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Social signature in an online environment: Stability and cognitive limits

Olessia Y. Koltsova [a], Larisa V. Mararitsa [a,b], Maxim A. Terpilovskii [a], Yadviga E. Sinyavskaya [a,*]

[a] Laboratory for Social & Cognitive Informatics, National Research University Higher School of Economics, 190008, Saint Petersburg, Sedova St., 55/2, Room 216, Russia

[b] Department of Social Psychology, Saint-Petersburg State University, 199034, Saint Petersburg, 7/9 Universitetskaya Emb, Russia

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ABSTRACT

Social tie maintenance has always had cognitive and emotional costs and has been leading to uneven distribution of communication volume among interaction partners of individuals. This distribution, known as social signature, is assumed to be stable for each person. Availability of digital traces of human communication allows testing whether this assumption is true and whether it holds in specific channels of computer-mediated communication. In this paper, we investigate private messaging on a popular social networking website on a sample of 39 users and 8063 communication partners of those users over the period of 18 months. We find that this communication channel does not reduce cognitive costs as the overall number of users' active contacts, on average, is equivalent to the cognitive limit known as Dunbar's number. Confirming some previous research, we show that the volume of communication is unevenly distributed, related to emotional closeness, and that changes in this distribution (that is, the changes in social signature) over time within an individual are smaller than the distances between social signatures of different individuals. However, as an absolutely novel finding, we demonstrate that the changes within individuals are statistically significant, thus questioning the concept of social signature as a stable phenomenon.

1. Introduction

Social tie maintenance, although being obviously rewarding, requires cognitive, emotional, and temporal investment (Miritello et al., 2013; Dunbar, 2018). This induces individuals to develop their communicative strategies that are likely to be dependent on their cognitive capacities and, therefore, to be constant in size and structure. In recent years, these strategies have attracted the attention of researchers from network science and psychology under an emerging term of social signature. As defined by Saramäki et al. (2014) who proposed this term, the social signature of an ego is a distribution of interaction intensity among different alters of this ego – a distribution that shows stability in time for each ego despite the turnover of alters, but varies between egos. In social network theory, an ego is a focal node of a network, such as an individual, and alters are the nodes whom the ego is directly connected to by a certain type of ties, such as friendship or exchange of messages.

Although research on social signature is just in its cradle, this phenomenon may turn to present a fundamental feature of human communication if it gets confirmed across different societies, types of communication, and communication channels. It will then be able to provide new evidence and development for a broader social brain theory proposed by evolutionary psychologist Robin Dunbar (Dunbar, 1998, 2009) and continued in the respective stream of further research (Centellegher et al., 2017; Godoy-Lorite et al., 2016; Heydari et al., 2018; Liu et al., 2018; Saramäki, 2014; Sutcliffe et al., 2012).

According to Dunbar's Human Social Brain (HSB) Hypothesis, the human brain owes its size to its ability to maintain social interactions with others in large and complex groups. Dunbar (1992) and other scholars (Sawaguchi & Kudo, 1990; Hill & Dunbar, 2003) observe a visible correlation between mean social group size and relative neocortical volume in primates which suggests that the former is limited by the latter. This means that primates are unable to process more social information and, therefore, to maintain more social ties than their brains allow. In humans, this cognitive limit, also known as Dunbar's number, has been empirically found to average 150 meaningful or stable contacts, within the bounds (100; 250) (Dunbar, 2018; Hill & Dunbar, 2003). Additionally, Dunbar and colleagues' social layers theory

* Corresponding author.
E-mail addresses: ekoltsova@hse.ru (O.Y. Koltsova), larisamararitsa@mail.ru (L.V. Mararitsa), maximtrp@gmail.com (M.A. Terpilovskii), ysinyawskaya@hse.ru (Y.E. Sinyavskaya).

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provides evidence for uneven and layered structure of emotional closeness in egos' social groups (Dunbar, 2016; Sutcliffe et al., 2012).

Saramäki's concept of social signature enriches HSB theory by hypothesizing that the distribution of interaction volume between egos' social group members is also invariant, stable, related to emotional closeness, as well as independent of the composition of alters and of major life changes. That is, while friends may come and go, an ego's strategy of distributing her communicative effort over the number of friends that her individual cognitive limit affords will stay untouched. However, all the evidence in favor of the social signature theory is based either on the data from voice telephone communication (Centellegher et al., 2017) which is mostly limited to the closest layers of alters, or on public communication on social networking sites (Heydari et al., 2018; Liu et al., 2018) which is neither representative of communication within one's social group (see reasons in the *Related Work* section further below). Thus, to date, social signature theory has limited empirical support. Furthermore, alternative theories claim that modern communication devices and services, such as online social networks (OSNs) may allow humans to break through their cognitive limits and reach the numbers of alters far greater than 150 or 250 (Wellman, 2011).

This work seeks to contribute to the theory of social signature and to the broader social brain theory by rigorously testing the core propositions of the former on the data from a private messenger service of a popular OSN. We assume that private messaging, unlike telephone communication, can accommodate all layers of social ties (due to its potential openness to strangers), but, unlike public communication, is free from the tasks of public self-presentation and other intervening influences (see *Related work* for more details). To additionally challenge the presumably universal character of social signature, we base our research on individuals from a society beyond Western Europe which to date has been the only region studied. Consistent with the HSB theory, we find that OSN technology offers no advantages for overcoming the upper limit of the number of contacts proposed by Dunbar and that, facing this limit, individuals choose to distribute the amount of their communication very unevenly, roughly according to the emotional closeness of their contacts. However, the phenomenon of social signature finds only partial support: while, in line with Saramäki, the change of individual social signatures over time is smaller than interpersonal differences in signatures, still the change is statistically significant.

Thus, our theoretical contribution is three-fold:

- We question the social signature hypothesis (Heydari et al., 2018; Saramäki, 2014) by providing evidence against its invariance and universal stability. We suggest that further theory should develop around the explanation of variance of social signature and of its stability among individuals where both social and cognitive factors are likely to play a role.
- We show that social brain hypothesis (Dunbar 1992, 1998, 2009) sustains in OSN private messaging as a communication channel, but suggest that the mechanism of OSNs' influence on the growth of individual social networks found by Wellman (2011) is different from a direct break-through Dunbar's number and that it should be captured by different research methods.
- We confirm the relation between communication volume and emotional closeness, but simultaneously show that it significantly varies across individuals and thus enrich the social layers theory (Dunbar, 2016; Sutcliffe et al., 2012) by proposing to refocus it on the factors explaining individual variance.

Apart from a theoretical contribution, our work has clear practical implications. Stability of social signature has been already found to be associated with personality traits (Centellegher et al., 2017). More broadly, various communication markers, such as interaction frequency, volume, number, and composition of partners are known to be behavioral predictors of mood disorders and mental health (Schelde, 1998; Faurholt-Jepsen et al., 2016; Rohani, 2018; Timon & Christoph, 2020). It is thus quite plausible that these conditions may be also predicted with abrupt changes in individual social signatures which means that a deep understanding of the latter may empower decision-making on individual and public monitoring of psychological well-being and adaptability.

Further, as an abrupt change in communication patterns is often associated with the decline in well-being, it may also predict dissatisfaction with and churn from a particular OSN. While a sharp decrease in communication via an OSN is a somewhat obvious indicator of the loss of interest in it, it is much less obvious that a sharp increase or abrupt structural change may predict the same. This may happen because the two latter changes may result from excessive communication forced by alters or by an OSN functionality and be manifestations of communication overload. Such overload has shown mixed effects on OSN fatigue (Cao & Sun, 2018; Lee et al., 2016), however, it was usually measured with self-reported data. More objective measurements justified theoretically and empirically by the research on social signatures and cognitive limits may help obtain more reliable evidence on the association between communication overload and consumer loyalty to an OSN. They thus can help build more user-friendly OSN functionalities informed with the knowledge about fundamental limits of human communication abilities.

Our findings are based on the data from 39 users of VKontakte (VK) – a Russian replica of Facebook and the most popular social networking site in Russia. Namely, we collect the data on their private messages – their timestamps, authors/recipients, and the number of characters and words – for the period of 18 months, thus obtaining information about 1 879 827 messages from/to 8063 alters. Additionally, we ask our respondents to answer several questions about each of their VK friends obtaining another set of 14 916 alters that intersects with the first set of alters at the number of 4958.

The rest of the paper is structured as follows: in the next section, we present the discussion about the potential ability of OSNs to break through the human cognitive limits and the state-of-the-art analysis of works on the social signature phenomenon. In section 3 we introduce our hypotheses and their theoretical foundations. Section *Data and Method* contains the details about our research design, including data collection and analysis. The *Results* section is organized in correspondence with the order of hypotheses presentation in section 3. Finally, we discuss key results and provide their interpretations and explanations in the section *Discussion and Conclusion*. At the end of this section we also reflect on limitations of our analysis and future research perspectives.

2. Related Work

Relationship formation, maintenance, and decay have since long been studied in psychology, sociology, communication research, and other relevant disciplines. Multiple studies have shown that the ability to maintain healthy and diverse ties is related to human well-being, health and success (Holt-Lunstad et al., 2010, 2015; House et al., 1988; Jokinen et al., 2008; Shor et al., 2013) which explains the constant interest of researchers to this topic. However, capturing communication patterns at scale has not been possible until the (quite recent) emergence and proliferation of digital traces. At the same time, digitalized forms of communication have not been merely reflecting what previously happened face-to-face; quite the reverse, human communication has been visibly reshaped by various digital channels.

