Persistence of social signatures in human communication

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The social network maintained by a focal individual, or ego, is intrinsically dynamic and typically exhibits some turnover in membership over time as personal circumstances change. However, the consequences of such changes on the distribution of an ego's network ties are not well understood. Here we use a unique 18-mo dataset that combines mobile phone calls and survey data to track changes in the ego networks and communication patterns of students making the transition from school to university or work. Our analysis reveals that individuals display a distinctive and robust social signature, captured by how interactions are distributed across different alters. Notably, for a given ego, these social signatures tend to persist over time, despite considerable turnover in the identity of alters in the ego network. Thus, as new network members are added, some old network members either are replaced or receive fewer calls, preserving the overall distribution of calls across network members. This is likely to reflect the consequences of finite resources such as the time available for communication, the cognitive and emotional effort required to sustain close relationships, and the ability to make emotional investments.

quantitative sociology | personal relationships

Social relationships play an important functional role in human society both at the collective level and by providing benefits to individuals. In particular, it appears that having strong and supportive relationships, characterized by closeness and emotional intensity, is essential for health and well-being in both humans and other primates (1, 2). At the same time, there is a higher cost to maintaining closer relationships, reflected in the amount of effort required to maintain a relation at the desired level of emotional closeness. Because of this, the number of emotionally intense relationships is typically small. Moreover, it has been suggested that ego networks, the sets of ties individuals (egos) have to their friends and family (alters), may be subject to more general constraints associated with limits on human abilities to interact with large numbers of alters (3–5). Although there are obvious constraints on the time available for interactions (5–7), additional constraints may also arise through limits on memory capacity (3, 8) or other cognitive abilities (9, 10).

Irrespective of the specific mechanisms that act to constrain ego networks, it is reasonable to ask whether such mechanisms shape these networks in similar ways under different circumstances, giving rise to some characteristic features that persist over time despite network turnover. Here, we explore this question with a detailed analysis of the communication patterns within ego networks in an empirical setting that results in large membership turnover and changes in the closeness of relationships. In particular, we focus on the way that egos divide their communication efforts among alters and how persistent the observed patterns are over time. We call these patterns, which may be expected to vary across individuals, social signatures.

Over the last decade, research on human communication has been given a significant boost by the widespread adoption of new communication technologies. The popularity of communication channels such as mobile phones and online environments has made it possible to capture microlevel quantitative data on human interactions automatically, in a way that circumvents biases inherent in retrospective self-reports (11). However, studies using electronic communication sources typically lack information on the nature of the social relationships (5, 12–15), whereas the challenge in using survey data alone has been that these give detailed information about the nature of the social relationships, but lack quantitative information about the actual patterns of communication (16). Further, in surveys the respondent burden from recording communication events with their entire ego network is very high (17) and people's accuracy in recalling detailed communication events is known to be limited (18).

We combine detailed, autorecorded data from mobile phone call records with survey data. These were collected during a study (19) that tracked changes in the ego networks of 24 students over 18 mo as they made the transition from school to university or work (details in *Materials and Methods*). These changes in personal circumstances result in a period of flux for the social relationships of the participants, with many alters both leaving and entering their networks. This provides a unique setting for studying network-level structure and its response to major changes in social circumstances. This dataset combines detailed data on communication patterns from mobile phone call records with questionnaire data that explore participants' own perceptions of the quality of the relationships with all of the members of their network. More importantly, call record data contain complete time-stamped records of all calls made by egos to alters in their network, rather than just a subset of calls egos make to alters who happened to be on the same mobile network as they are (as has usually been the case in previous work, e.g., ref. 12).

