strength is especially hard to measure, as this characteristic is not reported by the platform and all connections that users maintain are referred to as "friends" (Boyd and Ellison 2008). However, Gilbert and Karahalios (2009) show how to approximate tie strength with the accuracy of 80% by assessing the available network data related to the frequency and depth of communication as well as similarity characteristics between users. In our study we measure tie strength with several dimensions: i) closeness approximated by level of acquaintance; ii) affection approximated by the desire to develop a relationship; and iii) communication intensity on SNS. We want to explore how these measures of tie strength are related to the value of information users obtain from their networks.

Closeness

Distinguishing between indicators (actual components) and predictors (influencing factors) of tie strength, Mardsen and Campbell (1984) find that the best and not confounded by predictors indicator of tie strength is closeness between the users. Closeness is the measure of the intensity of a relationship (Mardsen and Campbell 1984) or level of acquaintance with the person (Petroczi et al. 2007). That is, weak ties are the ones which reflect lower levels of acquaintance, whereas strong ties – are those closer people in one's network. Mardsen and Campbell (1984) measure closeness on a three-point scale: acquaintance, a good friend, a very close friend. Gilbert and Karahalios (2009) measure tie strength subjectively by asking the respondents to indicate how strong is their relationship with the person on a continuous scale from barely know – very close. In line with these studies, we operationalize strong ties as those people users know well, and weak ties as all other people in the network.

Whether strong or weak ties are more advantageous contacts in a network has been a long running debate among the researchers. While at first it was established that strong ties are associated with information value (Coleman 1988), Granovetter (1972) advocated the strength of weak ties argument, which has been applied to multiple contexts. The functionality offered by the earlier generations of CMC, such as e-mail or discussion boards, lead the researchers to argue rather for the value of the weaker ties, as they were only possible to transmit very lean information (Daft et al. 1987) and were characterized by the lack of contextual cues (Miranda and Saunders 2003). Although the first empirical attempts supported the value of weak ties in CMC (Constant et al. 1996), the tests of the theory on new media have shown that given the time and increased frequency of interaction, they could be also used to support much richer communication than was originally assumed (Carlson and Zmud 1999).

Although weak ties provide people with access to information and resources beyond those available in their own network (Burt 1992), strong ties are more motivated to transfer all kinds and types of information (Reagans and McEvily 2003), resulting in a more efficient information exchange (Ghoshal et al. 1994, Hansen 1999). Strong ties might provide users with more valuable information due to: i) the increased frequency of interaction, and ii) the established shared meaning with these ties (Miranda and Saunders 2003). Increased frequency of communication might result in greater diversity and volume of novel information that flows between strong ties overtime compared to weak tie-relationships (Aral and Van Alstyne 2012). The shared meaning established in the long process of communication may help to transfer tacit and context-dependent information (Hansen 2002) as well as easily process information in the conditions of information overload (Carpenter 2003). In fact, on SNS users prefer information from their stronger ties, where tie strength overrides the impact of any other heuristic cues (Koroleva et al. 2011). We therefore hypothesize:

H1: *if users know the source of information well, they are more likely to pay attention to the information from this person on SNS.*

Affection

However, closeness is not the only dimension of tie strength. In fact, the three necessary and sufficient conditions of a relationship between two people are: i) somewhat frequent interaction; ii) usually a mutual affection; iii) a history of interaction that has lasted over an extended period of time (Krackhardt 1992). Strong relationships are the ones that are characterized by a high degree of mutual affection and a certain history of frequent interactions. Ties are considered weak, if they lack either the history of interaction and/or the mutual affection. Interestingly, tie strength is usually rather measured by the recency of contact or frequency of communication, but rarely by its affective dimension (Krackahrdt 1992). However, affection usually determines the relationship: if there was no mutual affection, there would be no need to interact and, therefore develop a relationship. As relationships are not formed instantly, affection for the large part is a catalysator of interaction and relationship development. It determines those weak ties that can become strong in the future, given the sufficient number of exchanges, from those weak ties that will most probably remain weak forever. The peculiar task of the new media is not only to provide ground for the already established relationships, but also to develop newly formed ones (Haythornthwaite 2002). The relaxed norms of communication and instant information updates on SNS are especially valuable as they provide ground for increased interaction especially for this type of ties. Therefore, users might also be interested in information on SNS coming from those with whom they are not yet close, but would like to develop a relationship. We hypothesize:

H2: *if users are interested in getting to know the source of information better, they are more likely to pay attention to the information from this source on SNS.*

Intensity of communication

Measuring tie strength by the frequency of communication has been proposed by Granovetter (1973) and used quite often by researchers ever since (Gilbert and Karahalios 2009, Mardsen and Campbell 1984, Krackhardt 1992). Intensity of communication represents the time dimension of tie strength (Mardsen and Campbell 1984). However, frequency of contact as a determinant of tie strength can be contaminated by the type of tie and thus might overestimate the strength of ties between co-workers and neighbors (Mardsen and Campbell 1984). The physical proximity of these types of people leads to frequent, however usually superficial interactions not characteristic of strong ties. Moreover, as SNS are rather known to possess value for the weak ties due to the low cost of maintenance of such contacts (Elisson et al. 2007), and users might prefer other means to communicate with their strong ties (Vitak et al. 2011), intensity of communication on SNS might not be a good indicator of tie strength. Comparing intensity of communication and similarity of interests as predictors of tie strength, Koroleva and Bolufe-Röhler (2012) find that the latter performs better. However, intensity of communication on SNS can be used as a predictor of tie strength as well (Koroleva and Bolufe-Röhler 2012). In fact, trying to estimate tie strength with the available network data, Gilbert and Karahalios (2009) achieve 80% accuracy in differentiating between strong and weak ties based on the myriad of factors largely related to the intensity and depth of communication on SNS. Therefore, users are also interested in information from those with whom they communicate frequently on SNS. We hypothesize:

H3: if users communicate with a person on Facebook frequently, users are more likely to pay attention to the information from that person on SNS.

Network Overlap

When we explore the impact of network structure on the value of information users derive from their network, we focus not only on tie strength, but also aim to assess the impact of the degree of relative overlap in user's networks. Several researchers were equating tie strength and network overlap, for example by using network overlap as indicator of tie strength (Mardsen and Campbell, 1984). In their attempt to approximate tie strength using available network data, Gilbert and Karahalios (2009) use structural variables, such as the number of mutual friends and groups in common as indicators of tie strength. We, however, recognize that tie strength and network overlap are two different dimensions that are merely correlated and can have very distinct impact on the value users derive from their network.

Network overlap is defined as the number of mutual contacts that the users have on the network relative to the absolute number of their connections. By depicting how interconnected the ties are between each other, network overlap can be used as a measure of network density and directly reflects the cohesion of the network. High network cohesion, as discussed in section "network structure", can be both beneficial and detrimental to social capital. On the one hand, the verifiability of information by others and the threat of sanctions makes trust more likely between people who have many mutual friends (Granovetter 1985) and thus may promote the interest in information coming from such people. On the other hand, high network density directly indicates the redundancy of user's networks, which may have detrimental impact on information value (Aral and Van Alstyne 2012) as this information can also be obtained from someone else in the network. As tie strength is a direct measure of the trustworthiness of a relationship whereas the cohesiveness of a network – an indirect one, we assume that on top of tie strength, network overlap might rather have a negative impact on information value on SNS. We hypothesize:

H4: *the more overlapping the networks of two users are, the less they are likely to pay attention to information from each other on SNS.*

Controls

Feedback

SNS provide certain social contextual cues for users to process information on SNS that were not present in earlier forms of electronic communications. Users not only have the opportunity to rate the information they interact with on the platform (e.g. with 'likes'), but can also register their opinions on the digital content they encounter (in comments). Reflecting the opinions of others in the social environment (Salancik and Pfeffer 1978), this social information might attract user's attention to certain information that is shared. Considering the increasing amount and varied quality of information on SNS (Koroleva et al. 2010), social context cues can make certain information more salient to the user in the general information flow (Salancik and Pfeffer 1978). In fact, feedback from others has proven valuable for ranking, filtering, and retrieving content (Bian et al. 2008). As users will be attracted to certain stimuli to determine which information to focus on, social information can serve as effective heuristic cue that focuses user's attention. Although ratings have been found to have a positive, whereas comments – negative impact on information value when users process information systematically (Koroleva et al. 2011), in the conditions of heuristic processing in our study, we assume that users will not dwell into determining the specific impact of ratings and comments, but be simply attracted by the information that has received some feedback as opposed to the one that has received none. We therefore hypothesize:

H5: *the presence of feedback from others in form of ratings (5a) and comments (5b) will induce users to pay attention to this information on SNS*

Study Design

We want to explore which factors induce users to pay attention to the information on their Newsfeed. For this, we program a Facebook application that allows to simulate the real environment of the user on Facebook by extracting posts directly from their Newsfeed. Users had to log-in to their Facebook accounts and install the application whereby give all the necessary privacy permissions for the application to access and collect their information. Participants were presented with 25 posts, which were randomly selected out of all posts on the user's Newsfeed over the last 72 hours (of all types, from both users and pages). The posts were retrieved from the Facebook database using Facebook query language (structure similar to SQL), which is an API (application programming interface) provided by Facebook (Facebook 2012). In the first stage, the users were asked to scroll down the 25 pieces of information and choose the ones which they would pay attention to (by clicking at the respective box near every post). As users were presented with a lot of information at once, they were induced to process information heuristically (Ajzen and Sexton 1999). In the second stage, as tie strength cannot be measured directly with the data available on the network, users were presented with pictures of the friends whose posts they evaluated in stage 1 and asked to select those who: i) they know well; ii) they would like to get to know better; and iii) the ones with whom they frequently communicate on Facebook, thus reflecting the three measures of tie strength used in the study. In the background, the application collected data about the post, most importantly the number of comments and likes it has received. At the same time the information about the relationship of the user and each poster was collcted: the number of friends and the number of mutual friends between participant and poster.

Methodology

The dependent variable (y) is equal to one if the user would pay attention to the post, otherwise zero. Tie strength is also a binary variable with strong ties operationalized in three ways: i) as those posters that the participant reports knowing well (1) and weak ties as all others (0); ii) those posters the participant wants to get to know better (1) or not (0); and iii) those posters the user communicates frequently on Facebook with (1) or not (0). We then operationalize feedback (ratings and comments) from other users as a dummy variable, which is equal to one if there was at least one 'like' and or comment on the post at the time the application accessed the information on participant's Newsfeed. We choose this approach as opposed to registering the number of disparate feedback, due to: i) too many outliers, especially when one compares the feedback on information posted by pages and users; ii) different presentation of these types of feedback for pages and users; iii) as users were presented with the information all at once, the exact number of likes and comments might not have been as important, compared to the fact that they were solely present (as opposed to a post without any likes and comments). What concerns the measure of network overlap, we calculate the percentage of the mutual friends the participant has with each poster relative to the total number of friends of the participant. We also add a squared version of the term in order to allow for an increasing or diminishing marginal impact of network overlap, as assuming a linear relationship would be too restrictive. Table 2 provides the descriptive statistics of the variables.

In order to operationalize Hypotheses 1 through 5, we make a number of assumptions about the relationship between our observed binary dependent variable, which takes on the value 1 if the participant marked the post as one (s)he would pay attention to and 0 otherwise, and our set of independent variables of interest (see Table 2). We postulate that the information value of a post can be represented by a continuous latent variable y*, which in its turn is a linear function of a set of post characteristics (included in matrix X) and variables depicting the relationship between the poster and participant, in particular the declared tie strength and network overlap variables (included in matrix W). To allow for deviation from our specification an idiosyncratic error term, ε, is included. Formally we then have:

$$y^* = X'\beta + W'\gamma + \varepsilon$$

When y* passes an unobservable – participant i specific – threshold μ_i, the respondent chooses to pay attention to the post in question. In our survey setup this is the equivalent of the participant i marking post j as one that (s)he would pay attention to. In that case our observable binary dependent variable takes on the value $y_{ij}=1$. The relationship between our dependent variable and X and W can be represented as:

$$y_{ij} = \begin{cases} 0 & \text{when } y^*_{ij} < \mu_i \\ 1 & \text{when } \mu_i < y^*_{ij} \end{cases}$$

