Accumulating social capital in a location-bounded network: The effects of user behaviors

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Abstract

The use of social network sites (SNS) helps people to make and maintain social ties, and thus to accumulate social capital which is increasingly important for individual success. There is a huge variation in the amount and structure of online ties, and to some extent this variation is contingent on specific online user behaviors which are to date under-researched. In this work, we examine an entire city-bounded friendship graph (N = 194,601) extracted from VK SNS to explore how specific SNS user behaviors are related to structural social capital in a network of geographically proximate ties. We find out that the number of online groups which a user belongs to is positively related to the user's brokerage, while certain types of incoming and outgoing communication and other features are also found to play a role.

Keywords: social capital; social network sites; friendship network; online user behavior; online communities; VKontakte

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Highlights

- Location-bounded online network represents a mixture of small-world and scale-free graph models
- Longer SNS use gives an advantage in making additional friendship ties
- Membership in more SNS groups increases user's brokerage capacity in the location-bounded friendship network
- The number of likes on a user’s wall is positively associated with network brokerage
- The share of local contacts among user’s SNS friends increases brokerage in the location-bounded network

Introduction

Social network sites (SNSs) are playing an increasingly important role in interpersonal relationship building, maintenance and outcomes. One of such outcomes is social capital, broadly understood as access to and use of social ties to achieve specific goals. Knowledge of factors influencing social capital can contribute to our understanding of individual differences in it, which, in turn, is important for interpreting and predicting such phenomena as successfulness of individual integration and societal cohesion. In particular, variation in online social capital, as a fraction of social capital that is gained and / or maintained online, is to some extent contingent on specific online user behaviors that still need rigorous research.

Early research on effects of SNS use on online social capital demonstrated that the overall use of SNSs, and particularly Facebook, is associated with the gain and maintenance of different types of ties and of social capital (Quan-Haase & Wellman, 2002; Ellison et al., 2007). More recent research (Burke et al., 2011; Johnston et al., 2013; Ellison et al., 2014a, 2014b; Brooks et al., 2014; Su and Chan, 2017; Ellison & Vitak, 2015) has employed more fine-grained metrics and identified specific user practices such as sharing identity information or commenting on a friend’s wall, that have different effects on social capital. However, there are still many gaps in the knowledge on mechanisms connecting SNS user practices and social capital.

First, most online studies have been bound to ego-network research (Brooks et al., 2011; 2014; Arnaboldi et al., 2012; McAuley & Leskovec, 2012; Bohn et al., 2014; Shen et al., 2014; Centellegher et al., 2017), although measures of social capital derived from an entire network have been considered richer and more informative (Borgatti et al., 1998). Moreover, according to multiple classic (Warner, 1963; Craven & Wellman, 1973) and more recent (Hampton & Wellman, 2003; Lin, 2004; Ellison et al., 2007, Hampton, 2007) studies, networking and social capital formation to a large extent take place in a broader context of some geographically concentrated population – a neighborhood, a village or a city. This is true not only for offline social capital formation (Wellman & Wortley, 1990), but for the online ties accumulation as well (Scellato et al., 2010; Kaltenbrunner et al., 2012), because much of the actual transfer of aid and resources is still possible only offline. In short, social capital is accumulated not only in an immediate environment of an individual, such as an ego-network, but in a much broader macro-structure involving many indirect ties (Lin, 2004), and this phenomenon calls for research.

Second, the existing research has mostly employed self-reported data on online social capital, which has its strengths, but also limitations. Some of the latter are subjectivity and poor scalability. Third, some obvious potential determinants of social capital have been omitted or under-researched, and the most notable of them is membership in online groups. Although access to diverse audiences provided by such membership should theoretically be related to tie accumulation (Blanchard & Hora, 2000; Lee & Lee, 2010), in practice this relation has not been tested.

This study aims to overcome the listed above limitations. Our goal is to figure out what types of SNS user behaviors contribute most to the increase of users' social capital in a location-bounded online network. In particular, we seek to find out how access to multiple online groups influences users' social capital within such network - a network that constitutes an online fraction of a city-level offline web of human ties.

For this goal, we examine a graph of SNS friendship that presents a collective digital trace of an entire geographically bounded population from a middle-sized city. We find out that such graph is both clustered and highly centralized which suggests the presence of an hierarchical structure: a set of sub-communities united by city-level hubs. Against this background, we find out that multiple group membership – even if they are not city-specific – is positively related to global brokerage and eigenvector centrality, and so is the share of local friends and a number of other factors. We thus contribute to the knowledge on formation of online social capital which has been for the first time studied at the level of a large and geographically bounded population.

To make these conclusions, we use the data from VK (VKontakte, http://vk.com) – the largest Russian-speaking social network site. We collect rich observational data consisting of 194,601 user accounts and 9,800,107 friendship ties from a typical middle-size Russian city of Vologda. While ethical considerations of such data collection are discussed further below, most of the data we use is publicly available either in full or in large part.

The rest of the paper is structured as follows. In Section 2 we outline the network vision of social capital. We review the relevant works on the relationship between online user behaviors and online social capital formation and formulate our argument and hypotheses. In Section 3 we describe the dataset, report the procedure of data collection, and examine structural properties of the entire SNS-based friendship network of users residing in Vologda. Section 4 introduces the empirical models predicting structural social capital in Vologda friendship network, and the discussion of the results is presented in Section 5.

Social capital and online social networks

A Network Conceptualization of Social Capital

Definitions of social capital are so diverse that it may be viewed as a family of different concepts rather than a single one. As our goal is to explain what influences individual network positions that may be used to a person's advantage, we focus on a network conceptualization of social capital. In addition to its relevance, this conception provides well established models and operationalizations of social capital suitable for the study of large populations represented through digital traces. The two most acknowledged network conceptualizations of social capital were elaborated by Lin (2004) and Burt (1995). Although both authors consider social capital an independent predictor of better social outcomes, their operationalizations of social capital can be used to examine factors influencing the very network positions of individuals. Both scholars underline the importance of structure and composition of social ties for gaining benefits, but explain the source of the individual network advantage in slightly different ways, and hence, suggest different measures of social capital.

Lin defines social capital as "the resources embedded in social networks accessed and used by actors for actions" (Lin, 2004, p.24-25). According to Lin, social capital is determined by (1) resources possessed by actor's contacts and embedded in their relationships, and (2) the network structure of actor's social relationships (Lin, 2004). Social capital could be measured either as capacity (resources accessed through network positions) or as actual uses for particular actions (mobilized resources) (Lin, 2008, p.64).

Lin connects social capital to valued social resources (such as wealth, power, and reputation) that are hierarchically distributed across population (Lin, 2004, p.75). Social network structure of a population is thus related to stratification structure of socioeconomic statuses (SES) in this population. Acknowledging the homophily principle, Lin assumes that most social ties should be within homogeneous groups, or clusters of people possessing similar resources and socioeconomic statuses. Following this logic, we can assume that the very number of connections might be one of such resources as they can indicate influential, popular and / or well-connected persons. This means that individual social capital should be determined rather by the entire network macro-structure and by the individual's position within it than by network micro-structure of direct ties in an individual's immediate environment. These two visions of social capital produce global and local metrics, correspondingly. Global measurement of social capital is often performed with *eigenvector centrality* (Bonacich, 1972) and its variations. As it can measure whether a person is well-connected to influential or other high status people, it can be termed here status social capital.

Lin proposes to assess social capital through measures of higher reachability, heterogeneity and extensity. Higher reachability accounts for resources of actor's contact with the highest SES; heterogeneity refers to the range of resources between contacts with the highest and the lowest SES; and extensity means diversity of resources or the number of accessible social groups via one's contacts (Lin, 2004, p. 62-63). Although network features – particularly used in this research – are not identical to the mentioned resources, and social capital cannot be simply reduced to network positions, networks provide access to embedded resources, and variations in network features, such as access to bridges and strength of ties, "may increase or decrease the likelihood of having a certain quantity or quality of resources embedded" (Lin, 2008, p.58). This argument finds some empirical support in literature discussed further below in relation to Burt's concepts.