Significance

We combine cell phone data with survey responses to show that a person's social signature, as we call the pattern of their interactions with different friends and family members, is remarkably robust. People focus a high proportion of their communication efforts on a small number of individuals, and this behavior persists even when there are changes in the identity of the individuals involved. Although social signatures vary between individuals, a given individual appears to retain a specific social signature over time. Our results are likely to reflect limitations in the ability of humans to maintain many emotionally close relationships, both because of limited time and because the emotional "capital" that individuals can allocate between family members and friends is finite.
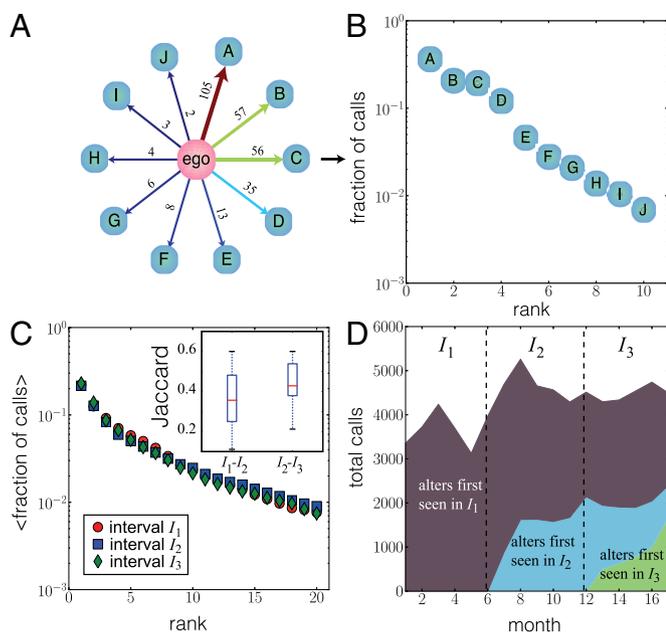
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Fig. 1. Social signatures and network turnover. (*A* and *B*) Social signatures are constructed for each ego by counting the number of calls to each of his or her alters, ranking the alters based on this number, and then calculating the fraction of calls to the alter of each rank. (*C*) When the signatures are averaged over the set of participants for three consecutive 6-mo intervals, it is seen that their shape is invariant although the personal networks display high turnover as indicated by the Jaccard indexes between sets of 20 top-ranking alters in consecutive intervals (*Inset*). In *D*, the network turnover is also clearly visible, which shows the total numbers of calls by the participants to their alters, divided between alters that have for the first time appeared in their networks in each of the intervals.

The questionnaires that augmented the call records provide information on the networks of participants that includes assessment of emotional closeness, time between face-to-face contact, and the phone numbers of alters. This allowed the call records of alters with several phone numbers (mobile phones, landlines) to be merged, giving a more accurate picture of communication between two individuals than that based on mobile phone calls alone.

These data enable us to uncover changes in the structure of the ego networks of the participants, reflected in their communication behavior. We find a consistent pattern that is seen to be persistent over time even when there is large network turnover.

This social signature is consistent with previously observed patterns of social network site use (20, 21) and text messaging (22, 23) in that a high proportion of communication is focused on a small number of alters. A detailed analysis of the social signatures of individual participants reveals that there is individual variation in the exact way their limited communication time is allocated across their network members. Although individual signatures show some response to network turnover, they surprisingly retain much of their distinctive variation over time despite this turnover.

Results

Emotional Closeness of Ego-Identified Relationships and Calling Behavior. Because the main results of this study refer to the egos' social signatures that are determined on the basis of phone records with no information about the content of the conversations, we first determine whether such signatures represent an acceptable proxy for the egos' own assessments of their relationships with the alters with whom they are communicating. To this end, we use data from questionnaires on the active personal networks of participants that were completed at three points in time: at the beginning of the study (t_1), at 9 mo (t_2), and at 18 mo (t_3). In these surveys, egos rated their alters (kin and friends/acquaintances) for emotional closeness and number of days since last face-to-face encounter. We use these self-rated estimates of relationship quality to determine whether the call data reflect egos' own views of their relationships.

To characterize egos' self-reporting of their relationships with alters we first use emotional closeness scores (scale of 1–10, with 1 the least and 10 the most emotionally intense relationship). Ego network data have a nested structure, where alters are clustered within participants, and thus alters cannot be treated as independent data points. We therefore used multilevel modeling, a modified form of multiple linear regression designed to deal with data with a hierarchical clustering structure (24) (details in *SI Text*). In Table 1 we present the relationship between emotional closeness and number of calls (log transformed to reduce the effect of outliers). Our results show that the number of calls significantly predicts emotional closeness. The regression coefficients are positive: Greater emotional closeness is associated with larger numbers of calls. Furthermore, there is a significant negative relationship between (log-transformed) number of days between face-to-face contacts and number of calls, indicating that larger numbers of calls relate to smaller number of days between contacts (*SI Text*). These results allow us to conclude that the phone call data provide a reliable estimate of relationship importance to ego.