The participant specific 'attention threshold' μ therefore includes all personal characteristics of the participant which (i) impact this theoretical 'attention threshold' such as and (ii) are constant over the twenty-five evaluated posts. This set includes all participant specific variables such as educational attainment and attitude towards the SNS[1]. While μ itself is unobservable, the twenty-five evaluations collected from each participant allow us to consistently estimate it while estimating the parameters of interest β and γ. This is done by rewriting the relationship between our dependent variable indicating whether the participant i would pay attention to post j (y_{ij}) and the vector of post characteristics (x_{ij}), variables indicating the type of relationship (x_{ij}), participant specific threshold (μ_i) and the idiosyncratic error term (ε_{ij}).

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[1] Note that μ includes such elusive unobservables such as the participant's general mood on the day of the survey for as far this variable impacts all of the evaluations equally.

$$y_{ij}^{**} = y_{ij}^{*} - \mu_i \Rightarrow y_{ij}^{**} = x_{ij}'\beta + w_{ij}'\gamma - \mu_i + \varepsilon_{ij}$$

with

$$y_{ij} = \begin{cases} 0 & \text{when } y_{ij}^{**} < 0 \\ 1 & \text{when } y_{ij}^{**} > 0 \end{cases}$$

If we now assume that ε_{ij} follows a logistic distribution with a (standardized) variance of 1, the above empirical specification can be estimated via a panelized version of a logistical regression, (Wooldridge 2002). The participant specific ‘attention threshold’ (μ_i) can then be estimated via *fixed effects*, which assume independence between the μ and ε, or *random effects*, which assume independence between μ and X and W.

Descriptives

The responses were collected using snowball sampling, that is virally marketed through friends of friends of the authors. In total, 152 people completed the survey. After removing respondents with unbalanced number of posts (less than 25), 3025 observations from 121 respondents were left for analysis. Our sample of 121 respondents consists of ca. 40% male and 60% female respondents, who are on average 25 years old (age range: 19-52). This can be considered quite representative of a lager part of Facebook population (insidefacebook.com). The operationalization of the main variables used in the study together with the means and standard deviations is presented in Table 2.

Table 2. Descriptives

Variable	Mean	Std. Dev
Dependent variable - y		
Pay attention to the information? (1 / 0)	0.203	0.402
Post specific variables - X		
Are there any likes under the post? (1/0)	0.640	0.474
Are there any comments under the post? (1/0)	0.501	0.5
Participant-Poster variables - W		
Tie Strength 1 - Know poster well? (1/0)	0.191	0.401
Tie Strength 2 - Want to get to know poster better? (1/0)	0.083	0.276
Tie Strength 3 - Communicate frequently with the poster on Facebook? (1/0)	0.086	0.281
Network overlap (% pts.)	5.864	9.011

As each user was presented with 25 posts that were directly collected from the user’s Newsfeed and asked to pick the ones (s)he would attend to, we can assess the overall usefulness of information that is provided on SNS. What we observe is that out of all 25 posts, users were on average interested in only ca. 20% of them (stdev: 0.14, range: 0-72%). If we look at the distribution of % of posts that attracted the attention of users presented in Figure 1, we see that most users are interested in not more than 40% of information that is provided on SNS.

What concerns tie strength, we see that most of the people who users list as ‘friends’ on Facebook are rather weak than strong ties: out of all friends whose information was evaluated, users identified 20% as strong ties, 8.3% as those weak ties that they want to get to know better and 8.6% as those they communicate frequently on Facebook with. This is quite realistic considering the immense networks users maintain: on average the people in our sample reported having 298 friends (st.dev: 215; range of 21-1390), which is much higher than the average of 130 reported by Facebook (2011).