Burt is known for his structural understanding of social capital which is defined by him as "the advantage created by a person's location in a structure of relationships" (Burt, 2005, p.4). Unlike Lin, who views social capital as both accessed and mobilized resources, Burt argues that individual advantage is created by the way people are connected and could be derived purely from the structure of one's social ties. Hence social capital is a structural asset per se.

Burt identifies two network structures as sources of social capital: *network closure* and *brokerage*. Closure is a network structure of bounded and tightly connected group of individuals. Networks with high closure facilitate better cooperation, resource mobilization, trust and reputation building, because, among people sharing many friends, these forms of behavior are stimulated by threat of sanctions. Brokerage is a network position that allows its holder to bridge otherwise segregated and heterogeneous groups. Brokerage capacity – the amount of non-redundant contacts accessed and bridged by an actor – depends on the number of *structural holes* around an individual which are gaps between disconnected parts of a broader network (Burt, 1995). Brokerage capacity reflects the diversity of accessible social contexts, opinions, activities and resources. Explaining the relation between brokerage and closure, Burt (2005, p.225) argues that, although there is a trade-off between them, their roles for maximizing actor's advantage are complementary: the maximum of this advantage occurs when an actor simultaneously belongs to a cohesive group and has bridging ties beyond the group.

There are two well established operationalizations of brokerage in terms of network models – *betweenness centrality* (Freeman, 1977) and *constraint index* (Burt, 1995); and one operationalization of closure – *transitivity* or local clustering coefficient (Watts & Strogatz, 1998). While closure is inherently local, for measuring brokerage, Freeman's betweenness centrality is preferable to constraint index, as it goes beyond individual ego-networks and accounts for the full set and structure of indirect ties. This fits better the object of our study – an entire location-bounded social network. At the same time, as Everett and Borgatti (2005) showed very strong correlation between ego-network betweenness and global betweenness centrality, and Burt (2018) showed strong correlation between constraint index and betweenness centrality (r = -0.92), there is no need for multiple measures in one research.

Summarizing Lin's and Burt's conceptualizations of social capital, we can conclude that Burt highlights group cohesiveness and the brokerage of structural holes between cohesive groups as a main source of social capital, while Lin emphasizes the access to resources of high SES contacts. Although brokerage and social resources explanations for network advantage are conceptually different, Lin's measures of extensity and heterogeneity are related to Burt's measures of access to structural holes (Burt, 2018). There is some evidence demonstrating the strong correlation between brokerage (network constraint and betweenness centrality) and social resources metrics (Burt, 2018). Campbell et al (1986) found that people with higher SES have larger, looser and more heterogeneous networks, i.e. have access to more diverse contacts. A more recent study of Facebook networks has indicated that users with higher SES have larger friendship ego-networks with higher average degrees (Brooks et al., 2011). This evidence allows, albeit with certain reservations, to consider structural network features acceptable approximations of social capital when information about SES of contacts and possessed resources is unavailable.

To examine brokerage, closure and status social capital, we choose to focus on a large and heterogeneous population bounded within a city. This choice has a number of important reasons. On the one hand, it allows us to account for the important effect of indirect ties – knowledge of someone who knows the "right" person (Craven & Wellman, 1973) in a broader context of the entire population. The importance of such ties as providers of practical aid was shown as early as in the study by Lee (1969) on search of abortionists. On the other hand, the city-level approach allows us to limit all online ties, which are of low cost to establish and, therefore, sometimes meaningless, by geographically proximate relationships that are more likely to provide access to tangible and location-related resources and aid (Craven & Wellman, 1973; Hampton, 2007) such as finding jobs (Granovetter, 1973), available housing rentals, medical services (Lee, 1969) or childcare opportunities (Wellman & Wortley, 1990). It is not by chance that online friendship and interaction, despite the potentially global character of SNSs, also tend to be geographically proximate (Scellato et al., 2010; Kaltenbrunner et al., 2012). Of course, the extent to which data derived from SNSs, telecommunications companies and from other digital traces represent human social networks as a whole, is still a matter of investigation (González-Bailón et al., 2014; Tufekci, 2014; Mislove et al., 2007). However, as SNSs are now an integral part of everyday life, social capital accumulated through them deserves research per se, even if it happens to be distinct from its offline counterpart. Here it is termed online social capital and it denotes a fraction of social capital gained and/or maintained online. Finally, social capital measured with observational network data here is termed structural, as opposed to perceived social capital, usually derived from self-reported data.

Online User Behaviors and Social Capital

Many studies have shown that intensity of Facebook use, which includes amount of time and the perceived role of Facebook in a person's life, was positively associated with social capital (Ellison et al., 2007; Johnston et al., 2013; Ahmad et al., 2016). Although it does not increase the size of personal social networks beyond a certain threshold – the Dunbar’s number (Gonçalves et al., 2011; Dunbar et al., 2015; Arnaboldi et al., 2015), there are still salient differences in the number and composition of online social ties among users, and to some extent these differences depend on specific online user behaviors.

The two most common approaches to measurement of user behavior are to measure the use of specific SNS features regardless of user's motivation (private messaging, liking, tagging, etc.) (Lee et al., 2014) and to measure meaningful intentions and practices regardless of the features employed to exercise them (information sharing, maintaining relationships) (Smock et al., 2011). Although the majority of works on social capital and SNS use are based on self-reported data and measures of perceived bridging and bonding social capital (Williams, 2006), most of them explicitly highlight mechanisms connecting user behavior to social capital which could be adapted for the network approach. Bridging and bonding social capitals as perceived resources/outcomes available from distant or close social relations are similar to network concepts of brokerage and closure (Shen et al., 2014; Sajuria et al., 2015), respectively (although the latter are more precisely defined and, therefore, easier operationalized which is why they are preferred in this research). Below we review the most relevant findings on mechanisms connecting online user behavior to social capital related to both measurement approaches.

Social information seeking has been defined as browsing profiles of those individuals with whom the user has an offline contact in order to learn more about them (Ellison et al., 2011). This practice enables conversion of latent ties into socially activated relationships (Haythornthwaite, 2005, p. 137), and it demonstrates a positive and strong effect on social capital. Since friendship ties are mutual, it is plausible that disclosure and availability of such social information should be able to increase social capital not only of the information seeker, but also of the information holder. Among many types of social information, identity information (such as hometown, place of education, key biography events or user interests) is the one that may provide missing social context cues and facilitate establishing common ground and further tie formation between the parties, thus serving as social lubricant. For instance, Lampe et al (2007) found out that filling profile fields on Facebook was positively associated with the number of Facebook friends. In terms of social capital metrics, identity information may facilitate both network closure and brokerage - through connecting to tightly connected groups (e.g. classmates) or separated non-redundant contacts (e.g. people with rare interests); this may contribute to status social capital through the overall growth of ties. This lets us to formulate our first hypothesis:

H1: The amount of publicly available identity information in a user's profile is positively related to his/her structural social capital (all measures).

Research on the use of *specific communication features* has shown mixed results. For instance, Burke et al (2011) investigated the effects of three distinct types of SNS use: *directed communication* which consists of personal, one-on-one exchanges (messages, likes etc.), *broadcasting* (information sharing with a broad audience) and *passive consumption* of social news. The authors found that only the amount of *incoming directed communication* acts had an impact on bridging social capital. Lee et al (2014) showed that bonding capital was higher among those who used *Like feature* more frequently and *Comment feature* less frequently, while bridging capital was associated with *posting on a friend's wall*. However, Su and Chan (2017) have demonstrated that *commenting*, along with *liking* and *sharing* were positively related to both bonding and bridging social capitals. Bohn et al (2014) argued that actual online interactions are a more reliable and accurate indicator of a social relationship than friendship ties. They found that the number of communication partners was positively associated with both network brokerage and closure in the interaction network, but the number of personalized outgoing communication ties had a positive effect only on brokerage. Apart from this, *Facebook relationship maintenance behavior* (FRMB), defined as a form of social grooming – an attention-signaling activity and engagement with a user's friend network through direct communication (such as likes, comments or posts on a friend's wall), was found to be positively and strongly related to both bridging and bonding social capital (Ellison et al., 2014a; 2014b;

Brooks et al., 2014; Weiqin et al., 2016). On the whole, outgoing communication seems to have received more attention than incoming communication. We assume that, as friendship is a mutual relationship, the incoming direct communication should be also related to structural social capital, and that, more broadly, engagement of others in communication on a user's wall might affect the user's network brokerage. At the same time, the larger the engagement of others in communication on a user's wall, the higher is the likelihood of new friendships among user's friends and, thus, of formation of closed triads in the user's network which contributes to the user's network closure. The potential effect on status social capital remains unclear.