Thus, OSNs have been seen as an efficient tool for broadcasting to relatively large personal networks at the scale never available before. However, this has come at the expense of the effect known as context collapse (Donath & boyd, 2004) – a situation when both intimate and distant contacts get exposed to the same information. This, in turn, has led to the development of novel communication strategies, including restriction of the revealed information (Lampinen et al., 2009, 2011). Texting and instant messaging, while avoiding this effect, have altered directed personal communication in their own way. First of all, the prevalence of text communication over voice calls has become salient

(Hayat et al., 2020), especially among the younger generation (Blaire et al., 2015). One possible reason for this is that private messaging is more flexible than both voice calls and public OSN posting in that it allows being used as both synchronous and asynchronous communication (Madell & Muncer, 2007). Compared to face-to-face interaction, it also allows reallocation of cognitive resources from environmental scanning and nonverbal management toward the composition of messages that are, furthermore, editable (Walther, 2007). This leads to greater control over involuntary expressions (Walther, 2007) with modest losses in speed.

2.1. Cognitive limits to communication network size

The aforementioned evidence creates grounds to assume that information-communication technologies (ICTs) may offer more cognitively efficient ways of communication and thus allow humans to transcend some of their cognitive limitations. The evidence for and against this is mixed.

Research confirming the persistence of the cognitive limit in ICT-mediated communication is prevailing and is mostly represented by the works of Robin Dunbar and collaborators. Although the amount of the evidence they offer is indeed impressive, this stream of works is not free from certain inconsistencies. Thus, MacCarron et al. (2016) find the number of contacts in telephone communication to be far lower than 150 in an entire year. Haerter et al. (2012) investigate E-mail communication in an organization and show that *on average* the limit is around 250 alters (not between 100 and 250). Neither of these works is thus a perfect match to the suggested threshold number of 150. Further, Pollet et al. (2011) convincingly show that the size of OSN networks is not related to the size of overall networks or to the average emotional closeness of “offline” friends, and those who do use OSNs do not have larger overall networks than those who do not. This indicates the existence of a cognitive limit, but does not suggest its threshold value. Gonçalves et al. (2011) find that from the moment a user starts using Twitter, the average number of tweets per alter increases until the number of alters in a user’s network reaches a threshold of 100–200 users. From this, however, it is hard to directly derive a conclusion that once any alter starts to receive a smaller number of messages, communication with him immediately turns “meaningless”. If it does not, then, perhaps, individuals can maintain a number of meaningful relations exceeding 100–200 despite a certain decline in frequency.

All this points to an important problem with the definition of Dunbar’s number as a limit to the amount of alters with whom an ego is able to maintain “meaningful” relations. The way meaningfulness is conceptualized may greatly influence the outcome of experiments on determining the threshold value, while the ability to predict this threshold is what provides meaningfulness for the SBH itself. Without a definition of meaningfulness, it is difficult to determine, for instance, whether the difference between the results of MacCarron and Haerter is determined by the incompleteness/excessiveness of the studied networks or by other factors. In one of his early works Dunbar (Hill & Dunbar, 2003) suggests that a single Christmas postcard per year should be sufficient to consider an alter a part of ego’s network; however, more universal and more ICT-relevant operationalizations are also needed. To date, this problem is unresolved.

Alternative theories claim that social networking sites are able to help individuals cut through the limit of the Dunbar’s number (Wellman, 2011). Thus, different studies find that heavy internet users tend to have larger offline and online networks than light users and gain more ties with time (Wang & Wellman, 2010); larger online ego-networks contribute to the increase of strong ties, albeit not as much as to the growth of weak ties (Manago et al., 2012), larger online ego-networks are associated with larger core discussion networks (Vriens & van Ingen, 2018), and certain types of heavy internet use contribute to higher numbers of social ties (Zhao, 2006). These results directly contradict Pollet et al. (2011) and suggest that OSNs, in fact, do help humans to grow their networks. Additionally, it has been shown that larger online personal networks are associated with higher perceived social capital – that is, the perceived amount of resources that alters can share with an ego, or the perceived amount of help an ego can get from them (Ellison et al., 2014). Wellman (Rainie & Wellman, 2012; Wellman, 2011) also reviews the works (e.g. Bernard et al., 2001; McCormick et al., 2010) that estimate human networks to be much larger than 150, amounting to 1000 and more, depending on how connections are understood. However, the works mentioned by Wellman are either based of self-reported (and therefore incomplete) data on personal networks or are mathematical estimations (that should lose some of their usefulness with the advent of large digital traces) More importantly, they aim at measuring the number of alters an ego knows, not the number of meaningful contacts.

2.2. Layers of closeness in personal networks

More recent versions of social brain theory incorporate the alternative findings reviewed above as additional layers of human networks (Dunbar, 2018). In total, Dunbar’s layer model, in its different versions, includes 4–7 layers, such as support clique, sympathy group, active network, and finally individuals whose names and faces can be matched by an ego (Dunbar, 2016; Dunbar et al., 2015; Sutcliffe et al., 2012). These layers are claimed to have a scaling ratio of roughly 3, starting from the average of 1.5 alters in the inner layer and ending with 1500 individuals in the outside layer (Dunbar, 2018). The definition of a tie as the ability to match a face and a name goes far beyond the initial idea of meaningful relations and adds complexity to the problem of finding the threshold number.

The theory of layers has also been criticized by Wellman (2011) who underscores that ego-network structure is consistently found to be more complicated, with clusters of functional roles of alters cutting across the layers of proximity. As cohesive subgroup detection has been one of the core fields of social network analysis for decades, there is little doubt that human networks, including online networks, are clustered. Online clusters have been identified based both on self-reported criteria (Kelley et al., 2011, pp. 216–233) and on observational data that include link distribution and node attributes (Traud et al., 2012; Petkos et al., 2015; Gaito et al., 2017). While Kelley and coauthors report users to single out such clusters as family, work, classmates, church, location-based, and “close friends”, among others, Traud et al. and Gaito et al. also identify a whole range of user features that predict their grouping.

Cluster structure, however, is not incompatible with a layer structure. Another finding that makes both streams of research compatible is that both groups of Dunbar (Saramäki et al., 2014) and Wellman (Parady et al., 2020) find a positive relation between emotional closeness and communication intensity, even though the latter may be measured differently. Finally, a highly uneven (power-law or similar) distribution of communication volume among ego’s alters has been confirmed in multiple works, both related and unrelated to Dunbar’s group, based on telephone calls (Saramäki et al., 2014; Raeder et al., 2011; Shi et al., 2018) and on some other types of communication, such as VK friends, posts, comments and likes [Rykov, 2015; Rykov, Nagornyy, & Koltsova, 2017].

2.3. Social signatures

Unlike the shape of the distribution of communication volume among alters, its stability, as mentioned in the introduction, has not been studied as much. There are only five works offering evidence in favor of the phenomenon of social signature, and none of them tests the hypothesis of the existence of social signature directly. Godoy-Lorite et al. (2016) show that the distributions of skewness values among all users are similar in different time periods – more precisely, they prove that the distributions of differences between the distributions of skewness values do not statistically differ one from another. This does not account for the changes within each of individuals who might “swap” their skewedness values with other persons over time. Centellegher et al. (2017) find that individuals with certain personality traits have significantly more stable signatures than individuals with other personality traits, not claiming the overall stability of social signatures. Liu et al. (2018) offer visual representations of contact distributions of different egos and base their conclusion about their similarity on raw values of Jensen-Shannon (JS) distances between individual distributions. This is problematic because no threshold separating “big” differences from “small” differences is available. Finally, Saramäki et al. (2014) and Heydari et al. (2018) go furthest by showing that JS distances between different periods of the same person are smaller than JS distances between different persons. Neither of them tests these differences statistically which is not a big problem for the latter study due to the size of the sample, but is a problem for the former. Thus, whether distributions of communication volume in personal networks are indeed stable or dynamic remains an open question.

Interestingly, social network dynamics for decades has been an established branch of social network analysis, but the latter has been always interested in a somewhat different set of research questions. Namely, networks dynamics has been mostly understood and studied as alter turnover – that is, substitution of individual ties, or re-wiring in networks (Degennea&Lebeaux, 2005), or stability of individual ties and its factors (Lubbers et al., 2010), or decay of individual ties and its factors (Raeder et al., 2011; Shi et al., 2018). These approaches, however, indirectly suggest certain volatility of both network size and the distribution of communication volume among alters across an ego’s life course. Thus, David-Barrett et al. (2016) find that telephone communication intensity with different types of family members is different and evolves differently along the life cycle of an ego. It has been also shown that the number of an ego’s interactions depends on such factors as age, education, number of hours to work, and having a partner (Van den Berg et al., 2012), while contact frequency with an alter has been similarly shown dependent on her age, family and employment status (Calastri et al., 2017). This research suggests that the change in the listed socio-demographic parameters may result in the growth or decay of personal social networks and in the redistribution of contacts within them between the alters of different degrees of closeness. However, we are aware of no research indicating the existence of short-term volatility of communication volume distribution.

To sum up, the research on personal network size, stability of contact distribution and the role ICTs for them has been rich and diverse, but to a certain extent fragmented. In what follows we will try to unite these three aspects in a single and rigorous research design.

3. Hypotheses

In our research, we begin with the core assumption of human social brain theory related to the maximal personal network size and then proceed to the theory’s extensions. To date, the persistence of the cognitive limit in interaction mediated by ICTs has been studied on such communication channels as telephone voice calls (MacCarron et al., 2016), E-mails (Haerter et al., 2012), microblogging services (Gonçalves et al., 2011), as well as applied to the static OSN friend networks (Dunbar, 2016). This evidence gives ground to assume that in OSN private messaging, too, the number of communication partners should average to Dunbar’s number – at least among those who use this channel to reach most of their meaningful contacts. Therefore, our first hypothesis sounds as follows:

H1A. Average number of alters in an ego-network of OSN private messaging is approximately equal to Dunbar’s number (150), within empirically justified bounds (100–250).