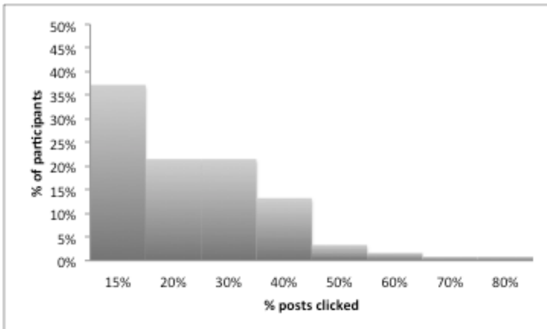

Figure 1. Heuristic Processing

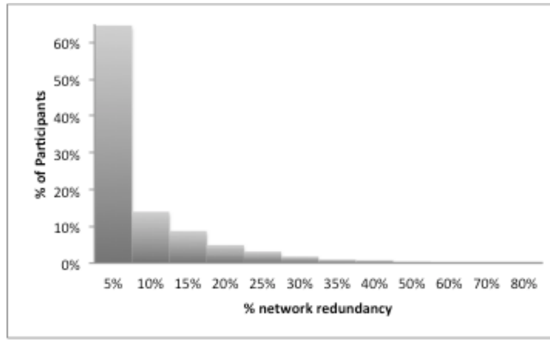

Figure 2. Network Redundancy

What concerns network overlap, users indicated that on average they had 14 friends in common (stdev: 25, range: 0-617). Compared to their absolute size of the network this figure is quite low at ca. 5% of the networks on average. The distribution of network redundancy in Figure 2 shows that for 80% of participants the average network overlap does not comprise more than 10%. However, for some networks the redundancy can also be as high as 73%.

Table 3. Pairwise Tetrachoric Correlations

	tie str. 1	tie str. 2	tie str. 3	network overlap
tie str. 1 (know well) [2]	1			
tie str. 2 (get to know) [2]	-0.274***	1		
tie str. 3 (comm. freq.) [2]	0.517***	-0.048	1	
network overlap[3]	0.202***	-0.015	0.064***	1

Concerning our explored variables, Table 3 gives an overview of correlations between the measures of tie strength and network overlap. We see that the tie strength 1 is significantly related to all the other variables, which implies that any prudent operationalization of this variable ought to include both the other two tie strength measures and the network overlap variable. Specifically, we find that tie strength 1 and 2 are negatively related: users clearly distinguish between those they know well and those they want to know better. Tie strength 1 and 3 however, are strongly related, from which we infer that users communicate more frequently with those they know well than other friends. We also find that network overlap and tie strength 1 are positively related, which indicates that users tend to share more friends with those they know well. Curiously enough, users don't report communicating (significantly) more frequently (tie str. 3) with those that they want to get to know better (tie str. 2) and neither do they share significantly more or – more plausibly – less of their network with these users. Finally, we see a significant, albeit not that strong, correlation between communication intensity (tie str. 3) and network overlap, implying that communication intensity coincides with having more mutual friends.

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[2] - Because our measures of tie strength are dichotomous, we calculate tetrachoric correlations

[3] - Because network overlap is an interval rather than binary variable, we calculate the pointwise biserial correlation coefficients instead of the tetrachoric ones.

However, already the descriptive statistics of network overlap and tie strength variables in Table 4 show that these two measures should be differentiated. Although network overlap exhibits moderate correlations with the main measure of tie strength (tie strength 1) and a low correlation with communication intensity (tie strength 3), these are merely correlations and not one-to-one relationships. However, if we map the information about the relationships between posters and users on the dimensions of weak vs. strong ties[4] and high vs. low network overlap[5], we find that the majority (68%) of the weak ties (80% of all ties) have low network overlap, whereas 13% have high network overlap. More importantly, the larger part (13%) of strong ties (19% of all ties) has low network overlap. Thus, we show that tie strength should not be equated with network overlap and proceed to explore the relationships of these variables with information value in detail.