H2: The engagement of others in communication on a user's wall is positively related to a user's brokerage capacity and network closure.

Although online group membership, as an SNS feature, should theoretically be important for social capital (Blanchard & Hora, 2000; Durlauf, 2008) it has been receiving a modest attention of researchers. Some studies suggest that participation in online groups should somehow facilitate networking behavior, because they allow users to "find common ground in their beliefs and interests" (Lee & Lee, 2010, p.712) and provides "opportunities to interact with people who share similar interests" (Lee et al., 2014, p.445). According to Horrigan (2001) the most popular online groups are professional groups, groups for people who share a hobby, interest or a lifestyle, fan groups of sports teams or TV shows, local community groups and health-related support groups (Horrigan, 2001, p.4). Hence, most online groups are some sort of interactive information media used primarily for satisfying specific cultural interests or practical needs of participants. However, the existing modest empirical research yields mixed results. Lee et al (2014) have established that self-reported *frequency of group feature use* was unrelated to social capital. Norris (2002), having used Pew Internet & American Life project survey data, found that reported membership in some *types of SNS groups* contributed to bridging and bonding social capital more than in others, although all contributions were modest. Kobayashi et al (2010) found out that gaming online group heterogeneity enhances tolerance and thus should affect bridging social capital, but the latter hypothesis was not tested in the study. Finally, Lee and Lee (2010) showed that the use of online groups is associated with perceived outcomes of social capital. Thus, the impact of online group membership on structural social capital stays under-researched. Given this, we assume that extensiveness of group membership should positively affect network brokerage, because it can provide access to more non-redundant contacts.

H3: The number of online groups a user belongs to is positively related to a user's brokerage capacity.

Finally, as we study social network of a geographically bounded population and leave the rest geographically distant ties beyond our focus, there is need to test how user's adherence to and boundedness by a local network might affect his/her within-city social capital. Dominance of local ties among a user's SNS friends means higher commitment to a given city community. Therefore, we expect that along with the absolute number of friends in the city, the share of local friends among all user's friends should affect his/her structural social capital.

H4: Share of local friends among all user's friends is positively related to structural social capital (all measures).

Summarizing the review and our hypotheses, we can conclude that the existing research is based on very different populations, methods and metrics, which is why, although quickly growing, it is still fragmentary and does not produce a coherent picture. Most of the studied user practices and types of social capital have been measured through surveys and represent self-reported data. Observational data have only been collected in the form of user ego-networks. The available research suggests that there are three main types of online user behavior based on main SNS functions that can contribute to accumulation of social capital: sharing identity information in a user profile, communicating via features available on individual pages and participating in online groups. Building upon these findings, in this research we seek to test how the use of these SNS features is related to structural (as opposed to perceived) social capital gain in a location-bounded network. To the best of our knowledge, there have been no studies investigating effects of SNS use on structural social capital at the level of an entire network representing a large human settlement as a whole.

Data and Methods

In this study, we examine structural social capital using observational data from an SNS. The object of this study is the users of the largest Russian SNS VK (About VK, 2017) from a Russian city of Vologda. It was selected because this is a typical middle-sized Russian city (population 313,012) with the average standard of living (38 out of 85 Russian regions by GRP) (Russian Federation federal state statistics service, 2017) and the average level of Internet penetration (Fund Public Opinion, 2018). In our choice we also avoided cities with specific ethnic composition, as well as cities close to the Russian borders, Moscow and St.Peterburg because they tend to have specific migration patterns. While this does not liberate our research from the limitations of case study approach, the results obtained from an average city may be expected to be more easily generalized to a larger number of Russian cities than the results from an outlier, although more research is needed to find out what Vologda patterns are universal, and what are unique. To date, the only other available study of VK network of another Russian city of Izhevsk reveals similar network structure (Kaveeva and Gurin, 2018).

Dataset: Vologda Friendship Network and Online User Behavior

VK provides functionality similar to Facebook. The data was collected automatically using application programming interface (API).The dataset includes all within-city friend links and information from users' profiles, such as counts of communication activity from their pages and metadata (gender, age, interests, education, etc). A separate subset is the data on features of VK groups to which users belong. Our data collection procedure was informed with the recent debates on big data ethics (Metcalf & Crawford, 2016; Zwitter, 2014; Moreno et al., 2013) that acknowledges the contradiction between the inapplicability of traditional ethical norms, such as informed consent, to data-driven research, on the one hand, and the need to protect human subjects from potential harm, on the other. In our research we, first, anonymized the data after the download. Second, we used only open access data legally available from VK server - that is the data that either cannot be hidden, according to VK terms, or the data a user chooses not to protect with privacy settings. According to our research of VK random samples, city of residence is usually available for two thirds of non-dormant accounts, while friend lists could not be hidden at the time of data collection. This makes our data quite complete. Most other data we used was fully available, or variables were constructed so that no missing data were possible. A more detailed information on data completeness is given in table 2.

Our initial population was 286,994 users who declared Vologda as their city of residence as of the date of data collection (04.09.2017). After filtering out banned users and those whose last visit to the VK was earlier than 01.06.2016, we constructed the graph of reciprocal friendship ties that included 196,684 users connected by 9,800,107 edges (graph metrics are shown in Table 1). After additional filtering, the final sample comprised 194,601 users; it was used for regression analysis. Overall, Vologda VK network has structural characteristics similar to other online social networks (Arnaboldi et al., 2015) and some random graph models. Particularly, it is similar to Watts-Strogatz small-world network model in terms of transitivity and modularity computed with Louvain community detection algorithm. At the same time our network is similar to Barabasi-Albert scale-free model in terms of degree centralization. Thus, we can say that this network consists of internally dense clusters and star-type nodes with a very high centrality, which is in line with the vision of city as a network of networks (Craven & Wellman, 1973; Pflieger & Rozenblat, 2010). As mentioned above, Vologda VK network structurally is also similar to another VK friendship network bounded within the city of Izhevsk (Kaveeva & Gurin, 2018), in particular by transitivity, assortativity by degree and modularity.

Tab.1.Graph metrics for Vologda friendship network and random graph models

Metrics	VK graphs		Random graph models		
	Vologda (giant component)	**Izhevsk**	**Erdos-Renyi**	**Scale-free**	**Small World (p=0.3)**
Nodes	196,630	477,057	196,630	196,630	196,630
Edges	9,800,077	17,742,662	9,800,077	9,830,225	9,831,500
Density	0.000507	0.000155	0.000507	0.000508	0.000508
Average degree	99.680		99.680	100	99.987
Connected components	1		1	1	1
Diameter	9		4	4	4
Average geodesic distance	3.15546	3.590	2.957603	2.889812	2.998528
Transitivity (global clustering coefficient)	0.080921	0.090	0.000508	0.003621	0.087468
Average clustering coefficient (Watts-Strogatz)	0.130105		0.000508	0.003529	0.088209
Average aggregate constraint	0.065472		0.010144	0.013402	0.011962
Centralization degree	0.033852		0.000245	0.022046	0.000168
Centralization betweenness	0.011070		0.000012	0.006248	0.000009
Assortativity by degree	0.140230	0.162	0.000289	0.003023	0.000017
Modularity	0.362820	0.377	0.070148	0.084263	0.361638
Clusters	21		8	9	4

Measures

The list of measures is given in Table 2.