At the same time, we cannot ignore the alternative theories and the concerns raised by Wellman and his colleagues (Wellman, 2011). As this stream of research claims that ICTS, and OSNs in particular, should extend human capacity to maintain social ties, rather than constrain it, it is logical to expect that if the amount of OSN-mediated ties does differ from Dunbar’s number it is hardly going to be lower:

H1B. Average number of alters in an ego-network of OSN private messaging is higher than Dunbar’s number (150).

A direct consequence of the HSB hypothesis is the skewness of the distribution of the communication volume among an ego’s alters that, as mentioned in the previous section, has been confirmed by both competing groups of relevant research (Centellegher et al., 2017; Godoy-Lorite et al., 2016; Heydari et al., 2018; Liu et al., 2018). It has been thought to be caused by selective investment of individuals into their connections determined by the limited capacity of their brains and time available. This selectiveness accounted for in the model of social layers reviewed above (Sutcliffe et al., 2012), in turn, is a development of an early sociological theory of weak and strong ties by Granovetter (1973). It is this idea of varying tie strength that has led to the works testing the relation between perceived strength or emotional closeness, and communication volume, measured either as contact frequency, overall time, or the number of messages (Saramäki et al., 2014; Parady et al., 2020). As the number of the works confirming this relation is limited and their context is different, we find it important to test whether this relation sustains in a different communication channel and a different sample before passing to examining the existence of the social signature phenomenon:

H2. Emotional closeness is positively related to the volume of communication.

Another and, in fact, more profound consequence of the cognitive limit hypothesis is the assumed existence of social signatures as stable distributions of egos’ contacts or communication volume among their alters. As mentioned in the literature review, this phenomenon still lacks confirmation because it was not tested in a rigorous way. The most precise method employed for this task was comparison of intra-personal and inter-personal distances between distributions of communication volume (Saramäki et al., 2014; Heydari et al., 2018). We, therefore, find it important to start from replicating this approach, albeit transferring it from exploratory to inferential research design via the formulation of the following hypothesis:

H3A. When distributions of egos’ contacts over their alters are compared both between different periods of the same person and between different persons, intra-personal differences will be significantly smaller than inter-personal differences.

However, the confirmation of this hypothesis cannot exclude the volatility of individual contact distributions over time: although intra-personal differences may be smaller than inter-personal, they still can be relatively high. And vica versa, if intra-personal differences are approximately equal to inter-personal differences, this may mean that all individuals are uniformly stable or uniformly unstable, and these two conditions are inseparable by testing H3A. A more straightforward and rigorous way to confirm the existence of stable social signatures is to directly test whether distributions of contacts of the same ego from different periods are statistically identical:

H3B. Distributions of egos’ contacts over their alters in different periods of time will be not significantly different one from another.

Thus, if both H3A and H3B are confirmed, it would be possible to conclude that stable social signatures exist, but they vary between individuals. For HSB theory it would mean that differences between individual strategies of investment into egos’ ties might be explained by certain fundamental and constant cognitive features. However, if only H3B is confirmed, the signatures, in addition to being stable for each individual, would be roughly the same among all individuals. This would lead to a much stronger claim of both temporal and inter-personal invariance of social signatures.

4. Data and methodology

In this section we provide the outline of our methodological approach. First, we justify the choice of a particular Russian OSN - Vkontakte.ru. Next follows the subsection describing the process of data collection and sample characteristics. Finally, we conclude with a detailed specification of methods used for hypotheses testing.

4.1. Vkontakte: our communication channel as a research site

Vkontakte social networking site (or VK; previously: Vkontakte.ru; now: vk.com) is to a certain degree a replica of Facebook in terms of the interface and functionality. Vkontakte user's individual page allows customizable privacy settings and is structured very similarly to Facebook featuring user profile information, a "wall" for messages, photo, video, and audio repositories, and others. Additionally, just like Facebook, VK includes a private instant messaging service that allows both individual and small group communication.

The choice of Vkontakte for the study was motivated by two main considerations.

First, in contrast to other Western countries dominated by Facebook, it is Vkontakte that is the regional leader in many post-soviet countries, especially in Russia (Mediascope Web Index, 2019; Russian center for public opinion research, 2018). To date, the official VK registry numbers more than half a billion personal accounts (VKregistry, 2021). The monthly reach of VKontakte is around 38 million visitors, while the number of active users producing the content varies between 30 and 35 (Mediascope Web Index, 2019). What is most important for our research, by the time of data collection, VK messenger left behind both WhatsApp and Facebook messengers in terms of daily reach (Mediascope Web Index, 2018).

Second, Vkontakte still remains relatively open for third-parties such as external research groups. Unlike Facebook which severely restricted access to its API from 2016, Vkontakte provides legal access to users' publicly available digital traces. Moreover, at the time of data collection and it was still possible to request (by a user's consent) the details about communication in VK private messenger. Access to this unique information was crucial for our research goal.

Taken together, among all other social networks popular in Russia, the Vkontakte OSN seems to have a greater potential to represent communication behavior of social networks users in its entirety.

4.2. Data collection

Each respondent was presented with a specially developed application interface by a trained interviewer in person. First, a respondent was asked to login in his/her VK account and give access to his/her private messages. The interviewer explained that the application only counted the number of characters and words, but did not download the texts. Next, the respondent was shown the pictures and names of his VK friends and asked to submit the answers to seven questions about each of them into the interface. The research protocol was approved by the Institutional Review Board of the National Research University Higher School of Economics. The present paper uses the data from only one of the seven questions, namely "How close is this person to you emotionally?" (0 not at all, 9 – very close).

4.3. Participants

Our respondent selection procedure consisted of seven filter questions. To be excluded from the sample, it was sufficient that a respondent gave a positive answer either to the question "Have you ever bulk deleted your VK private messages?" or to any of two other questions. All the rest questions were aimed at selection of those VK users who claim to maintain most of their significant contacts via VK, and do it relatively regularly. This selection procedure was meant to filter non-users, past users or occasional users whose online networks were nothing close to their overall amount of contacts and were just insufficient for analysis. Additionally, the minimum amount of friends for individuals to be included in the survey was set to 100 (with one exception of 96); this was done to put the testing of H1A in more difficult conditions and to ask: are those people who claim to have relatively many friends able to really communicate with the numbers beyond Dunbar's number? Next, we selected only the respondents who registered not later than 3.5 years prior to our research so the depth of observation for each of them would be no less than 18 months and unaffected by the novelty of VK use. Finally, respondents were sampled from a young urban population aged 22–30 as the group prevailing in VK. It served the goal of selecting those people for whom the given channel of communication was most likely culturally natural. Also, it guaranteed that all respondents had been off-age by the date from which their private message data were collected.

The data were collected between January and March 2018. In total, 42 respondents completed our survey which resulted in 39 valid observations. The sample is not free from certain gender bias with 28 females against 11 males. Table 1 shows the basic descriptive statistics, including the number of alters who either received or sent at least one message from/to the ego, the number of VK friends and the number at which both sets intersect. The intensity of communication is measured as the total number of characters, since users vary greatly in their inclination to split their utterances into several messages, and word delimitation is very difficult in informal texts (which is why neither message nor word counts are accurate).

4.4. Data analysis design

To test H1A we used TOST (two one-sided T-tests R package that either confirms or rejects equivalence of means) (Lakens et al., 2018) with theoretically justified bounds – 100 and 250 active contacts — and theoretical mean equal to Dunbar's number (150 contacts). An active contact was defined as an alter who both received and sent at least one message to/from the ego during the last year. We based this choice on the work of Hill and Dunbar (2003) where they used acts of sending Christmas cards as indicators of tie maintenance. However, we defined active contacts in a more demanding way as at least one reciprocated message per year to avoid unresponded spam messages, as well as failed one-way attempts to communicate.

For H1B we chose a one-sided one sample T-test which tests the null hypothesis (in our case: mean N of contacts is not different from or is significantly smaller than Dunbar's number). For H2 a multilevel random-slope random-intercept regression model was used, with the data being logarithmized before model fit.

To test H3A&B we borrowed much from the approaches of Saramaki (Saramäki et al., 2014) and Heydari (Heydari et al., 2018). We constructed each social signature as the function NC = f(R), where NC is the number of characters received or sent to/by a given ego's alter, and R is the rank of this alter in the list of this ego's alters sorted by the number of characters sent/received. Such distributions were constructed for three consecutive 6-month periods T1, T2, and T3. Since different egos had different numbers of contacts, we limited the distributions by two thresholds – either 20 or 40, and added zeros to the ends of those

Table 1
Sample descriptive statistics.

	Mean	Median	Min	Max	SD
Age	25.33	24	20	30	2.83
N of characters, 18 months	2384446	1442998	31682	7558178	2119474
N of alters contacted, 18 months	221.38	168	30	1250	212.34
N of friends	382.92	268	96	1703	325.35
N of friends contacted	135.18	110	28	665	115.65
Average closeness	2.18	2.36	0.27	4.80	1.156

distributions that were shorter. A 40-alter threshold might theoretically give us a more complete picture, but as these distributions ended up containing more zeros, this might artificially inflate their similarity, which is why we decided to work with two different thresholds.

To compare social signatures we, in accordance with Saramaki's and Heydai's method, computed Jensen-Shannon distances (JS) (1) between different egos of the same period, thus obtaining six sets of inter-personal distances corresponding to the three periods of time and the two thresholds (JS20-alterT1, JS20-alterT2, JS20-alterT3, JS40-alterT1, JS40-alterT2, JS40-alterT3), and (2) between different periods of the same ego, which formed six sets of intra-personal distances corresponding to the three pairs of periods compared and the two thresholds (JS20-selfT1/T2, JS20-selfT2/T3, JS20-selfT1/T3, JS40-selfT1/T2, JS40-selfT2/T3, JS40-selfT2/T3). Next, we went beyond the initial Saramäki's approach and applied a set of statistical tests to check whether the visually observed differences are significant.