Table 4. Tie Strength vs. Network Overlap

		Tie Strength		
		weak	strong[4]	
Network overlap	high[5]	457 (12.89%)	217 (6.12%)	674 (19.01%)
	low	2412 (68.04%)	459 (12.95%)	2871 (80.99%)
		2869 (80.93%)	676 (19.07%)	3545 (100%)

Results

The estimation results are presented in Table 5. Looking at estimates of the full model we find that tie strength positively and significantly (at 1% sig.) correlates with attention of users towards the information on SNS. We can thus empirically confirm Hypothesis 1. Furthermore, we see that the desire to develop the relationship also has a positive and equally significant (at 1% sig.), yet lower, impact on in the valuation of information. We thus confirm hypothesis 2. Specifically, people prefer posts either form those they are already close with or want to become close to in the future. Controlling for these two measures of tie strength, the impact of self-reported communication frequency (tie str. 3) has no significant impact on attention towards information. Thus, we reject hypothesis 3. Note that this implies that self reported communication intensity can be considered *redundant* as a measure of tie strength in the presence of self reported closeness (tie str. 1). We find a negative and statistically significant relationship between network overlap and attention of users towards the post, indicating the presence of network redundancy and thereby confirming Hypothesis 4. We also find a small, but statistically significant (at 1%), curvature in this effect. This implies that the strength of this negative redundancy effect is marginally diminishing (i.e. a 'half' U-shaped relationship). The presence of ratings the information has received correlates positively and significantly (at 1% sig.) with user attention, whereas the presence of comments is not significant in attracting user attention. Thus, we can empirically support only the Hypothesis 5a.

As reported in Table 3, we find a statistically significant positive point biserial correlation (0.202, significant at 1%) between close ties (tie str. 1) and network overlap. That is, participants tend to have more network overlap with their close ties. The same however doesn't hold for those users would like to know better (tie str. 2). Due to the positive correlation, and conceptual ease of doing so, it is therefore

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[4] - According to table 2, strong ties constitute 19.07% of all ties, the rest 81% are weak ties.

[5] - In order to estimate the cut-off point for the continuous variable of network overlap, we calculate its 81th percentile which is equal to 11.6%. This means that network overlap > 11.6% of any two users is considered high.

quite natural to conflate tie strength with network overlap. Our results however indicate that when both are included together in a regression framework their effects are measured to be opposite. To further illustrate this point, the specifications have been reestimated first without network overlap (column 2 in Table 5) and then without tie strength (column 3 in Table 5). As tie strength and network overlap are correlated, if we exclude one of them, then a part of one variable will be included into the impact of the other and therefore we will not be able to discern the impact of each of them – known as omitted variable bias. If the effects of these variables differ, this omission might make the coefficients smaller or render them insignificant because it pushes them back to 0. We see that in the first case the estimated coefficient on tie strength 1 goes from 1.028 to 0.919 while the one on tie strength 2 goes from 0.597 to 0.550. Similarly, if our measures of tie strength are excluded, the coefficients on network overlap become smaller in absolute value (from -0.054 to -0.032). Therefore, by excluding either tie strength or network overlap from the regression model, researchers run the risk of the omitted variable bias.

Table 5. Estimation Results of the Random Effects Logit Model

	Full model	Tie strength only	Network overlap only	Tie strength 1	Tie strength 2	Tie strength 3
tie str. 1 (know well)	1.028***	0.919***		0.971***		
	(0.156)	(0.153)		(0.140)		
tie str. 2 (get to know)	0.597***	0.550***			0.381*	
	(0.192)	(0.204)			(0.198)	
tie str. 3 (comm. freq.)	0.028	-0.026				0.371
	(0.226)	(0.223)				(0.227)
network overlap (% pts.)	-0.054***		-0.032*	-0.051**	-0.033*	-0.035*
	(0.019)		(0.019)	(0.020)	(0.017)	(0.018)
network overlap² (% pts.)	0.001*		0.001	0.001*	0.001*	0.001*
	(0.001)		0.000	(0.001)	0.000	0.000
likes (1/0)	0.415***	0.466***	0.352***	0.417***	0.348**	0.349**
	(0.134)	(0.127)	(0.136)	(0.143)	(0.146)	(0.140)
comments (1/0)	0.151	0.161	0.126	0.138	0.134	0.139
	(0.106)	(0.115)	(0.112)	(0.107)	(0.114)	(0.110)
constant	-2.000***	-2.187***	-1.735***	-1.933***	-1.770***	-1.763***
	(0.168)	(0.149)	(0.159)	(0.171)	(0.156)	(0.160)
observations	3025 (121 respondents, 25 post evaluations each)					

Bootstrapped (500 repetition) standard errors in parentheses, based on 121 clusters.