Social capital. As mentioned above, in this study we follow network conceptualization of social capital. SNS friendship is a relation based on mutual recognition that makes friend's updates and posts visible in a user's newsfeed (Ellison & boyd, 2013). The latter is important for receiving social news, maintaining relationships and for responding to help requests (Ellison et al., 2011; 2014b). In this research we use both local metrics based on immediate user ties and global metrics based on ties going beyond users' ego-networks. For closure, which by its nature can only be local, we use transitivity (local clustering coefficient) (Watts & Strogatz, 1998) calculated as the share of closed triads among all the triads in an ego-network. It reflects the embeddedness of an individual in a tightly connected group. For brokerage we use betweenness centrality (Freeman, 1977), a global metric calculating the number of the shortest paths passing through a node. It estimates an individual's ability to bridge disconnected and distant nodes or clusters at the scale of an entire network. Finally, we use eigenvector centrality (Bonacich, 1972) accounting for degree of connected nodes as a global metric capturing Lin's idea about actor's social capital dependence on status, resources or, in our case, social ties of related others.

Communication activity. It has been measured by a number of simple metrics, such as the absolute number of posts, likes, comments and reposts on a user's wall, and by some relative metrics, such as the share of posts of others on a user's wall, to account for the engagement of others. Reposts were excluded from the final analysis due to multicollinearity. Also, an aggregate index of activity dropped out from the final models because it obviously had a smaller explanatory power than the variables that it had been constructed of.

Availability of identity information. This category included all fields from the users' profiles that were reasonably well populated. As we were interested in the amount of publicly available identity information, not in its content, we used simple counts for such variables as Photos, as well as the additive index of Interests and Beliefs. If the data were not shared publicly by a user, they were coded as zero.

Extensiveness of online group membership has been measured with only one variable – the number of online groups to which a user belongs.

Network metrics were computed using igraph R package. The natural log transformation was performed for all dependent variables and for a number of independent variables to correct for the skewedness in the data. OLS regression was chosen, despite its limitations for clustered data, as inference for network predictions stays one of the unresolved problems in the field (Li et al., 2018).

Tab.2. Study Variables

Variable	Description
	Dependent Variables*
Transitivity (local clustering coefficient)	Ratio of all existing ties between alters in an ego-network to all possible ties between alters in this ego-network. Varies between 0 and 1, where 1 is the clique – fully connected ego-network (Watts & Strogatz, 1998). Indicator of network closure.
Betweenness centrality	Number of shortest paths going through the vertex (Freeman, 1977). Indicator of brokerage capacity.
Eigenvector centrality	Relative score of a node's centrality that depends on centralities of the node's neighbors (Bonacich, 1972). Indicator of status social capital.
	Independent Variables
Controlling variables	
Age	User age indicated in the profile (100% available with the used API)
Gender	User gender indicated in the profile (100% available with the used API)
Occupation type	Availability of the main occupational activity (school, university, work, none)
Duration	Number of days since the date of a user's registration in VK (100% available with the used API)
Share of local friends	Share of user's fiends residing in Vologda among all user's friends in VK (available for all users in the sample based on approx. two thirds of their friends)

Communication activity**

Activity index	Sum of all posts, comments and likes on a user's wall
Posts	Total number of posts on a user's wall
Likes	Total number of likes to posts on a user's wall
Comments	Total number of comments to posts on a user's wall
Reposts	Total number of reposts of posts from a user's wall
Share of others' posts	Share of posts written by other users on a user's wall among all posts on the wall
Availability of identity information	
Photos	Total number of photos publicly shared on a user's page
Audios	Total number of audio records publicly shared on a user's page
Interests & beliefs	Number of fields filled in a user's profile and available publicly; they reflect interests, beliefs and values: «Attitude to alcohol», «Attitude to smoking», «Religion/World view», «Personal priority/the main thing in a life», «Important in others», «Political views», «Inspired by», «Activity», «About me», «Interests», «Favorite music», «Favorite movies», «Favorite TV shows», «Favorite games», «Favorite books», «Favorite quotes». Varies between 0 and 16.
School	Public availability of information about user's school on the page (0 or 1)
University	Public availability of information about a user's university on the page (0 or 1)
Relatives	Public availability of links to pages indicated as relatives on a user's page (0 or 1)
Access to multiple groups**	
Online groups	Number of online groups in VK in which a user is a member

*VK allowed for no more than five hidden friends who usually could be retrieved from the pages of their counterparts. Completeness of this data is close to 100%.

** These data are incomplete which is why three strategies of dealing with the missing data were applied (including modeling only those observations for which full data was available). As all models produced very similar results, we report the most complete models where missing observations were coded as zeros, and all observations were kept in the model.

Data on VK groups

As one of our major goals was to explain the influence of online group membership on social capital, we collected available data on their features. VK terms its non-individual accounts *online groups* and offers two major types of them, similar to those of Facebook: public *pages* whose content cannot be hidden, and *online communities* of whom only 10% in fact do restrict access to their content for non-members[c]. 80% of groups (both pages and communities) allow some user activity on their walls, but while 34% of communities permit unlimited activity, while pages never do this. For each user in the sample, we retrieved the lists of both types of groups that happened to be open for about 87% of users. For each group we collected its title, size,

[c] VK officially uses different terms, but we adopt our terms so as to avoid confusion.

location, metrics of openness, activity restrictions, and some others. Some of the fields were incomplete; however, this data was analyzed only descriptively.

Results

Table 3 presents the final OLS linear regression models predicting betweenness centrality, transitivity and eigenvector centrality in the social network of Vologda. The higher the betweenness centrality, the more structural holes and bridging ties are around a user, which may be used to gain brokerage benefits. The higher the transitivity, the more likely the formation of closed triangles among user's neighbors and the higher the density of connections among them. The higher the eigenvector centrality, the higher the aggregate centrality of user’s friends. Brokerage regression model (betweenness centrality) demonstrates quite high predictive power and explains 49% of variance (adjusted $R^2 = 0.487$). The model for network closure (transitivity) demonstrates moderate predictive power and explains 33% of the variance (adjusted $R^2 = 0.326$). Finally, the model for status social capital (eigenvector centrality) explains 40% of the variance (adjusted $R^2 = 0.407$). Overall, regression models demonstrate predictive power comparable to or a little higher that obtained in the existing research (Brooks et al., 2011; 2014; Ellison et al., 2011; Bohn et al., 2014; Lee et al., 2014).

Two other general notes should be made. First, nearly all effects are significant, but we should keep in mind that with our sample size much more attention should be paid to the effect size than to its significance. Most variables have small regression coefficients and tend to randomly flip their signs when model parameters are slightly changed. It means that these predictors have no stable relation to the dependent variables. However, six variables highlighted in Italic have demonstrated the strong and stable pattern of association across all models; models based on only those six variables explain 92-95% of the variance explained by the full models.

Second, closure has consistently demonstrated the inverse direction of association with most predictors, as compared to two other types of social capital. All three dependent variables turned to be highly correlated, especially when logarithmized, with transitivity being negatively related to the other two. This indicates the existence of trade-off between closure and brokerage acknowledged by Burt (2005), however, it contradicts his argument about the complementary character of those two that should be possible in parallel with this trade-off. The most plausible explanation of this effect is as follows. High closure values are only possible in small networks which is confirmed by the strong negative correlation between closure and degree (number of friends). Once a user starts growing his/her network and especially accumulating bridging ties, the overall transitivity decreases.

As models predicting all three types of social capital are similar, the results are reviewed according to independent variables further below.