Table 1. Multilevel regression models show that the number of calls made to alters significantly predicts emotional closeness to alters

Parameters†	Model 1, time t_1	Model 2, time t_2	Model 3, time t_3
Regression coefficients, fixed effects			
Intercept	6.13 (0.20)***	5.47 (0.42)***	6.34 (0.41)***
No. calls, log	1.63 (0.19)***	1.62 (0.22)***	1.35 (0.29)***
Variance components, random effects			
Residual	3.23 (0.26)***	5.47 (0.43)***	4.08 (0.42)***
Intercept	0.42 (0.20)*	3.21 (1.09)**	2.82 (1.12)*
Slope	0.08 (0.13)		0.30 (0.50)
Model summary			
Deviance statistic, −2LL	1,436.351	1,649.51	1,008.18
No. estimated parameters	5	4	5
PRV	0.27	0.39	0.38

2LL, twice the log likelihood.
*$P < 0.05$; **$P < 0.01$; ***$P < 0.001$.
†Parameter estimate SEs are listed in parentheses. PRV, the proportional reduction in variance.

Social Signatures and Turnover in Close Relationships. To study the changes in participants' communication patterns, we have divided the 18-mo observation period into three consecutive intervals I_1, I_2, and I_3, of 6 mo each. The participants took their final examinations at school at month 4 of the study (I_1) and left the school; 18 of the 24 participants subsequently went to university and the beginning of I_2 coincides with the beginning of their first university year.

To build the social signature of each ego for each of the intervals, we first count the number of calls to each alter (friend, acquaintance, kin) in the call records and subsequently rank the alters based on this number (*Materials and Methods*). Then we calculate the fraction of calls as a function of alter rank to establish the social signatures for each ego in each interval, as illustrated in Fig. 1 *A* and *B*.

For almost all survey participants, the signatures are characterized by a heavy tail that decreases slower than exponentially, as seen in Fig. 1C, which shows the social signatures averaged over the set of participants. A large fraction of communication is typically allocated to a small number of top-ranked alters: For female (male) participants, the fraction of calls to the top alter is on average 0.25 ± 0.08 (0.20 ± 0.09), and the fraction of calls to the top three alters is 0.48 ± 0.10 (0.40 ± 0.12). This is in line with earlier observations in static settings, where the numbers of calls and text messages have been aggregated over some fixed time window (20, 22, 23), as well as the frequency of face-to-face encounters (25). It is clear that this characteristic shape of the social signatures shows considerable stability in time (Fig. 1) and the signatures retain their characteristic shape despite the large turnover in network membership (Fig. 1).

To quantitatively measure the level of turnover in the networks of each ego, we compare the sets of alters, composing their networks into two consecutive intervals, using the Jaccard index (*Materials and Methods*). The high level of turnover is clearly indicated by the low average values of the Jaccard indexes between successive ego networks: For the entire networks of participants, $\langle J(I_1, I_2) \rangle = 0.22 \pm 0.09$ and $\langle J(I_2, I_3) \rangle = 0.27 \pm 0.09$. The largest turnover is between intervals I_1 and I_2 [$\langle J(I_1, I_2) \rangle < \langle J(I_2, I_3) \rangle$ with

$P = 0.001$, paired t test]; this coincides with the participants finishing school in I_1 and the subsequent major transition in their social circumstances. Focusing on the closest relationships, the Jaccard indexes for the top 20 ranking alters are $\langle J(I_1, I_2) \rangle = 0.36 \pm 0.13$ and $\langle J(I_2, I_3) \rangle = 0.44 \pm 0.10$ (Fig. 1C, *Inset*) and for the top 5 ranking alters are $\langle J(I_1, I_2) \rangle = 0.39 \pm 0.23$ and $\langle J(I_2, I_3) \rangle = 0.39 \pm 0.22$. Note that here, turnover includes alters dropping in rank below the top 20 or top 5.

The above results indicate that whereas the turnover is the largest among lower-ranking alters, there is nevertheless significant turnover even at the level of top-ranked alters. Over the entire cohort, new alters enter the signatures at all ranks during both time points I_2, and I_3 with considerably high likelihood: The fraction of new alters entering at I_2 within all top 20 ranked alters is 41% (21% for I_3). For the top 5, the corresponding fraction is 29% for I_2 and 12% for I_3. Besides alters entering and leaving the networks, there are considerable dynamics in the ranks of alters: Even for the top-ranked alters, only 42% retain their specific rank from I_1 to I_2 (54% from I_2 to I_3). For a more detailed overview of turnover and rank dynamics, see *SI Text*.