* significant at 10%; ** significant at 5%; *** significant at 1%

The last three columns of Table 5 give an idea of the biases which occur if one focuses only on a single measure of tie strength. Tie strength 1 – knowing the poster well – seems least affected by omitted variable bias and the estimated coefficient barely changes when the other two measures are excluded. However, because users tend to know posters they want to know better (tie str. 2) less well (see negative correlation between tie str. 1 and 2 in Table 3 above), the exclusion of tie strength 1 from the specification leads to a downward bias in the estimated effect of tie strength 2. Finally, we note that only focusing on communication intensity (tie str. 3) as a measure of tie strength inflates this otherwise redundant variable (see the coefficient estimate on tie str. 3 in the first column of Table 5). The upward bias in this case however doesn't lead to statistical significance at any reasonable significance level.

In terms of robustness the specifications have been estimated with robust standard errors derived through bootstrapping with 500 repetitions (Wooldridge, 2002). In addition, to assess the assumptions of independence between the 'attention threshold' μ (the random effect) and the explanatory variables in the random effects specification, we reestimate the full model via Fixed Effects and perform a Hausman test (Hausman 1978). Under the null hypothesis both of these specifications are properly specified and there are no systematic differences between the estimates. The resulting test statistic is Chi-squared distributed with six degrees of freedom and yields a value of 8.55 (p-value 0.286), which leads us not to reject the null hypothesis.

Discussion

In this paper we measure the impact of network structure on the information value users derive from their networks. The first important contribution of our study is that we are able to measure the network structure of users in two ways: objectively by collecting the data about their network sizes and relative network overlap as well as subjectively by eliciting their underlying relationship with the people whose information they are asked to evaluate. Previously researchers had to invest a lot of effort to measure network structure of users, but SNS offer unprecedented environments in this respect. The inability to measure the network structure objectively has lead many researchers to equate tie strength with the redundancy of the network. Although we find that these two measures of network structure are correlated, we confirm that tie strength and network overlap have a diverging impact on the information value users derive from their network.

First of all, we explore the impact of several measures of network structure – underlying tie strength, desire to develop a relationship and intensity of communication on the network – on the attention of users to information on SNS. We show that the underlying closeness of the relationship is the best indicator of tie strength, which is also the main factor that leads users to pay attention to information on SNS: they prefer information from their stronger ties on the network as opposed to their weaker acquaintances. Although this finding is quite intuitive and has been supported in previous studies, we show the persistence of this effect in all of the models we test. As stronger ties comprise only a smaller part of the individuals' networks, we additionally find that users are also interested in information about their weaker ties that they want to get to know better in the future. By providing constant information updates from these people, SNS environments provide good opportunities to develop these relationships.

However, the most widely used and objectively collectable communication intensity as a measure of tie strength did not have any impact on information value. This may be due to the fact that communication intensity on SNS is not necessarily an indicator of tie strength: in fact, users might prefer other channels to communicate with their close friends. Moreover, communication on SNS might be rather arbitrary, largely determined by other factors, such as the activity of the people on the network or the context of communication rather than tie strength. Although this result could also be due to the size of our sample: if two other measures of tie strength are excluded, communication intensity exhibits a high coefficient. Communication intensity on the network could thus also be used as a proxy of tie strength if other measures of tie strength are not available. However, if combined with the underlying closeness of the relationship, this measure of tie strength tends to be redundant.