Tab.3. OLS regression predicting structural social capital of friendship network within local urban community

	Brokerage Betweenness centrality	Closure Transitivity	Status social capital Eigenvector centrality
Controlling variables			
Gender (male)	0.029*** (0.008)	0.064*** (0.003)	-0.068*** (0.008)
Age	-0.088*** (0.0004)	-0.021*** (0.0001)	-0.003*** (0.0004)
Occupation:school	0.004 (0.020)	0.054*** (0.007)	-0.103*** (0.020)
Occupation:university	0.030** (0.011)	-0.039*** (0.004)	0.061*** (0.011)
Occupation:work	*0.079*** (0.012)*	*-0.046*** (0.004)*	*0.089*** (0.012)*
Duration	*0.218*** (0.00)*	*-0.226*** (0.000)*	*0.215*** (0.000)*
Communication activity			
Posts (log)	-0.161*** (0.004)	0.158*** (0.001)	-0.027*** (0.004)
Likes (log)	*0.370*** (0.004)*	*-0.322*** (0.001)*	*0.204*** (0.004)*
Comments (log)	0.024*** (0.003)	-0.0001 (0.001)	-0.001 (0.003)
Share of others' posts	0.018 (0.016)	0.027*** (0.006)	-0.039** (0.016)
Identity information			
Photos (log)	*0.162*** (0.003)*	*-0.111*** (0.001)*	*0.123*** (0.003)*
Audios (log)	-0.010*** (0.002)	-0.017*** (0.001)	-0.003* (0.002)
Interests & believes (log)	-0.002 (0.007)	-0.013*** (0.002)	0.049*** (0.007)
School	-0.018 (0.013)	0.017*** (0.004)	-0.018* (0.013)
University	-0.012 (0.016)	-0.006 (0.006)	0.022(0.016)
Relatives	0.011 (0.012)	0.032*** (0.004)	-0.053*** (0.012)
Extensiveness of group membership			
Online groups (log)	*0.241*** (0.003)*	*-0.176*** (0.001)*	*0.231*** (0.003)*
User's engagement with the local network			
Share of local friends	*0.284*** (0.022)*	*-0.157*** (0.008)*	*0.179*** (0.022)*
Constant	0.000 (0.028)	0.000 (0.010)	0.000 (0.027)
Observations	186,962	183,818	191,772
Adjusted R^2	0,487	0,326	0,407

Note: Standardized coefficients and standard errors in brackets are reported

*p<0.05 **p<0.001 ***p<0.001

Controlling variables

Of all controlling variables only two have a stable effect on structural social capital. The first is usage duration – the time that passed since a user registered on VK. This result demonstrates the effect of preferential attachment mechanism on the network formation – users who have been on VK for a longer period of time get an advantage in making additional ties which contributes to their network brokerage and status social capital (Barabási & Albert, 1999). At the same time the association between duration and transitivity is negative, and this means that the longer an individual uses VK, the less closed his/her friendship network is. This, again, happens mostly because user networks grow with time and are therefore unable to preserve high values of transitivity (see our reflection on this in the previous section). The second meaningful relation of social capital is to occupational status: those individuals who indicate work as the current occupation tend to have higher brokerage and status social capital, and lower closure, than those who do not declare or indicate other occupational status. The relation of other two types of occupation – secondary school and university studentships – to social capital is unstable across models, as is the relation of gender and age.

Communication activity

Communication activity and engagement of others with a user's wall was measured as the total number of posts, the share of posts written by others among all posts, and as the number of likes and comments, since the latter are mostly produced by page visitors. As these data are incomplete, in our analysis we also use a set of models run on the subset of about 35,000 users for whom all the data, including the number of online groups, is available. These models (not reported in tables) produce similar quality and regression coefficients, and exactly the same set of six stable variables, with duration being a little less important and group membership being a little more important. Communication activity variables stay unaffected across models.

Of all types of communication activity, only the number of likes has a strong and stable effect on social capital: it is positively related to betweenness and eigenvector centrality, and negatively – to transitivity. Hence the more likes a user receives, the higher is his/her brokerage and status social capital in the location-bounded network. However, network closure decreases with the growth of the number of likes although one might expect that cohesive groups with tighter relations might produce more likes. Here, it is important to note that the direction of causality between likes and structural social capital may be inverse to what was initially assumed in our regression models. Likes can indicate not only emotional support and approval, presumably typical for cohesive groups, but also popularity and the desire to appropriate some portion of high status of the popular person. Therefore, likes might be a result of a person's good connectedness both to well-connected people and to disjoint clusters of users. On the contrary, in a cohesive and, consequently, small network a user, even when receiving more likes from each of his/her friends might end up with a smaller overall amount of likes due to redundancy of his/her contacts.

A surprising result is that the number of comments is not associated either with brokerage or network closure in VK, which contradicts our assumption. Among other things, we expected that high frequency of communication of others on a user's wall would increase mutual visibility of user's friends and the likelihood of friendship among them (Ellison et al., 2014b) that was to contribute to higher transitivity. According to McLaughlin & Vitak (2012), incoming directed communication was also to be related to bridging social capital which is similar to brokerage. We can assume that writing comments, being much more expensive type of communication act than liking, may be more constrained by cognitive limits such as the Dunbar number (Dunbar et al., 2015). Indeed, comments are much less common even among the subset of users who do not restrict access to them, and it is plausible that they come mostly from a user's cohesive group rather than from distant communities the user is bridging or has a potential to bridge. Alternatively, comments may represent communication acts that are not as directed as we initially assumed: commentators, instead of addressing the page owner or his/her specific friend, may target the entire audience of the page, without fully knowing its composition. Thus at least some comments may in fact represent broadcasting rather than directed communication.

Therefore, hypothesis H2 is partially supported, since not all types of engagement of others on a user's wall are found to be related to social capital.

Identity Information

The overall contribution of identity information into social capital is much lower than that of communication activity on a user's wall. The relatively large and stable effect has been demonstrated only by the number of photos which is positively related to betweenness and eigenvector centralities, and negatively – to transitivity. The larger the number of photos, the higher the network brokerage and status capital, and the lower the network closure. The fact that it is photos that have an effect on social capital might have a number of explanations. First, photos is the most heavily used feature among all identity information features. Second, photos is what visualizes users' identity by picturing events, objects and people a user finds to be important and worthy of displaying; hence, this feature facilitates finding a common ground between users. Thus, we partially confirm hypothesis H1.

VK online groups

The number of online groups in which a user is a member has a strong positive effect on brokerage and status social capital, and a strong negative effect on closure. These results clearly support H3. Since this has been our central hypothesis, we report additional analysis of Vologda users' groups to get richer interpretations of this relation. We find that although none of the group types (public pages or communities) outnumbers the other in the user lists, pages still account for 78% of memberships. This happens because pages are larger and many of them function as mass media rather than as genuine communities. Thus, 65% of page subscriptions occur in pages of over a million subscribers that constitute only 2.5% among pages of Vologda users. However, around 65% of community memberships occur in communities of less than 8,000 members (that constitute 89% of communities), with a sharp peak of membership in the communities between one and two thousand accounts. It thus can be seen that users tend to share their membership evenly between media-like and community-like accounts, but the latter are more fragmented.

Selective analysis of group titles suggests that both types are mostly devoted to leisure and entertainment (e.g. humor, beauty or cars), hobbies and common interests (e.g. sport clubs or maternity communities) and practical issues (e.g. job search, announcements, mutual aid or dating). Many groups are maintained by small businesses with 15% of pages and 30% of communities offering the functionality of online shops. Local businesses often merge with groups of interest (e.g. local fitness clubs). Here, again, we can see a mixture of consumer behavior and self-organization, the latter being predominantly small scale and non-contentious.

While pages in our sample are mostly "placeless", two thirds of communities indicate their location. Among them, Vologda communities constitute 15% of all communities with disclosed location, and account for nearly 60% of memberships. However, users who claim to reside in Vologda comprise only 6% of memberships in all communities indicating Vologda as their location. Overall, the list of cities amounts to 8,000 titles with Moscow and St.Petersburg being the leaders. Location of online groups is thus much of a convention, however, we can still see that belonging to a larger number of groups strengthens in-city social capital. This might occur because, although group members have more chances to meet people from other cities, their chance to meet and befriend a person from their own town is still higher than if they would try to search for friends outside groups (at random).