For H3A we performed 18 one-sided Mann-Whitney tests that compared all 20-alter-based inter-personal distances to all corresponding intra-personal distances, and did the same for the sets of 40-alter-based distances. Mann-Whitney test was chosen based on the analysis of the data distribution.

For H3B we first performed a series of Kolmogorov-Smirnov tests (KS) each of which compared a pair of social signature distributions of the same person from two different periods T1/T2, T2/T3 or T1/T3, based either on top-20 or top-40 alters. We thus obtained six sets of different results (39 individual results in total) that had to be generalized. To test the global hypothesis of the overall equivalence of all distributions within each given person, we chose the Stouffer test as the most powerful in its category (Futschik et al., 2019) and performed it for each of the six sets of individual results.

Finally, in line with Saramaki, we controlled for the alter turnover effect, that is, we checked whether the possible change of social signature over time could be affected by the dropout and the acquisition of alters. The turnover was measured by the Jaccard index that compared the sets of either top 20 or top 40 alters (who sent or received messages to/from an ego) between periods T1/T2, T2/T3, or T1/T3. The relation of Jaccard index values to intra-personal JS distances was tested with six multilevel linear regression models run for each pair of periods and for the two thresholds – 20 and 40, and, additionally, with six Pearson correlation tests.

5. Results

Below we describe our results in accordance with our three hypotheses.

5.1. Cognitive limits

As identified by TOST (two one-sided T-tests), the average number of alters with whom an ego has had at least some private messaging during a year does not significantly differ from Dunbar's number (150), within the empirically grounded bounds (100–250) (see Table 2A, B). Actually, the observed mean lies within narrower bounds (128–215) which confirms H1A. This makes testing H1B redundant.

Table 2
Equivalence of average alter number to Dunbar's number: (A) tests results, (B) specified equivalence bounds.

(A) Tests results				
	t	**df**	**P-value**	
***t*-test**	0.8424443	38	0.4048105	
TOST Upper	−3.059614	38	0.0020254	
TOST Lower	2.793473	38	0.0040616	
(B) Equivalence Bounds				
	Low	**High**	**Lower**	**Upper**
Cohen's d	−0.3124147	0.6248294		
Raw	−50.00000	100.0000	−21.61706	64.79654

As predicted, we find that the amount of communication is very unevenly distributed among the alters of the same ego. The best-fit distribution of the total number of characters sent or received in the three periods is truncated power-law with an exponential cutoff. Fig. 1A–C shows the distributions of the number of characters over egos' alters in the three periods. Prior research observes similar distributions of likes, comments, and friends over SNS users (Rykov, Nagornyy, & Koltsova, 2017; Rykov, 2015).

5.2. Communication volume and emotional closeness

To see whether the observed skewness is related to emotional closeness, we first plot the distribution of closeness classes (0–9) over all alters (Fig. 2A and B) and the median number of characters per alter in each closeness class as the function of the size of the closeness class (e.i. the number of alters in each closeness class) (Fig. 3).

We can see that in their friending behavior egos fall into two groups: those who are inclusive (Fig. 2A) and those who limit friending emotionally distant others (Fig. 2B). The former have more friends and a long-tail distribution similar to those shown in Fig. 1, while the latter have bell-shaped distributions and fewer friends. Fig. 3 plots all groups of closeness against their size and the median amount of communication between the members of each group and their respective egos. It roughly shows that the amount of communication increases with closeness and decreases with the group size, which is also inversely related to closeness. These trends are much more pronounced when means are plotted instead of medians (not reported here), but medians are more appropriate in our case due to the nature of the data distribution. Also, the graph includes those friends whom the respondents could not remember and whose closeness therefore they were not asked to evaluate, as well as those correspondents who are not friends at all. On average, the latter get more attention from egos than friends with closeness 0–2, but the median shows us that the mean of this class must be artificially inflated by a limited number of hyper-communicative non-friends, while the majority of them are the least communicated category among all groups of alters. Finally, we should note that Fig. 3 excludes an outlier respondent who skews the overall distribution. However, when added to the regression reported below, she does not alter its results.

Table 3 which shows the results of a multilevel regression confirms the close association between the reported emotional closeness of alters to egos and the amount of communication between them, which allows accepting H2. In particular, with the dependent variable (number of characters) having been log-transformed, the table shows that, on average, an increase in emotional closeness by one level brings a 126.5% increase in the number of characters sent and received (CI = 108,6–145,8). Conditional R^2 of 0.388 as compared to marginal R^2 = 0.224 tells us that variation between respondents is large, however, as shown in Table 3, they differ much more by the intercept than by the slope. In other words, the magnitude of relation between closeness and the amount of communication is not very different between respondents, while they differ much more in terms of the absolute number of characters sent and received. Examination of individual slopes (see appendix 1) also tells us that no respondents have a negative relation between the closeness of their alters and the amount of communication with them, which means that this relation is universal and is not influenced by the distribution of emotional class sizes shown in Fig. 2. However, linear approximations of individual distributions of the amount of communication over closeness classes may obscure their not perfectly linear character. As Fig. 4 shows, in fact respondents invest very different amount of effort into communication with alters from different closeness classes which is consistent with (Tamarit et al., 2018).

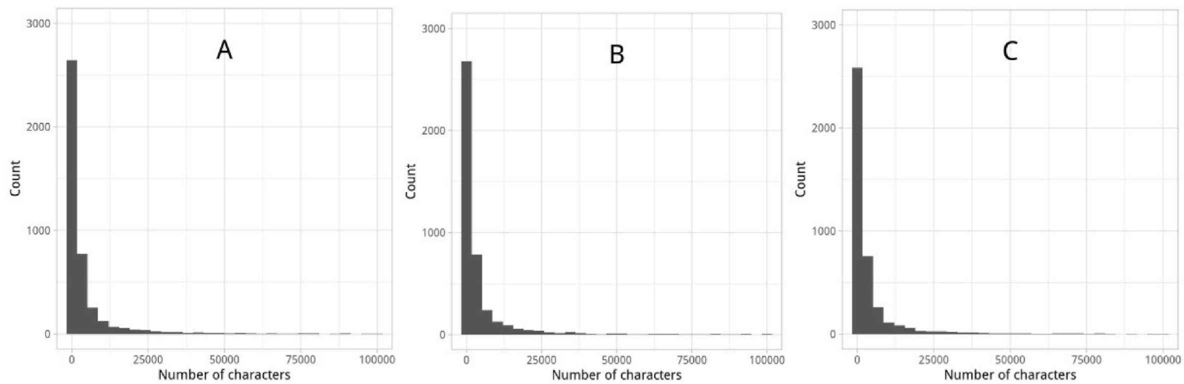

Fig. 1. Distributions of the number of characters over egos' alters in the three periods. (A) Period 1. (B) Period 2. (C) Period 3.

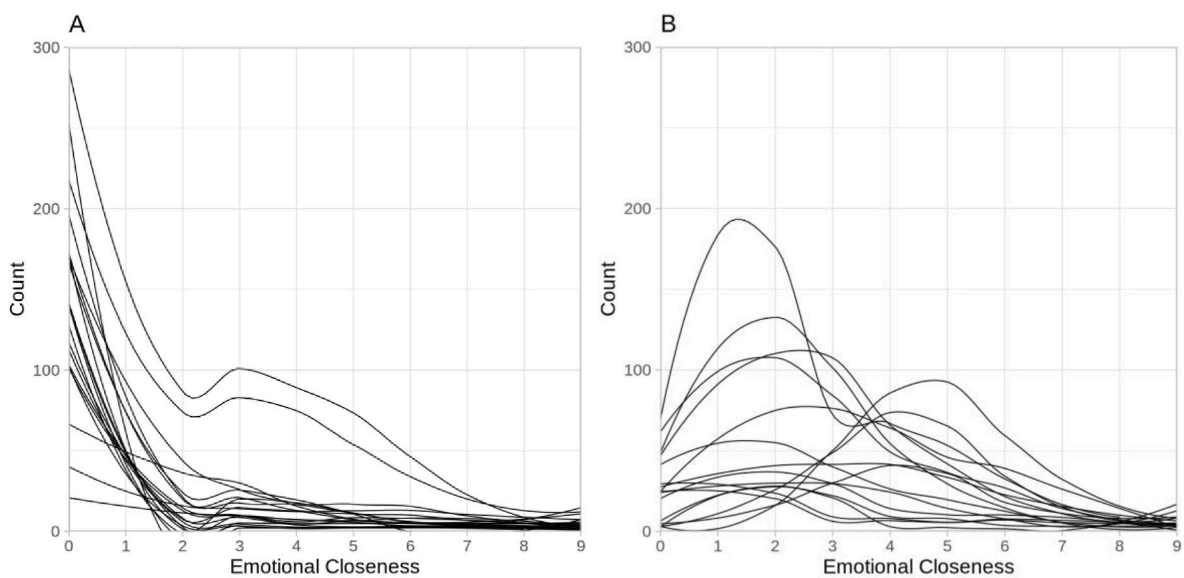

Fig. 2. Distribution of egos' alters number by their reported emotional closeness. A. Egos for whom 0 is the largest class (2 egos with 768 and 462 0-class friends excluded for better visualization). B. Egos for whom 0 is not the largest class.