Persistence of Individual Social Signatures. The above analysis indicates that the pattern in which top-ranked alters receive a substantial fraction of communication remains persistent over time, even as those alters change. We next turn to characterizing the stability of individual social signatures of egos in more detail. Fig. 2 illustrates the evolution of two of these signatures for the three intervals, with colors indicating alters that enter their networks at different times. Both signatures retain much of their shape despite network turnover.

For quantifying the similarity of signatures, we introduce the Jensen–Shannon divergence (JSD) (*Materials and Methods*) as a measure of distance (shape difference) between two signatures. The aim is to investigate the similarity of the shape of an ego's social signature in different time intervals, using the distances to the signatures of all other egos as a reference. To this end, for each ego i, we first calculate JSD values d for the two pairs of social signatures in consecutive time intervals (I_1, I_2) and (I_2, I_3)
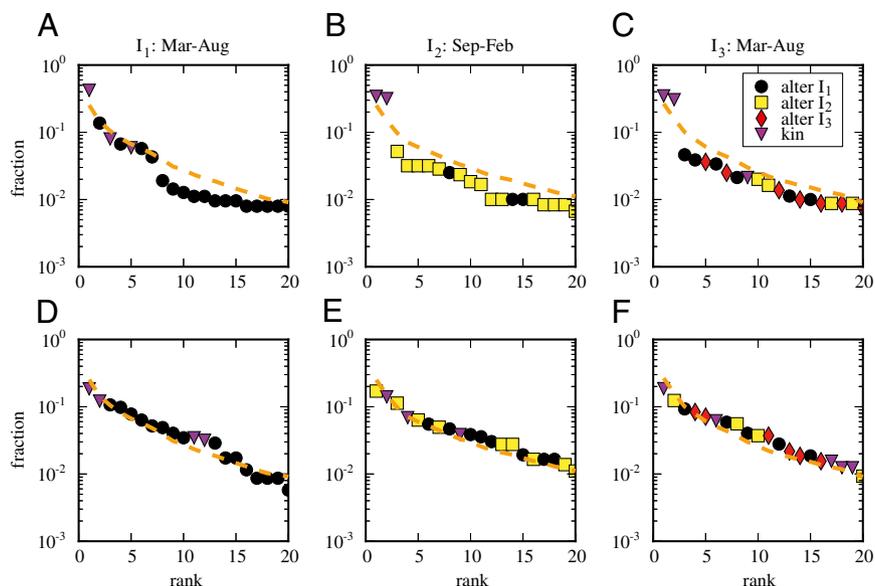
Fig. 2. Individual-level variation in social signatures and their evolution. *Upper* (*A*–*C*) and *Lower* (*D*–*F*) depict the time evolution of the social signatures of two different male participants who both went to university in another city. The symbols correspond to alters observed for the first time in intervals I_1 (circles), I_2 (squares), and I_3 (diamonds) or to kin (triangles) as reported by the egos. The large turnover in the networks of the participants is clearly visible. The dashed line indicates the social signature averaged over all 24 egos. In the social signatures depicted in *A*–*C*, two kin alters receive a higher-than-average fraction of outbound calls, whereas the signatures *D*–*F* do not deviate much from the average. In both cases, this individual-level variation persists through all time intervals.

and average over these two values to obtain the ego's self-distance $d_{self}(i)$. Denoting the JSD distances between the social signatures of egos i and j in intervals a and b by d_{ab}^{ij}, we first calculate ego i's self-distances between intervals (I_1, I_2) and (I_2, I_3) as $d_{12}^{self}(i) = d_{12}^{ii}$ and $d_{23}^{self}(i) = d_{23}^{ii}$. Then we average over these to get the self-distance $d_{self}(i) = \frac{1}{2}[d_{12}^{self}(i) + d_{23}^{self}(i)]$ (Fig. 3A). Low values of d_{self} then denote a high similarity between the ego's signatures in consecutive intervals. For reference, we calculate the distances between the signatures of the focal ego i and those of all other egos j for each of the three intervals, e.g., for focal ego i, interval I_1, and reference ego j, the reference distance d_{ref} is d_{11}^{ij}.