Users' adherence to within-city network

Share of friends located in Vologda among all user's VK friends is normally distributed – this means that the majority of people tend to have relatively even proportions of friends within and outside the city, while only minorities are embedded entirely either within or outside Vologda. The share of local friends has positive effect on brokerage and status social capital and negative – on closure, hence the more adherent a user is to the city of his/her residence, the higher is his/her brokerage and status social capital in the city-bounded friendship network. Since the entire social network is quite clustered, local friends of a user with high share of them among all his/her VK friends are more likely be distributed in different clusters than for someone with lower share of local friends. Thus, hypothesis 4 is fully supported.

Discussion

Transitivity as Problematic Indicator of Network Closure

Burt (2005, p.225) argues that closure and brokerage are complementary network structures augmenting each other in creating social capital, because the maximum individual advantage is achieved at extreme levels of brokerage and closure, when an actor simultaneously belongs to a cohesive group and has bridging ties beyond it. However, since in our data transitivity (as an indicator of closure) is inversely related to betweenness (the Spearman correlation is -0.54), empirically their relation turns out to be rather mutually exclusive than complementary. This finding partially coincides with Brooks et al (2014) who found that transitivity in friendship ego-networks negatively correlated with the number of clusters and modularity (which are indicators of network brokerage). Thus, a drawback of transitivity is that it actually measures the overall tendency of an ego-network to form a single clique but not the cliquishness of separate clusters in an ego-network. Transitivity might be equally low for same size ego-networks with very different structures: both for those with cohesive but disconnected clusters (i.e. with actually high closure by Burt's definition), and for those with looser but more interconnected clusters (with actually low closure). Burt stressed that closure is a feature of a group/cluster, and since an individual can engage with a number of distinct clusters, another metric is needed to capture how dense separate clusters in a user's network are. In our research, we see that the entire city-bounded network is a loose collection of tighter clusters, and transitivity drops rapidly for those engaged with more than one cluster. Such engagement should not exclude high closure, but transitivity does not account for it. This means that transitivity is not good enough as an indicator of network closure.

Online groups as a Source of Network Brokerage

We have found out that the more online groups a user belongs to, the higher his/her network brokerage is, i.e. the more various social milieus a user connects to and bridges between. In a large and heterogeneous social network bounded within the same city, membership in online groups many of which are not city-bounded paradoxically contributes to gain of geographically proximate bridging ties. A possible mechanism causing this effect needs to be discussed. Formally, being a member of an online group and making friendships with its members are two distinct types of online behavior. However, there is a substantial body of literature exploring network structures of different types of online groups including online forums (Cobb et al., 2010), social news sites (Hogan, 2008), twitter #hashtag communities (Gruzd and Haythornthwaite, 2013), Facebook groups (Rieder, 2013), and VK groups (Gruzd and Tsyganova, 2015; Rykov et al., 2016; 2017). These studies demonstrate that despite different network patterns (Himelboim et al., 2017), dense and tightly connected clusters of friendship are usually formed in most online groups. This suggests that at least one friendship with another group member may provide access to a whole bunch of social contacts, and a user joining such clusters in multiple groups inevitably becomes a broker. Thus, the more online groups a user joins in SNS, the higher chances to have more non-redundant connections with local citizens.

Disclosed Identity Information and Social Lubricant Effect

Social lubricant effect appears when identity information in SNS is used for searching and establishing common ground between users (Ellison et al., 2011; Ellison & Vitak, 2015). While previous research (Lampe et al., 2007) found out that the amount of identity information has a weak positive relation to the number of friends on Facebook, we find the effect of most types of such information so small that it cannot be treated as able to substantially affect social capital. This, combined with the established effect of the number of photos on network brokerage, needs interpretation. While a user providing no information might indeed have low chances to find many friends, once the information is provided, it might serve both for friend acquisition and filtering. That is why, after initial identity "saturation", friendship gain may stop. A more nuanced research is needed to find out whether coinciding identity information, such as the same school or common interests, really increases probability of friendship tie formation more than a mere amount of information. Meanwhile, the number of photos increases network brokerage, regardless of their content. Among all other types of identity information, a photo is the most emotional and the most easy-to-consume way of self-disclosure; posts with photos are known to generate much more likes than regular posts (Corliss, 2012), while some research finds that positive feedback (of which likes are a type) is positively related to perceived bridging social capital and even mediates the effect of self-disclosure (Liu & Brown 2014). Therefore, compared to a profile with relevant, but non-visualized information, profile full of photos is more likely to quickly provide information sufficient for establishing common ground with a social information seeker and to attract positive feedback from "well-matching" seekers. This might be a possible explanation of why specifically photos play the role of social lubricant on SNS.

Engagement of Other Users as an Attention Signaling Activity

The fact that engagement of others in the form of likes contributes to brokerage, but not to closure, deserves special consideration. If explained with relationship maintenance behavior, engagement of others on a user's wall should increase brokerage of others, not of the wall owner. Those who use the friend's wall become exposed or gain an access to friends of the wall owner, and therefore can establish new ties possibly including non-redundant contacts. In this case, brokerage of the wall owner should decrease, while closure should increase, which is exactly the opposite to our finding. Burke et al (2011) who also find that incoming (and not outgoing) communication is positively related to bridging capital offer the following explanation: it is the feedback that signals a user about the existence of a tie. Developing this claim, we may say that outgoing communication, i.e. broadcasting on the user's wall, is only an attempted relationship maintenance activity. The reciprocated act of communication is a confirmation of this activity being successful. And it is likes – the low-cost signals of attention and social approval – that allow such confirmation (Su & Chan, 2017). Given our earlier reflections on the direction of causality between likes and social capital, we can assume that high numbers of likes plausibly come as confirmation of the gained brokerage ability rather than its cause.

Conclusion and further research

This study, to the best of our knowledge, has been the first examination of effects of SNS user behaviors on structural social capital within a large geographically localized population – in our case, a middle-sized city. As opposed to studies of independent ego-networks, typical for the field, the focus on a city has, first, allowed us to examine social capital calculated from an entire network. This, in turn, has enabled accounting for the effect of indirect connections – those leading to "right" persons (Craven & Wellman, 1973) – and the effect of social proximity to the network hubs – that is, possession of ties leading to influential persons. Second, our approach has given us an opportunity to examine geographically proximate relations whose advantage over all user's online ties is that it allows access to potentially more tangible and location-related resources such as information about local jobs (Granovetter, 1973), housing rentals, medical aid (Lee, 1969) or childcare services (Wellman & Wortley, 1990).

We have found out that the global structure of the location-bounded network presents a combination of small-world and core-periphery graphs containing dense clusters and star-type nodes with outstanding centrality. This suggests presence of a hierarchical structure in the network: although this relatively big community breaks into small sub-communities (high global transitivity), it is also connected by a small number of city-level hubs (high degree and betweenness centralization, and comparatively high assortativity by degree). Further, the city-level network has no clear boundaries since the majority of users have equal proportions of their friends inside and outside the city of their residence. However, the adherence to and isolation within the city network is directly related to users' in-city social capital, especially to within-city brokerage. The availability of rich geographically related network data on VK opens wide possibilities for further comparative analysis of regions, cities, or urban and rural communities, and thus provides ways to overcome the limitations of a case-study approach.

The focus on an entire location-bounded network has made possible our major finding about the effect of online groups membership on within-city social capital and its interpretation. Surprisingly, this obvious hypothesis had not been tested before, perhaps, because such data was hard to obtain. We have found out that globally measured social capital, including brokerage, is positively related to the number of groups a user belongs to, while closure demonstrates an inverse relation. Online groups naturally serve gateways to new social milieus where new friends may be acquired for whom a user becomes a broker connecting them to the rest of his/her network. Most plausibly, it is online communities – being smaller, more interactive and thus more suitable for practical needs – that play a leading role here, while pages function more like mass media. Paradoxically, social capital gain in a city-bounded network is associated with multiple membership in online groups although most of them have no location or are located outside the studied city. Perhaps, the effect of groups on social capital might be stronger if local groups could be singled out from the overall amount of groups for each user, or if social capital was calculated based on all ties, including location-independent friendships, which are potential questions for further research.