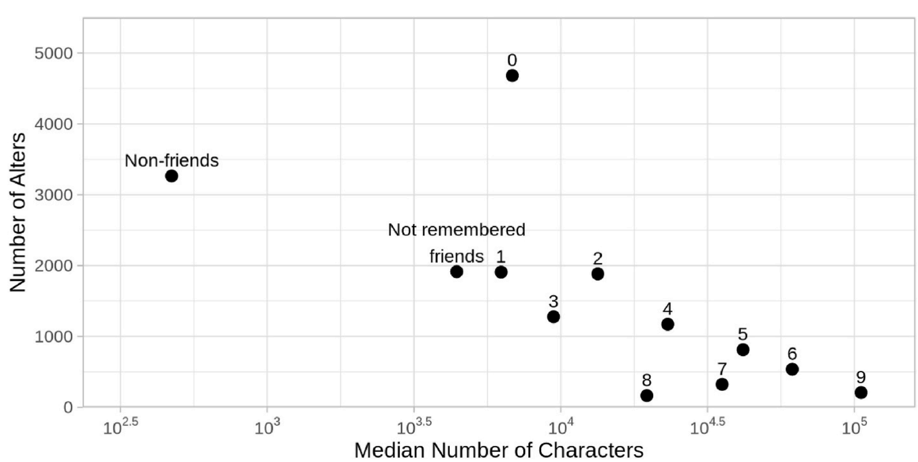

Fig. 3. Relation of communication intensity to emotional closeness. X-axis: median number of characters exchanged with alters in a given emotional class by all egos in period 3, log scale; Y-axis: number of alters in the emotional class across all egos.

5.3. Social signatures

Finally, we pass to hypothesis 3 which tests the existence of social signature as a stable communication pattern by comparing distributions of communication volume over egos' alters between different egos and between different periods of time of the same ego. However, before doing this we check whether the changes in these distributions might be related to the friend turnover – i.e. we check whether the burnout of old

Table 3
Relation of the emotional closeness of alters to the amount of communication between alters and egos. Multilevel linear regression with random slopes & intercepts; level 1 = respondents (egos), $N_1 = 39$; level 2 = alters, $N_2 = 12964$.

Dependent:	*number of characters, log-transformed*				
Random effects:					
Groups	**Name**	**Variance**	**Std. Dev.**	**Corr**	
resp_id	(Intercept)	1.95964	1.400		
closeness		0.05905	0.243	0.01	
Residual		9.38124	3.063		
Fixed Effects:					
	Estimate	**Std. Error**	**df**	**t value**	**Pr(>|t|)**
(Intercept)	0.83440	0.22944	36.65595	3.637	0.000843 ***
Closeness	0.81738	0.04184	38.86022	19.534	<2e-16 ***

friends and the influx of new friends might be responsible for social signature change. As evaluated by both Pearson correlation and linear regression, the relation is exceptionally weak and insignificant (for details, see Appendix 1).

In 16 out of 18 Mann-Whitney tests employed to test H3A intra-personal differences are significantly smaller than inter-personal ($p < 0.05$, and mostly $p < 0.01$). The two insignificant tests ($p = 0.288$ and 0.068) involve JS distances between periods 1 and 3 that reflect the cumulative change of social signature during the entire period of study. As Fig. 5 shows, cumulative self-distances are generally larger than distances both between T1 and T2, and between T2 and T3. We thus can confirm H3A and conclude that changes of social signature within individuals – or, more precisely, short-term changes – are indeed smaller than differences between social signatures of different individuals within any given period.

Passing to H3B, we present the summary of the Kolmogorov-Smirnov tests performed to compare distributions of the amount of communication of the same egos between different periods of time (see Tables 4 and 5). As Table 5 shows, we can observe a mixture of more and less stable respondents. Overall, the majority of changes in all but one category presented in Table 4 are significant. It can be seen that

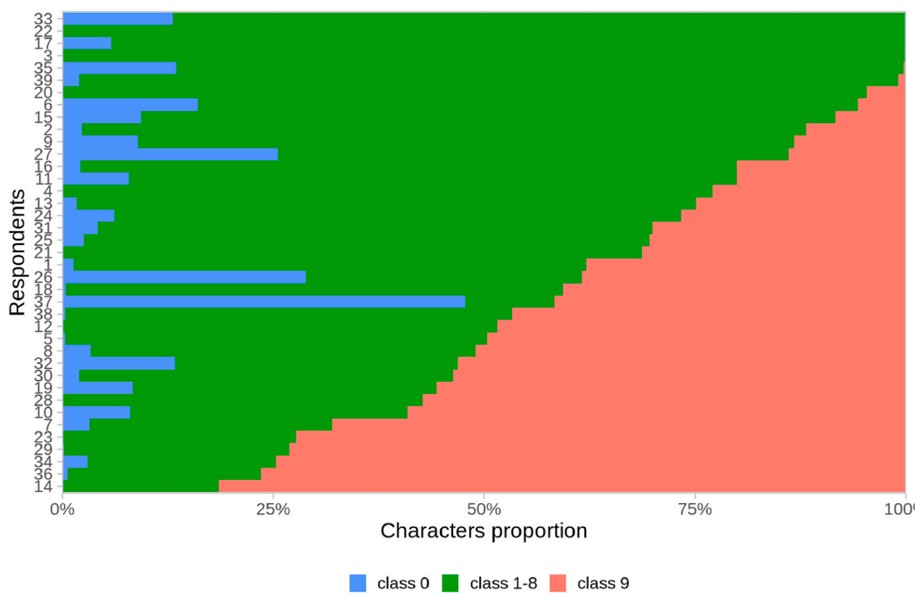

Fig. 4. The amount of communication between egos and their alters in T3. X axis: share of the number of characters exchanged with the alters of a given emotional class (group of classes), among the total number of characters. Y axis: individual respondent's ID sorted by the amount of communication with class 9 alters. Blue: class 0, red: classes 1–8; green: class 9 (the closest alters).

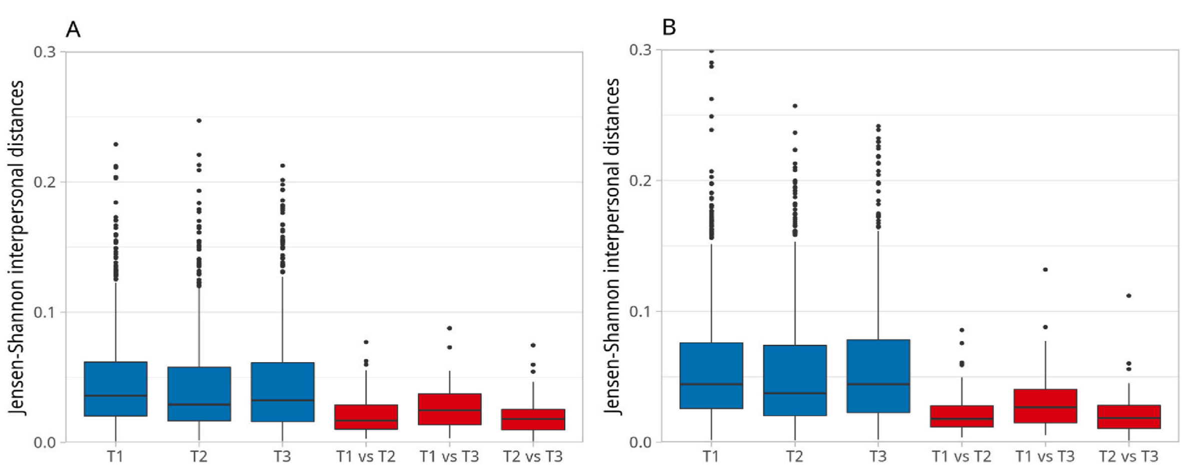

Fig. 5. Average intra-personal and inter-personal differences measured as Jensen-Shannon distances. A: differences between distributions of communication among top 20 alters; B: the same based on top 40 alters. Blue: differences between different egos in the same period T1, T2 or T3. Red: differences between different periods of time T1 and T2, T2 and T3 or T1 and T3 of the same egos.

Table 4
Comparison of social signatures of the same egos between different periods of time, Kolmogorov-Smirnov test.

		T1 vs T2	T2 vs T3	T1 vs T3
Top 20 friends	Significant ($p < 0.05$)	16	21	22
	Non-significant	23	18	17
Top 40 friends	Significant ($p < 0.05$)	21	25	27
	Non-significant	18	14	12

Table 5
Distribution of respondents by the number of significant changes in their social signatures, as determined by Kolmogorov-Smirnov tests comparing periods T1 vs T2, T2 vs T3 and T1 vs T3.

	Top 20 friends	Top 40 friends
3 non-significant changes	8	3
2 non-significant changes	8	6
1 non-significant change	18	23
All changes significant	5	7

significant changes occur more often between periods 1 and 3 which is expectable as this change takes place over a longer period of time. Also, changes in social signatures based on top 40 friends are larger than in those based on top 20 friends although visually this does not seem to be the case (Fig. 5). As our sample is relatively small, this evidence is of suggestive nature which is why we apply the Stouffer test as a meta-analytic metric that tests the global null hypothesis about overall insignificance of p-values. For all six categories (three pairs of periods compared based on top 20 and top 40 friends) the null hypothesis was rejected with the global p-value < 0.01. This means that in general we cannot claim that social signatures tend to be stable over time and should reject H3B.

6. Discussion and conclusion

In our research we obtained several empirical findings that are important for the development of human communication theory, specifically in relation to the phenomenon of social signature, its stability, "size", shape, relation to alters' turnover and emotional proximity with an ego. Our findings are summarized and interpreted below.

6.1. OSNs may help go around cognitive limits only indirectly, if at all

We show that the studied OSN does not give individuals any advantages for cutting through Dunbar's number and for growing their network of active contacts. This happens despite our decision to adopt a very mild definition of an active contact – at least one reciprocal contact in a year – and despite pre-selection of only those users who claim to maintain relations with $\geq$80% of their important alters via VKontakte. A simplest explanation would be that either the studied OSN or OSNs, in general, are not suitable for cutting through Dunbar's number, or that such break-through is not possible at all.

However, since a positive relationship between internet use and the size of offline networks has been shown in several studies referred to above (Wang & Wellman, 2010; Zhao, 2006), the situation may have more profound theoretical explanations. First, the causation in these studies may be reverse: large offline networks might be not an outcome of heavy internet use, but a cause – in other words, individuals with higher cognitive capacity might channel communication with their larger networks both offline and online. Moreover, it might be the case that only these individuals would be able to make use of OSNs for the growth of their ego-networks, while others would lose offline contacts due to the inability to include OSNs into their communicative toolkit. Thus, OSNs might play a polarizing role while still keeping the average size of ego-networks around the magic number of 150. This is a new possible view of the role of OSNs for human personal networks, distinct from both Wellman's and Dunbar's interpretations.