The results in Fig. 3 clearly indicate that on average, the shapes of the social signatures of participants show a tendency to persist in time, as the distances between one participant's consecutive signatures d_{self} are on average much smaller than the reference distances to the signatures of other participants d_{ref}. Fig. 3B displays the self-distances and distributions of reference distances to the signatures of all other participants for four example egos, and Fig. 3C shows the distributions of all self-distances $P(d_{self})$ and reference distances $P(d_{ref})$. On average, for each ego, $82\% \pm 12\%$ of the distances to others d_{ref} were greater than d_{self}. Averaged over all egos, the average self-distance is $\langle d_{self} \rangle = 0.036 \pm 0.014$ whereas the average distance to other egos is $\langle d_{ref} \rangle = 0.086 \pm 0.055$ ($\langle d_{self} \rangle < \langle d_{ref} \rangle$ with $P < 10^{-4}$, Welch's t test). For verification, we used the ℓ^2 norm as an alternative distance measure (*Materials and Methods*); this yields a qualitatively similar outcome $\langle d_{self} \rangle = 0.096 \pm 0.039$, $\langle d_{ref} \rangle = 0.154 \pm 0.084$, $\langle d_{self} \rangle < \langle d_{ref} \rangle$ with $P < 10^{-4}$.

Although the individual signatures retain much of their shape, there is nevertheless some variation in their persistence, as seen in the distribution of self-distances in Fig. 3C. One plausible candidate explanation for this is the level of turnover in the egos' networks. To determine whether turnover in relationships has an effect on the persistence of signatures, we examined the relationship between the self-distances and the Jaccard indexes. For each ego i, we determined the Jaccard indexes for the two pairs of intervals $J_{12}(i) = J(I_1, I_2; i)$ and $J_{23}(i) = J(I_2, I_3; i)$ and the corresponding self-distances $d_{12}^{self}(i)$ and $d_{23}^{self}(i)$. Fig. 3D shows a scatter plot of these $N = 48$ pairs of values (circles), indicating a moderate level of correlation (Pearson correlation coefficient $r = -0.41$, $P = 0.0034$). However, even with this variation, most signatures retain their distinctive characteristics, as the scatter of the self-distance values is systematically below the scatter of the reference distances $d_{22}^{ref}(i) = \frac{1}{N_{egos}-1}\sum_{j \neq i} d_{22}^{ij}$ and $d_{33}^{ref}(i) = \frac{1}{N_{egos}-1}\sum_{j \neq i} d_{33}^{ij}$.

displayed in the same plot (squares). For Jaccard indexes calculated for the top 5 and top 10 alters only, the correlation is no longer significant ($r = -0.029$ with $P = 0.84$ and $r = -0.19$ with $P = 0.20$, respectively), indicating that turnover among the closest relationships alone does not explain the variation in self-distances.

Discussion

Our results establish three unique findings: (*i*) There is a consistent, broad, and robust pattern in the way people allocate their communication across the members of their social network, with a small number of top-ranked, emotionally close alters receiving a disproportionately large fraction of calls; (*ii*) within this general pattern, there is clear individual-level variation so that each individual has a characteristic social signature depicting his or her particular way of communication allocation; and (*iii*) this individual social signature remains stable and retains its characteristic shape over time and is only weakly affected by network turnover. Thus, individuals appear to differ in how they allocate their available time to their alters, irrespective of who these alters are. Further, our subsidiary analyses (*SI Text*) suggest that this finding applies not just to call frequencies, because the frequency of calls to an alter correlates with emotional closeness and frequency of face-to-face interactions.