In this paper we have also shown that some types of outgoing (photos) and incoming (likes) activities in a users' profile are positively related to his/her brokerage and status social capital in the location-bounded network. While photos visualize user's identity and thus provide social information seekers with necessary context for linking with the page owner, likes seem to work differently. They serve as signals for page owners that their ties are "alive" and usable, and may be rather consequences (or indicators) of high status capital and brokerage that their antecedents. A limitation of our study is that we have not used the data about a user activity outside their walls, such as liking or commenting on a friends' pages, which is an important part of social grooming behavior. This is one of the ways to develop this research.

Finally, we found that transitivity strongly and negatively correlates with betweenness centrality. This means that transitivity is hardly a good measure for closure, because the latter should rather complement brokerage than replace it. Combined with findings of Brooks et al (2014), this calls for a deeper investigation into empirical and conceptual validity of network measures to social capital concepts. Ultimately, it calls for further clarification of the concept that is being measured.

References

About VK, 2017. VK Audience. Available from: https://vk.com/page-47200925_44240810. Date accessed: March 19, 2018.

Ahmad, S., Mustafa, M., Ullah, A., 2016. Association of demographics, motives and intensity of using Social Networking Sites with the formation of bonding and bridging social capital in Pakistan. Computers in Human Behavior 57, 107–114. https://doi.org/10.1016/j.chb.2015.12.027

Arnaboldi, V., Conti, M., Passarella, A., Pezzoni, F., 2012. Analysis of ego network structure in online social networks. In Privacy, security, risk and trust (PASSAT), 2012 international conference on social computing (SocialCom). IEEE. pp. 31-40.

Arnaboldi, V., Passarella, A., Conti, M., Dunba, R.I.M., 2015. Online Social Networks: Human Cognitive Constraints in Facebook and Twitter Personal Graphs.https://doi.org/10.1016/C2014-0-02436-7

Barabási, A.-L., Albert, R., 1999. Emergence of Scaling in Random Networks. Science 286, 509–512. https://doi.org/10.1126/science.286.5439.509

Blanchard, A., Horan, T. 2000. Virtual communities and social capital. In Social dimensions of information technology: Issues for the new millennium (pp. 6-22). IGI Global.

Bohn, A., Buchta, C., Hornik, K., Mair, P., 2014. Making friends and communicating on Facebook: Implications for the access to social capital. Social Networks 37, 29–41. https://doi.org/10.1016/j.socnet.2013.11.003

Bonacich, P., 1972. Factoring and weighting approaches to status scores and clique identification. Journal of mathematical sociology 2(1), 113-120.

Borgatti, S.P., Jones, C., Everett, M.G., 1998. Network Measures of Social Capital. Connections 21 (2): 27-36.

Brooks, B., Hogan, B., Ellison, N., Lampe, C., Vitak, J., 2014. Assessing structural correlates to social capital in Facebook ego networks. Social Networks 38, 1–15. https://doi.org/10.1016/j.socnet.2014.01.002

Brooks, B., Welser, H.T., Hogan, B., Titsworth, S., 2011. Socioeconomic Status Updates. Information, Communication & Society 14, 529–549. https://doi.org/10.1080/1369118X.2011.562221

Burke, M., Kraut, R., Marlow, C., 2011. Social Capital on Facebook: Differentiating Uses and Users, in: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, CHI ’11. ACM, New York, NY, USA, pp. 571–580. https://doi.org/10.1145/1978942.1979023

Burt, R. S., 1995. Structural Holes: The Social Structure of Competition. Harvard University Press, Cambridge, MA.

Burt, R. S., 2005. Brokerage and Closure: An Introduction to Social Capital. Oxford University Press, Oxford, UK.

Burt, R.S., 2018. Nan Lin and Social Capital. December 2018 Working Paper. Retrieved on 04.01.2019 from http://faculty.chicagobooth.edu/ronald.burt/research/files/NLSC.pdf

Centellegher, S., López, E., Saramäki, J., Lepri, B., 2017. Personality traits and ego-network dynamics. PLOS ONE 12, e0173110. https://doi.org/10.1371/journal.pone.0173110

Cobb, N.K., Graham, A.L., Abrams, D.B., 2010. Social Network Structure of a Large Online Community for Smoking Cessation. American Journal of Public Health 100, 1282–9.

Corliss R. Photos on Facebook Generate 53% More Likes Than the Average Post. 2012.Available at: https://blog.hubspot.com/blog/tabid/6307/bid/33800/photos-on-facebook-generate-53-more-likes-than-the-average-post-new-data.aspx. Date accessed: March 19, 2018.

Craven, P., Wellman, B., 1973. The Network City*. Sociological Inquiry 43, 57–88. https://doi.org/10.1111/j.1475-682X.1973.tb00003.x

Dunbar, R.I.M., Arnaboldi, V., Conti, M., Passarella, A., 2015. The structure of online social networks mirrors those in the offline world. Social Networks 43, 39–47. https://doi.org/10.1016/j.socnet.2015.04.005

Ellison, N.B., boyd, D.M., 2013. Sociality Through Social Network Sites. https://doi.org/10.1093/oxfordhb/9780199589074.013.0008

Ellison, N.B., Gray, R., Lampe, C., Fiore, A.T., 2014a. Social capital and resource requests on Facebook. New Media Society 16, 1104–1121. https://doi.org/10.1177/1461444814543998

Ellison, N.B., Steinfield, C., Lampe, C., 2007. The Benefits of Facebook “Friends:” Social Capital and College Students’ Use of Online Social Network Sites. Journal of Computer-Mediated Communication 12, 1143–1168. https://doi.org/10.1111/j.1083-6101.2007.00367.x

Ellison, N.B., Steinfield, C., Lampe, C., 2011. Connection strategies: Social capital implications of Facebook-enabled communication practices. New Media Society 13, 873–892. https://doi.org/10.1177/1461444810385389

Ellison, N.B., Vitak, J., 2015. Social Network Site Affordances and Their Relationship to Social Capital Processes, in: Sundar, S.S. (Ed.), The Handbook of the Psychology of Communication Technology. John Wiley & Sons, Ltd, pp. 203–227. https://doi.org/10.1002/9781118426456.ch9

Ellison, N.B., Vitak, J., Gray, R., Lampe, C., 2014b. Cultivating Social Resources on Social Network Sites: Facebook Relationship Maintenance Behaviors and Their Role in Social Capital Processes. J Comput-MediatComm 19, 855–870. https://doi.org/10.1111/jcc4.12078

Everett, M., Borgatti, S.P., 2005. Ego network betweenness. Social Networks 27, 31–38. https://doi.org/10.1016/j.socnet.2004.11.007

Freeman, L. C., 1977. A set of measures of centrality based on betweenness. Sociometry 40, 35–41.

Fund Public Opinion. (2018) Internet in Russia: the dynamics of penetration. Winter 2017–2018. Available at: https://fom.ru/SMI-i-internet/13999. Date accessed: January 12, 2019.

Gonçalves, B., Perra, N., Vespignani, A., 2011. Modeling Users' Activity on Twitter Networks: Validation of Dunbar's Number. PLOS ONE 6, e22656. https://doi.org/10.1371/journal.pone.002265

González-Bailón, S., Wang, N., Rivero, A., Borge-Holthoefer, J., Moreno, Y., 2014. Assessing the bias in samples of large online networks. Social Networks, 38, 16-27.

Granovetter, M., 1973. The strength of weak ties. American journal of sociology 78(6), 1360–1380.

Gruzd, A., Haythornthwaite, C., 2013. Enabling Community Through Social Media. Journal of Medical Internet Research 15, e248. https://doi.org/10.2196/jmir.2796

Gruzd, A., Tsyganova, K., 2015. Information Wars and Online Activism During the 2013/2014 Crisis in Ukraine: Examining the Social Structures of Pro- and Anti-Maidan Groups. Policy & Internet 7, 121–158. https://doi.org/10.1002/poi3.91

Hampton, K.N., 2007. Neighborhoods in the Network Society the e-Neighbors study. Information, Communication & Society 10, 714–748. https://doi.org/10.1080/13691180701658061

Hampton, K., Wellman, B., 2003. Neighboring in Netville: How the Internet supports community and social capital in a wired suburb. City & Community, 2(4), 277-311.