Second, the ability of OSNs to expand ego-networks might work in a subtle way that is not captured by our research design but is in line with the assumption made by Wellman (Rainie & Wellman, 2012). When our respondents claim that they maintain most of their significant contacts via VK they, first, do not claim to do it solely via private messaging, and second, they do not claim doing it solely via VKontakte. Apart from private messages, OSNs offer a diverse functionality, such as simultaneous reach of large numbers of alters with public posts, cheap reactions in the form of likes and others. Taken together, these functionalities may allow users to rotate the most intensively contacted alters, temporarily including some of their friends into active private messaging, but keeping many more in the loop via different, less time-consuming functionalities. Such dormant contacts that are likely to die out offline may be easier activated if they are "conserved and stored" online. This might let users if not directly break through Dunbar's number, then go around it. Among other things, the ability to activate dormant contacts is one of the possible explanations of OSN's efficiency for social capital accumulation and mobilization.

6.2. Communication volume and emotional closeness are related, but highly individual

Our next finding is generally in line with the theory of social layers (Sutcliffe et al., 2012). As in Saramaki (Saramäki et al., 2014), we find that the amount of communication with alters is very unevenly distributed and related to their emotional closeness. However, we should note that emotional closeness is far from explaining all the variance in the amount of communication. Moreover, since in our model conditional R^2 is larger than marginal R^2, the variation among individuals by the strength of their relation between closeness and communication volume is in fact higher than the overall effect of closeness on communication volume. In other words, while some individuals invest most of their communicative effort into their closest alters, others spread their communication much more evenly which means that, for their private messaging strategy, emotional closeness is of little or no significance. This can also be seen from Fig. 4. Furthermore, we show that a large portion of our sample prefers to filter emotionally distant alters out of their online friends, while another large portion is much more inclusive. These details add a lot of complexity to the social layers theory questioning the focus on their average sizes and calling for the focus on factors influencing individual variation of layer sizes, proportions, and composition.

6.3. Online social signatures are not stable over time

Finally, our third finding is about stability – and, therefore, the very existence – of social signature as a constant feature of an individual. Here, we have compared individual distributions of the number of contacts among alters, and we have done those comparisons both between different individuals and between different periods of the same individual. We find that intra-personal differences are smaller than interpersonal, still they are significant. In other words, communication strategies both vary among humans and change with time, but short-term changes are smaller than the variation between humans. Moreover, we find that differences between non-neighbor periods are larger than between neighbor periods. It is thus quite plausible that periods can be found that are long enough to make the difference between intrapersonal and interpersonal distances insignificant or non-existent.

These findings provide more support for the indirect evidence about the changeability of the communication structure over time found in the number of the reviewed works (Calastri et al., 2017; David-Barrett et al., 2016; Van den Berg et al., 2012) rather than to the social signature hypothesis. Interestingly, in his recent work, "The anatomy of friendship" (Dunbar, 2018, p. 34) Dunbar also cites studies showing that the size of ego-networks tends to change during the human life-cycle – expanding in the young age and shrinking in the middle age and especially in the old age. Moreover, he points at the possibility of not only network size, but also the distribution of communication over contacts to change with time: "once reproduction sets in, many of the less congenial relationships are shed in order to concentrate what time and effort is available on the relationships that matter most" (Dunbar, 2018, p. 34).

All this goes against the very core of the idea of social signature and against conclusions of Saramaki (Saramäki et al., 2014), Heydari (Heydari et al., 2018) and Liu (Liu et al., 2018). However, three reservations should be made here.

First, the existing research provides indirect evidence on long-term volatility of communication volume distributions while we so far find short-term volatility that might have different explanations. Switching between the channels of communication is one of them. If for some individuals no single communication channel accumulates the lion share of communication volume, their entire communication networks may turn to be both more or less stable, and they may also turn to be bigger and exhibit different distributions. Second, if we examine individual signatures in our sample, we see that some individuals, albeit a minority, pass the test for social signature stability. As Centellegher et al. (2017) show, the degree of stability may be related to certain personality traits which means that the social signature hypothesis may hold for some population subgroups, but not the others.

Third, the definition of social signature stability is still an open question. How similar should two distributions be to be considered roughly the same? We apply the Kolmogorov-Smirnov test whose null hypothesis assumes that the two compared samples have been drawn from the same population and, therefore, should have identical distributions. KS test is a natural choice for comparison of distributions, however, alternative methods might be offered that would be directly grounded in the theory of psychology and cognitive science. Our findings thus show that social signature theory has a lot of room for enrichment and refinement with a whole range of nuances. We demonstrate that social signature stability can hold only for certain populations, in certain channels or, perhaps, only across them, and under a certain definition of stability to be defined.

6.4. Practical significance

Additionally, our research has several practical implications some of which were anticipated (see introduction) while others were not. The first is associated with confirming the existence of the cognitive limit to communication in private messaging. Struggling for user retention, OSNs often seek to increase user engagement which creates information and communication overload and may in the end contribute to user churn. Knowledge of cognitive limitations may help OSNs develop strategies of engaging users without overloading them. Instead of only offering more and more new friends, OSNs could also offer users handy functionalities for navigating, filtering, and categorizing their networks without doing it entirely manually.

A second practical implication follows from our observation of a relatively high variation in the distribution of emotional closeness and communication volume over alters, both between the egos and the different periods of the same ego. Although we do not find social signature stability we find variation that if studied may shed light on individuals' strategies of social media use in terms of communication intensity and emotional engagement. This in turn may help develop OSN functionalities that meet individual communicative goals. We also observe the individual and the overall bounds for social signature volatility. While just any statistically significant change may be unable to indicate any meaningful changes in user conditions or intentions, the change beyond the empirically grounded bounds does seem able to indicate the fall of well-being, satisfaction with OSN, or churn intention.

6.5. Limitations and future research

As follows from sections 6.1-6.3, some of our results may be interpreted only after additional research which is needed to overcome certain limitations present in this study.

First, our work shares the limitations of all case studies: our evidence against the idea of social signature is based on one communication channel (private messages in an OSN), one OSN (VKontakte), and one society (Russia) – just as the previous evidence in favor of social signature was also based on separately studied cases. A more profound limitation of all this group of studies, including ours, is that few individuals in modern societies use only one channel of communication, and thus single-channel approaches can never reveal complete personal networks. A more interesting research question in this context is not whether social signature holds within a specific channel, but whether it holds in complete individual communication networks of those who have e.g. social media among their communication channels and those who have not. This question is extremely difficult to answer given the unavailability of face-to-face communication traces right now, therefore, it will be waiting for a suitable technology to develop. Meanwhile, more single-channel replication studies are needed.

A related question of interest in this context is whether social media and other ICTs help expand personal networks not by direct breakthrough the Dunbar's number, but via functionalities able to reduce cognitive load. The meaningfulness of human relations is often determined by the possibility to rely on alters when help is needed; social media allow users to quickly mobilize help without maintaining time-consuming or cognitively expensive relations. This may lead to the expansion of the number of meaningful others beyond Dunbar's number without either the growth of communication volume or the increase in the number of emotionally close alters. In fact, communication volume, emotional closeness, and helpfulness may get detached from one another as a result OSN influence on human communication (which is suggested by our exploratory analysis of emotional closeness distributions). Studying whether all this is really so requires research designs that are different from ours, and looks like a promising direction for future research.

Finally, talking about the meaning of meaningfulness we should once again point at the underdevelopment of definitions of core concepts that underlie both HSB theory and social signature theory as its part. Above all, these include the concept of meaningful relations and the concept of social signature stability. This underdevelopment has not been fully overcome in our work either. Our design based on digital traces does not allow measuring meaningfulness, while our way to measure stability is not the only one possible. More theoretical and empirical work is needed to develop these definitions. Once this goal is reached, it will become possible to more precisely determine the conditions under which the social signature hypothesis holds – whether it be a certain communication channel or a certain set of personality traits or a certain period in a life cycle. These questions form an agenda for a whole stream of future studies.

Declaration of competing interest

Authors report no conflicts of interest.

Acknowledgement

We would like to express special gratitude to Ekaterina Titkova and Maxim Koltsov for developing the software for collecting data and interviewing respondents. Our sincere thanks also go to Sergey Titov who participated in creating the initial study design and data processing; his bright ideas, assistance, and interest in the study helped us go through many difficulties and see the first results.

Appendix

Hypothesis formulation

At the initial stage of our research, we first formulated hypotheses conceptually as accurately as possible. We then reviewed and carefully examined the relevant statistical methods that we could use to test the corresponding null hypotheses. After that, we made important clarifying and final edits to the wordings of our hypotheses, trying to eliminate any inaccuracies, discrepancies, and redundancies. Thus, we were guided by several principles and by the fact that the wordings of the hypotheses should be uncluttered and at the same time conceptually concise, statistically correct and contain critical statistical details for a reader to grasp the context that we put across our hypotheses.

In our hypotheses, we used the concepts from social network analysis (alters and ego-network) and from HSB theory (Dunbar's number), which allowed us to convey the intended meaning very accurately. When formulating H1A, we kept in mind the assumptions of the TOST test, which was used for verification and which requires setting the values of the equivalence bounds that are essential for outlining the scope of this hypothesis. The bounds are required because the assumption tested by TOST (and interesting to us) is essentially negative - we assume the absence of difference from, while usually the presence of difference is tested. Furthermore, we assume the absence of difference of a sample mean from a number, not from a mean of another sample, as it is usually done. Therefore, the presence of exact bounds that might complicate the hypothesis' comprehension was found to be necessary.