Second, although tie strength is generally positively associated with the attention of users to information on SNS, network overlap has a negative impact. Specifically, we find the users evaluate the information from those friends with whom they have a lot of mutual friends negatively, compared to those with whom they have less of them. Presumably, the more mutual friends users have, the more redundant information they provide and therefore the less they are prone to pay attention to this information. Thus, our findings explain why people might be more interested in information from someone with whom they share less mutual friends, but a strong relationship (for example, a lover) as opposed to someone with whom they have more mutual friends, such as close friend. This is quite an interesting result, as on average mutual friends do not comprise a large part of the user's network (according to Figure 2, for 60% of the users these are on average just 5%). Moreover, the information about mutual friends is not directly available when users are evaluating information, but only if participants go directly to the profile of a user. That means that this effect is quite implicit, reflecting the subjective perception of the redundancy of the network that leads users to choose information from those less cohesive ties. We also found that the strength of the negative relationship between network overlap and information value diminishes as network overlap increases. In its turn this implies that past a certain network density, the marginal decrease in information value is negligible.

By distinguishing between network overlap and tie strength we are able to resolve the conflicting findings about the value of weak and strong ties as well as cohesive networks vs. those rich in structural holes on information value, which has persisted since Granovetter (1973). Our study reveals that the benefits depend on the level of network analysis and confirms that both network structures can provide informational benefits to SNS users, only the sources of these benefits differ. Although tie strength is a more important determinant of information value than network overlap, on top of tie strength network overlap has a negative effect on the attention of users towards information. That is, considering two ties with similar tie strength, SNS users will be more interested in those users with whom they have less mutual friends. Thus we empirically confirm the theory of network redundancy proposed by Burt (1992). At the same time, considering two users with a similar number of mutual friends, users will be more interested in those with whom they have a stronger relationship. Thus we at the same time confirm the theory of Coleman (1988). Taken together, our results suggest that the most beneficial people in the network are those who balance between the least possible number of friends and the strongest possible tie strength. However, it is hard to have many such people in the network, as these two measures are correlated: with increasing tie strength, the number of mutual friends increases as well.

Third, we also find support for the impact of social information on information value on SNS. The presence of ratings from other users tends to attract the attention of users and induce them to choose information which has received more feedback from other members of their networks. This is in line with the previous findings about the impact of ratings on information value (Koroleva et al. 2011). Interestingly, we do not find any significant association between the presence of comments and attention of users towards the information that is presented to them. This can be explained by the dual impact of comments on user attention: on the one hand, they might attract the attention of the user to the information that is shared, although on the other hand might create information overload.

Our findings also several valuable implications for network providers. The fact that tie strength and network overlap have a diverging impact on user evaluations has to be considered when filtering information. The number of mutual friends is recorded by the platform and as our study shows could serve as a cue to provide users with information they desire. However, this should be done with care, as the underlying relationship is a better determinant of information value than network overlap. Although network providers can not unambiguously determine the underlying tie strength between the users, they can use the information available on the network to proxy it. For example, our study shows that communication intensity can be used as one such measure. However, network providers could consider enhancing this measure with other indicators, such as similarity of interests or depth of communication, as communicatino intensity on the network alone is not enough to predict tie strength.

Conclusion

In our study we show the importance of empirically distinguishing between network overlap and tie strength when assessing how users value information on SNS. The positive correlation between these two dimensions – one is indeed more likely to have more mutual friends with the people that one knows well – and their opposing impact on information value shows that the failure to differentiate between these two measures empirically might lead to biased results. We conclude that any empirical investigation into the value of information on SNS needs to ensure that these two dimensions are addressed independently. Moreover, we show that the underlying closeness of the relationship is the best indicator of tie strength, surpassing the usually employed intensity of communication.

In our study most of the employed variables were binary which automatically limits the conclusions one can draw on the basis of the results. In terms of operationalization future research should therefore aim to nuance and expand the measurement of both the dependent variable as well as various measures of tie strength. Moreover, tie strength is measured by the subjective evaluations of users which may not necessarily correspond with their real behaviors. Although the underlying tie strength is not reported by the platform, one could consider verifying the findings of this study by approximating tie strength using the myriad of objective data on user interactions available on SNS. These approximations, however, would not be as good as the measure of the underlying tie strength.

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