Haythornthwaite, C., 2005. Social networks and Internet connectivity effects. Information, Communication & Society 8, 125–147. https://doi.org/10.1080/13691180500146185

Himelboim, I., Smith, M.A., Rainie, L., Shneiderman, B., Espina, C., 2017. Classifying Twitter Topic-Networks Using Social Network Analysis. Social Media + Society 3, 2056305117691545. https://doi.org/10.1177/2056305117691545

Hogan, B., 2008. Analyzing Social Networks via the Internet, in: The SAGE Handbook of Online Research Methods. SAGE Publications, pp. 141–160. https://doi.org/10.4135/9780857020055

Johnston, K., Tanner, M., Lalla, N., Kawalski, D., 2013. Social capital: the benefit of Facebook 'friends.' Behaviour& Information Technology 32, 24–36. https://doi.org/10.1080/0144929X.2010.550063

Kaltenbrunner, A., Scellato, S., Volkovich, Y., Laniado, D., Currie, D., Jutemar, E.J., Mascolo, C., 2012. Far from the Eyes, Close on the Web: Impact of Geographic Distance on Online Social Interactions, in: Proceedings of the 2012 ACM Workshop on Workshop on Online Social Networks, WOSN '12. ACM, New York, NY, USA, pp. 19–24. https://doi.org/10.1145/2342549.2342555

Kaveeva, A.D., Gurin, K.E., 2018. VKontakte' local friendship networks: identifying the missed residence of users in profile data. Monitoring of Public Opinion: Economic and Social Changes 3, 78—90. https://doi.org/10.14515/monitoring.2018.3.05

Kobayashi, T., 2010. Bridging Social Capital in Online Communities: Heterogeneity and Social Tolerance of Online Game Players in Japan. Human Communication Research 36, 546–569. https://doi.org/10.1111/j.1468-2958.2010.01388.x

Lampe, C., Ellison, N., Steinfield, C., 2007. A Familiar Face(Book): Profile Elements As Signals in an Online Social Network, in: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, CHI '07. ACM, New York, NY, USA, pp. 435–444. https://doi.org/10.1145/1240624.1240695

Lee, N.H., 1969. The Search for an Abortionist. University of Chicago Press, Chicago.

Lee, E., Kim, Y.J., Ahn, J., 2014. How do people use Facebook features to manage social capital? Computers in Human Behavior 36, 440–445. https://doi.org/10.1016/j.chb.2014.04.007

Lee, J., Lee, H., 2010. The computer-mediated communication network: exploring the linkage between the online community and social capital. New Media & Society 12, 711–727.

Li, T., Levina, E., Zhu, J., 2016. Prediction models for network-linked data. arXiv:1602.01192 [stat].

Lin, N., 2004. Social Capital: A Theory of Structure and Action, Cambridge University Press.

Lin, N., 2008. Chapter 2. A network theory of social capital, in: Castiglione, D., Van Deth, J.W., Guglielmo W. (Eds.), The Handbook of Social Capital. Oxford University Press, pp. 50-69.

Liu, D., Brown, B.B., 2014. Self-disclosure on social networking sites, positive feedback, and social capital among Chinese college students. Computers in Human Behavior 38, 213–219. https://doi.org/10.1016/j.chb.2014.06.003

McAuley, J., Leskovec, J., 2012. Learning to Discover Social Circles in Ego Networks, in: Proceedings of the 25th International Conference on Neural Information Processing Systems, NIPS'12. Curran Associates Inc., USA, pp. 539–547.

McLaughlin, C., Vitak, J., 2012. Norm evolution and violation on Facebook. New media & society, 14(2), 299-315.

Metcalf, J., Crawford, K., 2016. Where are human subjects in big data research? The emerging ethics divide. Big Data & Society, 3(1), 2053951716650211.

Moreno, M. A., Goniu, N., Moreno, P. S., Diekema, D., 2013. Ethics of social media research: common concerns and practical considerations. Cyberpsychology, behavior, and social networking, 16(9), 708-713.

Norris, P., 2002. The Bridging and Bonding Role of Online Communities. Harvard International Journal of Press/Politics 7, 3–13. https://doi.org/10.1177/1081180X0200700301

Pflieger, G., Rozenblat, C., 2010. Introduction. Urban Networks and Network Theory: The City as the Connector of Multiple Networks. Urban Studies 47(13) 2723–2735.

Quan-Haase, A., Wellman, B., Witte, J. C., Hampton, K. N., 2002. Capitalizing on the net: Social contact, civic engagement, and sense of community. The Internet in everyday life, 291-324.

Rieder, B., 2013. Studying Facebook via Data Extraction: The Netvizz Application, in: Proceedings of the 5th Annual ACM Web Science Conference, WebSci '13. ACM, New York, NY, USA, pp. 346–355. https://doi.org/10.1145/2464464.2464475

Russian Federation federal state statistics service. (2017). Russian regions. Socio-Economic statistical indexes. 2017: Vol.32 / Rosstat. - Moscow. p. 1402.

Rykov, Y.G., Meylakhs, P.A., Sinyavskaya, Y.E., 2017. Network Structure of an AIDS-Denialist Online Community: Identifying Core Members and the Risk Group. American Behavioral Scientist 61, 688–706. https://doi.org/10.1177/0002764217717565

Rykov, Yu.G., Koltsova, O. Yu., Meylakhs, P. A., 2016. Structure and Functions of Online Communities: Network Mapping of HIV-relevant groups in VK.com SNS. Sotsiologicheskieissledovaniya 8, 30-42

Sajuria, J., van Heerde-Hudson, J., Hudson, D., Dasandi, N., Theocharis, Y., 2015. Tweeting Alone? An Analysis of Bridging and Bonding Social Capital in Online Networks. American Politics Research 43, 708–738. https://doi.org/10.1177/1532673X14557942

Scellato, S., Mascolo, C., Musolesi, M., Latora, V., 2010. Distance Matters: Geo-social Metrics for Online Social Networks, in: Proceedings of the 3rd Wonference on Online Social Networks, WOSN'10. USENIX Association, Berkeley, CA, USA, pp. 8–8.

Shen, C., Monge, P., Williams, D., 2014. Virtual Brokerage and Closure: Network Structure and Social Capital in a Massively Multiplayer Online Game. Communication Research 41, 459–480. https://doi.org/10.1177/0093650212455197

Smock, A.D., Ellison, N.B., Lampe, C., Wohn, D.Y., 2011. Facebook as a toolkit: A uses and gratification approach to unbundling feature use. Computers in Human Behavior 27, 2322–2329. https://doi.org/10.1016/j.chb.2011.07.011

Su, C.C., Chan, N.K., 2017. Predicting social capital on Facebook: The implications of use intensity, perceived content desirability, and Facebook-enabled communication practices. Computers in Human Behavior 72, 259–268. https://doi.org/10.1016/j.chb.2017.02.058

Tufekci, Z. 2014. Big Questions for Social Media Big Data: Representativeness, Validity and Other Methodological Pitfalls. ICWSM, 14, 505-514.

Warner, W. L., 1963. Yankee City. Yale University Press.

Watts, D.J., Strogatz, S.H., 1998. Collective dynamics of `small-world' networks. Nature 393 (6684), 440 - 442.

Weiqin, E.L., Campbell, M., Kimpton, M., Wozencroft, K., Orel, A., 2016. Social Capital on Facebook: The Impact of Personality and Online Communication Behaviors. Journal of Educational Computing Research 54, 747–786. https://doi.org/10.1177/0735633116631886

Wellman, B., Wortley, S., 1990. Different Strokes from Different Folks: Community Ties and Social Support. American Journal of Sociology 96, 558–588.

Williams, D., 2006. On and Off the 'Net: Scales for Social Capital in an Online Era. Journal of Computer-Mediated Communication 11, 593–628. https://doi.org/10.1111/j.1083-6101.2006.00029.x

Zwitter, A., 2014. Big data ethics. Big Data & Society, 1(2), 2053951714559253.