Hypothesis H1B required fewer numeric values than hypothesis H1A. But we could not omit such details completely, and clearly stated the value of Dunbar's number to avoid any ambiguity. Here we also used the terminology from social network analysis.

Hypothesis H2 is stated succinctly. We clearly propose the positive association between two variables—emotional closeness and volume of communication. This hypothesis is also in full agreement with the underlying statistical procedure—multilevel regression analysis—that we used to verify it.

The wordings of hypotheses H3B and especially H3A had to be made longer in accordance with the complex nature of the assumption tested. Instead of just stating that we expect social signature to be a stable phenomenon, we chose much more technical wordings in order to precisely determine what will be tested and to justify why the assumption has to be broken into two hypotheses, and how exactly they differ. Simultaneously, to keep the reader in context, we chose to explain what is meant by inter-personal and intra-personal distance right within the formulation of H3A.

Formulating H3B presented a challenge similar to that with H1A as our assumption was negative - that is, we expected the difference between the two tested values to be insignificant. This is unusual as, most often, what is being tested are assumptions about the presence of statistical difference, not its absence. We chose to state this plainly and in a technical manner.

Analyzing the average number of alters

Our hypotheses concerning the average number of alters in an ego-network of OSN private messaging determined the choice of two appropriate statistical tests: 1) two one-sided T-tests (TOST) for hypothesis H1A, 2) an ordinary one-sided one sample T-test for hypothesis H1B.

TOST tests the null hypothesis that two mean values (two-sample test), or a mean value and a theoretical value (one-sample test), are not equivalent, and the alternative hypothesis is that they are equivalent within some practical limit that should be specified by the researcher. TOST consists of two one-sided T-tests that are used to test the estimate against values of lower and upper equivalence bounds (ΔL and ΔU). To draw a conclusion of statistical equivalence, both tests must be statistically significant (p value < alpha). We used its implementation in TOSTER R package.

One-sided T-test checks the null hypothesis that a true mean is less than or not different from the theoretical number or a population mean. The alternative hypothesis is that a true mean is greater than population one, which corresponds to our formulation of hypothesis H1B.

Association between emotional closeness and the volume of communication

Our data possess a clear hierarchical structure, with alters, being the lowest level, nested within egos (the second level). Thus, to estimate the association between emotional closeness and the volume of communication, we used multilevel regression modeling. R packages *lmerTest* and *lme4*—widely accepted and stable solutions—were chosen to carry out modeling. We have built several linear models with *lmer* function: random intercept only, random slope only, random intercept and slope. The fitted models were compared and the best model was chosen based on the following metrics: AIC, BIC, log-likelihood. To calculate conditional and marginal r^2, we used *performance* package.

Prior to multilevel modeling, we analyzed the distribution of the total number of characters sent and received between an ego and an alter with *powerlaw* package for Python programming language. This package offers goodness-of-fit tests for various distributions. The obtained results show that our data are best approximated by truncated power-law distribution ($\alpha = 1.834$, $\lambda = 4.431\text{e-}7$). Thus, we applied natural logarithm transformation to the total number of characters to meet the linear regression assumption of data and residuals normality.

Social signature analysis

The methodology of social signature analysis, due to its complexity, has got a relatively detailed description within our paper; here, we repeat the core aspects of the methodology while supplementing them with some additional details.

We constructed social signatures for all egos as the distributions of the total number of sent/received characters by their alters, corresponding to the function NC = f(R), where NC is the number of characters either sent or received by a given ego's alter, and R is the rank of this alter in the list of this ego's alters sorted by the number of characters sent/received. These distributions were created for three consecutive 6-month periods T1, T2, and T3, limited by two thresholds—20 and 40 alters—and padded with zeros if shorter.

To compare social signatures, we applied Saramaki's and Heydai's method and estimated Jensen-Shannon distances (JS) using *distance* function from *philentropy* R package. Given three periods of time and two thresholds, six sets of distances were calculated: (1) interpersonal, between egos of the same period (JS20-alterT1, JS20-alterT2, JS20-alterT3, JS40-alterT1, JS40-alterT2, JS40-alterT3), (2) intrapersonal, between different periods of the same ego (JS20-selfT1/T2, JS20-selfT2/T3, JS20-selfT1/T3, JS40-selfT1/T2, JS40-selfT2/T3, JS40-selfT2/T3). Furthermore, we modified the initial

Saramäki's approach by introducing a set of statistical tests to check whether the visually observed differences are significant: 1) Mann-Whitney rank test (for hypothesis 3A), 2) Kolmogorov-Smirnov two-sample test (for hypothesis 3B).

Mann-Whitney rank test was chosen because of non-normal distributions of JS distances in all inter- and intra-personal sets. We used wilcox.*test* function from *stats* R package which offers the default implementation of this test. We performed 18 one-sided Mann-Whitney tests comparing all 20- and 40-alter-based interpersonal distances to all corresponding interpersonal distances.

We chose the Kolmogorov-Smirnov test (KS) and its standard implementation in *ks.test* function from *stats* R package to compare social signature distributions of egos intrapersonally. First, we performed a series of KS tests comparing two social signature distributions of the same ego from two different time periods and for two thresholds (20 and 40 alters): T1 vs T2, T2 vs T3, or T1 vs T3. Thus, we obtained six sets of different results (39 individual results in each) that had to be further generalized. To test the global hypothesis of the overall equivalence of all distributions within each pair of time periods and threshold (alters limit), we selected the Stouffer test as the most statistically powerful in its category (Futschik et al., 2019), and applied it to six sets of individual results. We used its implementation in *poolr* R package.

Following Saramaki's approach, we carried out further analysis to figure out if the change of social signature over time could be affected by alters turnover. We estimated alters turnover using the Jaccard index that compared the sets of top 20 or 40 alters who sent or received messages to/from an ego between periods T1/T2, T2/T3, or T1/T3:

$$J\left(A_i, A_j\right) = \frac{A_i \cap A_j}{A_i \cup A_j}$$

The association between Jaccard indices and intra-personal JS distances was analyzed using Pearson correlation tests and multilevel linear regression models built for each pair of periods and both thresholds–20 and 40 (six tests and six models, in total).

Credit author statement

Olessia Koltsova: Supervision, Project administration, Conceptualization, Methodology, Writing – original draft, Writing – review & editing. Larisa Mararitsa: Conceptualization, Methodology, Investigation, Writing – review & editing. Maxim Terpilovskii: Formal analysis, Data curation, Visualization, Software, Writing – original draft, Writing – review & editing. Yadviga Sinyavskaya: Project administration, Investigation, Data curation, Writing – review & editing.

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References

Bernard, H. R., Killworth, P. D., Johnsen, E. C., Shelley, G. A., & McCarty, C. (2001). Estimating the ripple effect of a disaster. *Connections, 24*(2), 18–22.
Blair, B. L., Fletcher, A. C., & Gaskin, E. R. (2015). Cell phone decision making: Adolescents' perceptions of how and why they make the choice to text or call. *Youth & Society, 47*(3), 395–411.
Calastri, C., Hess, S., Daly, A., Maness, M., Kowald, M., & Axhausen, K. (2017). Modeling contact mode and frequency of interactions with social network members using the multiple discrete–continuous extreme value model. *Transportation Research Part C: Emerging Technologies, 76*, 16–34.
Cao, X., & Sun, J. (2018). Exploring the effect of overload on the discontinuous intention of social media users: An S-O-R perspective. *Computers in Human Behavior, 81*, 10–18.
Centellegher, S., López, E., Saramäki, J., & Lepri, B. (2017). Personality traits and ego-network dynamics. *PloS One, 12*(3).
David-Barrett, T., Kertesz, J., Rotkirch, A., Ghosh, A., Bhattacharya, K., Monsivais, D., & Kaski, K. (2016). Communication with family and friends across the life course. *PloS One, 11*(11), Article e0165687.
Degenne, A., & Lebeaux, M. O. (2005). The dynamics of personal networks at the time of entry into adult life. *Social Networks, 27*(4), 337–358.
Donath, J., & boyd, d. (2004). Public displays of connection. *BT Technology Journal, 22*(4), 71–82.
Dunbar, R. I. (1992). Neocortex size as a constraint on group size in primates. *Journal of Human Evolution, 22*(6), 469–493.
Dunbar, R. I. M. (1998). The social brain hypothesis. *Evolutionary Anthropology: Issues, News, and Reviews, 6*(5), 178–190.
Dunbar, R. I. M. (2009). The social brain hypothesis and its implications for social evolution. *Annals of Human Biology, 36*(5), 562–572.
Dunbar, R. I. M. (2016). Do online social media cut through the constraints that limit the size of offline social networks? *Royal Society Open Science, 3*(1).
Dunbar, R. I. M. (2018). The anatomy of friendship. *Trends in Cognitive Sciences, 22*(1), 32–51.
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.
Ellison, N. B., Vitak, J., Gray, R., & Lampe, C. (2014). Cultivating social resources on social network sites: Facebook relationship maintenance behaviors and their role in social capital processes. *Journal of Computer-Mediated Communication, 19*(4), 855–870.
Faurholt-Jepsen, M., Vinberg, M., Frost, M., Debel, S., Margrethe Christensen, E., Bardram, J. E., & Kessing, L. V. (2016). Behavioral activities collected through smartphones and the association with illness activity in bipolar disorder. *International Journal of Methods in Psychiatric Research, 25*(4), 309–323.
Futschik, A., Taus, T., & Zehetmayer, S. (2019). An omnibus test for the global null hypothesis. *Statistical Methods in Medical Research, 28*(8), 2292–2304.
Gaito, S., Quadri, C., Rossi, G. P., & Zignani, M. (2017). *Urban communications and social interactions through the lens of mobile phone data. 1* pp. 70–81). Online Social Networks and Media.
Godoy-Lorite, A., Guimerà, R., & Sales-Pardo, M. (2016). Long-term evolution of email networks: Statistical regularities, predictability and stability of social behaviors. *PloS One, 11*(1).
Gonçalves, B., Perra, N., & Vespignani, A. (2011). Modeling users' activity on twitter networks: Validation of dunbar's number. *PloS One, 6*(8), Article e22656.
Granovetter, M. S. (1973). The strength of weak ties: A network theory revisited. *Sociological Theory, 1*, 201–233.
Haerter, J. O., Jamtveit, B., & Mathiesen, J. (2012). Communication dynamics in finite capacity social networks. *Physical Review Letters, 109*(16), 168701.
Hayat, S., Rextin, A., Idris, A., & Nasim, M. (2020). Text and phone calls: User behaviour and dual-channel communication prediction. *Human-centric Computing and Information Sciences, 10*, 1–18.
Heydari, S., Roberts, S. G., Dunbar, R. I., & Saramäki, J. (2018). Multichannel social signatures and persistent features of ego networks. *Applied network science, 3*(1), 8.
Hill, R. A., & Dunbar, R. I. M. (2003). Social network size in humans. *Human Nature, 14*(1), 53–72.
Holt-Lunstad, J., Smith, T. B., Baker, M., Harris, T., & Stephenson, D. (2015). Loneliness and social isolation as risk factors for mortality: A meta-analytic review. *Perspectives on Psychological Science, 10*(2), 227–237.
Holt-Lunstad, J., Smith, T. B., & Layton, J. B. (2010). Social relationships and mortality risk: A meta-analytic review. *PLoS Medicine, 7*(7).
House, J. S., Landis, K. R., & Umberson, D. (1988). Social relationships and health. *Science, 241*(4865), 540–545.
Jokinen, T., Brewster, C., & Suutari, V. (2008). Career capital during international work experiences: Contrasting self-initiated expatriate experiences and assigned expatriation. *International Journal of Human Resource Management, 19*(6), 979–998.
Kelley, P. G., Brewer, R., Mayer, Y., Cranor, L. F., & Sadeh, N. (2011). An investigation into Facebook friend grouping. *IFIP conference on human-computer interaction*. Berlin, Heidelberg: Springer.
Lakens, D., Scheel, A. M., & Isager, P. M. (2018). Equivalence testing for psychological research: A tutorial. *Advances in Methods and Practices in Psychological Science, 1*(2), 259–269.
Lampinen, A., Lehtinen, V., Lehmuskallio, A., & Tamminen, S. (2011). We're in it together: Interpersonal management of disclosure in social network services. In

Proceedings of the SIGCHI conference on human factors in computing systems (pp. 3217–3226). New York: ACM.
Lampinen, A., Tamminen, S., & Oulasvirta, A. (2009). All my people right here, right now: Management of group co-presence on a social networking site. In *Proceedings of GROUP '09* (pp. 281–290). New York: ACM.
Lee, A. R., Son, S.-M., & Kim, K. K. (2016). Information and communication technology overload and social networking service fatigue: A stress perspective (Part A) *Computers in Human Behavior, 55*, 51–61.
Liu, J. G., Guo, Q., & Zhang, Y. C. (2018). Collective iteration behavior for online social networks. *Physica A: Statistical Mechanics and Its Applications, 499*, 490–497.
Lubbers, M. J., Molina, J. L., Lerner, J., Brandes, U., Ávila, J., & McCarty, C. (2010). Longitudinal analysis of personal networks. The case of Argentinean migrants in Spain. *Social Networks, 32*(1), 91–104.
MacCarron, P., Kaski, K., & Dunbar, R. (2016). Calling Dunbar's numbers. *Social Networks, 47*, 151–155.
Madell, D. E., & Muncer, S. J. (2007). Control over social interactions: An important reason for young people's use of the internet and mobile phones for communication? *CyberPsychology and Behavior, 10*(1), 137–140.
Manago, A. M., Taylor, T., & Greenfield, P. M. (2012). Me and my 400 friends: The anatomy of college students' Facebook networks, their communication patterns, and well-being. *Developmental Psychology, 48*(2), 369.
McCormick, T. H., Salganik, M. J., & Zheng, T. (2010). How many people do you know?: Efficiently estimating personal network size. *Journal of the American Statistical Association, 105*(489), 59–70.
Miritello, G., Moro, E., Lara, R., Martínez-López, R., Belchamber, J., Roberts, S. G., & Dunbar, R. I. (2013). Time as a limited resource: Communication strategy in mobile phone networks. *Social Networks, 35*(1), 89–95.
Parady, G. T., Frei, A., Kowald, M., Guidon, S., Wicki, M., van den Berg, P., & Axhausen, K. W. (2020). A comparative study of contact frequencies among social network members in five countries. In *99th annual meeting of the transportation research board: New mobility and transportation technology takeaways (TRB 2020)*. ETH Zurich: IVT, 20-00676.
Petkos, G., Papadopoulos, S., & Kompatsiaris, Y. (2015). Social circle discovery in ego-networks by mining the latent structure of user connections and profile attributes. In *2015 IEEE/ACM international conference on advances in social networks analysis and mining (ASONAM)* (pp. 880–887). IEEE.
Pollet, T. V., Roberts, S. G., & Dunbar, R. I. M. (2011). Use of social network sites and instant messaging does not lead to increased offline social network size, or to emotionally closer relationships with offline network members. *Cyberpsychology, Behavior, and Social Networking, 14*(4), 253–258.
Raeder, T., Lizardo, O., Hachen, D., & Chawla, N. V. (2011). Predictors of short-term decay of cell phone contacts in a large-scale communication network. *Social Networks, 33*(4), 245–257.
Rainie, H., & Wellman, B. (2012). *Networked: The new social operating system* (Vol. 419). Cambridge, MA: MIT Press.
Rohani, D. A., Faurholt-Jepsen, M., Kessing, L. V., & Bardram, J. E. (2018). Correlations between objective behavioral features collected from mobile and wearable devices and depressive mood symptoms in patients with affective disorders: A systematic review. *JMIR mHealth and uHealth, 6*(8).
Russian center for public opinion research. (2018). Statistical report on the social networking sites engagement among users of different ages in Russia. Available at: https://wciom.ru/index.php?id=236&uid=116691/. (Accessed 25 July 2020).
Rykov, Y. (2015). Network inequality and the structure of online communities. *Journal of Sociology and Social Anthropology, 18*(4), 144–156.
Rykov, Y., Nagornyy, O., & Koltsova, O. (2017). Digital inequality in Russia through the use of a social network site: A cross-regional comparison. In *International Conference on Digital Transformation and Global Society* (pp. 70–83). Cham: Springer.
Saramäki, J., Leicht, E. A., López, E., Roberts, S. G., Reed-Tsochas, F., & Dunbar, R. I. (2014). Persistence of social signatures in human communication. *Proceedings of the National Academy of Sciences, 111*(3), 942–947.
Sawaguchi, T., & Kudo, H. (1990). Neocortical development and social structure in primates. *Primates, 31*(2), 283–289.
Schelde, J. T. M. (1998). Major depression: Behavioral markers of depression and recovery. *The Journal of Nervous and Mental Disease, 186*(3), 133–140.
Shi, M., Yang, B., & Chiang, J. (2018). Dyad calling behavior: Asymmetric power and tie strength dynamics. *Journal of Interactive Marketing, 42*, 63–79.
Shor, E., Roelfs, D. J., & Yogev, T. (2013). The strength of family ties: A meta-analysis and meta-regression of self-reported social support and mortality. *Social Networks, 35*, 626–638.
Sutcliffe, A., Dunbar, R., Binder, J., & Arrow, H. (2012). Relationships and the social brain: Integrating psychological and evolutionary perspectives. *British Journal of Psychology, 103*(2), 149–168.
Tamarit, I., Cuesta, J. A., Dunbar, R. I., & Sánchez, A. (2018). Cognitive resource allocation determines the organization of personal networks. *Proceedings of the National Academy of Sciences, 115*(33), 8316–8321.
Timon, E., & Christoph, S. (2020). Depressive symptoms are associated with social isolation in face-to-face interaction networks. *Scientific Reports, 10*(1).
Traud, A. L., Mucha, P. J., & Porter, M. A. (2012). Social structure of Facebook networks. *Physica A: Statistical Mechanics and Its Applications, 391*(16), 4165–4180.
Van den Berg, P. E., Arentze, T. A., & Timmermans, H. J. (2012). New ICTs and social interaction: Modelling communication frequency and communication mode choice. *New Media & Society, 14*(6), 987–1003.
VK registry. (2021). Available at: https://vk.com/catalog.php?selection=636-16-35/. (Accessed 18 January 2021).
Vriens, E., & van Ingen, E. (2018). Does the rise of the internet bring erosion of strong ties? Analyses of social media use and changes in core discussion networks. *New Media & Society, 20*(7), 2432–2449.
Walther, J. B. (2007). Selective self-presentation in computer-mediated communication: Hyperpersonal dimensions of technology, language, and cognition. *Computers in Human Behavior, 23*(5), 2538–2557.
Wang, H., & Wellman, B. (2010). Social connectivity in America: Changes in adult friendship network size from 2002 to 2007. *American Behavioral Scientist, 53*(8), 1148–1169.
Webindex, Mediascope (2018). *Average daily reach.* https://mediascope.net/data/?FILTER_TYPE=internet/. (Accessed 25 July 2020).
Webindex, Mediascope. (2019). Monthly reach. Available at: https://mediascope.net/data/?FILTER_TYPE=internet/. (Accessed 25 July 2020).
Wellman, B. (2011). Is Dunbar's number up? *British Journal of Psychology, 103*(2), 174–176.
Zhao, S. (2006). Do internet users have more social ties? A call for differentiated analyses of internet use. *Journal of Computer-Mediated Communication, 11*(3), 844–862.