The patterns displayed in the social signatures reflect the fact that ego networks are typically layered into a series of hierarchically inclusive subsets of relationships of different quality. This pattern has been noted, for example, in shipboard networks (3) as well as friendship social networks and the structure of natural human communities (26). Bernard and Killworth (3) were perhaps the first to suggest that this structuring was likely due to a psychological (i.e., cognitive) constraint. An alternative (but not necessarily mutually exclusive) possibility is that they arise from the fact that the time available for interaction is limited, and individuals partition their available social time to reflect their social or emotional preferences (27). One problem is that it may be difficult to separate out the cognitive and time aspects of relationships, because it seems that the time invested in a relationship may determine its emotional quality (25, 27). A rather different kind of cognitive mechanism derives from the social brain hypothesis (4): Recent neuroimaging studies of humans demonstrate a correlation at the individual level between core brain regions (notably those in the prefrontal cortex) and size of the innermost layers of ego networks (10, 28), with similar findings reported for monkeys (29). More importantly,
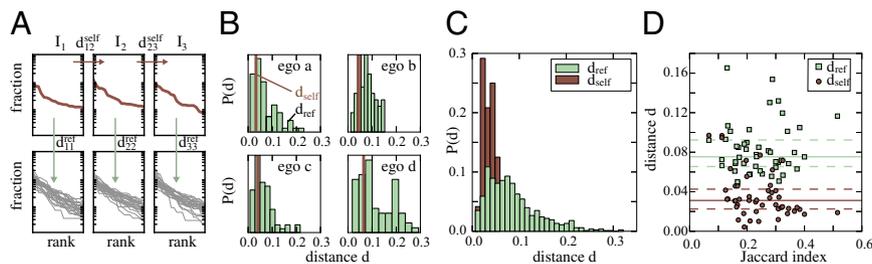
Fig. 3. Evidence for the persistence of social signatures at the individual level, in terms of distances between the shapes of signatures. (*A*) A schematic of how the distances between signatures are calculated, based on Jensen–Shannon divergences. For the focal ego (*Upper*), self-distances d_{self} are calculated for signatures in consecutive intervals and averaged. Reference distances d_{ref} are calculated for each interval between the signatures of the focal ego and all other egos (*Lower*). These are averaged over the three intervals for each pair of egos (focal, other). (*B*) The values of the average self-distances d_{self} and histograms for reference distances d_{ref} for four sample egos, indicating that the shapes of each ego's signatures in consecutive intervals are typically more similar than they are to those of other egos. (*C*) The distributions of all self-distances d_{self} and reference distances d_{ref}, for all egos, verifying the larger similarities between egos' signatures in consecutive intervals. (*D*) The self-distances d_{self} show a moderate level of correlation ($r = -0.41$, $P = 0.0034$) with turnover as measured with the Jaccard index J, but nevertheless mostly remain below reference distances. The scatter plot shows the coordinate pairs $\{J_{12}(i), d_{12}^{self}(i)\}$ and $\{J_{23}(i), d_{23}^{self}(i)\}$ for each ego i (circles). For comparison, reference distances are also displayed as the coordinate pairs $\{J_{12}(i), d_{22}^{ref}(i)\}$ and $\{J_{23}(i), d_{33}^{ref}(i)\}$. Solid and dashed lines denote the median and the quartiles.

Powell et al. (10) were able to show that this relationship between brain region volume and network size is mediated by forms of social cognition known as "mentalizing" (or mind reading). Individuals' mentalizing competences may limit the numbers of individuals they can maintain at any given level of emotional closeness (25). An alternative (yet not necessarily mutually exclusive) possibility is that the constraint arises from differences in personality, with some individuals preferring to have a few, intense relationships and others preferring more, less intense ones (30). Determining the extent to which the unique pattern represented by an individual's social signature is a consequence of time, cognitive, or other constraints will require more detailed study of rather different kinds of data.

Whatever the mechanism involves, it seems that, because of these constraints, individuals cannot increase the number of alters they communicate with at maximum rate, but must downgrade (or drop) some individuals if they wish to add new ones to their preferred network at a high level of emotional intensity. As a result, the overall shape of their social signature is preserved. Indeed, our findings can be taken to suggest that these signatures are so prescribed that even the efficiencies provided by some forms of digital communication (in this case, cell phones) are insufficient to alter them. This might explain the observation that most of the traffic on social networking sites (SNSs) is directed at a very small number of individuals (20) and that this appears to be resistant to change (31) no matter how SNSs attempt to engineer a wider circle of social contacts. It would be particularly instructive to explore the implications of this study on large-scale datasets derived from electronic media where a wider variety of personal circumstances can be explored. Even though these offer only limited kinds of data, our findings at least suggest that these would provide reasonable proxies for relationship quality. Doing so would enable us to explore differences due to age, sex, and personality, as well as the consequences of the slower pattern of network turnover that occurs naturally over time as individuals switch the focus of their social investment.

Materials and Methods

Personal Network Survey and Call Records. We used longitudinal data on the social networks of 30 participants (15 males and 15 females, aged 17–19 y old) in their last year of secondary school, collected over an 18-mo period during the transition from school to university or work (for full details, see ref. 16). Participants completed a questionnaire on their active personal network at three points in time: at the beginning of the study (t_1), at 9 mo (t_2), and at 18 mo (t_3). The analysis in this study is based on the 24 participants (12 males, 12 females) who completed all three questionnaires and used their mobile phones throughout the study. To elicit their ego network, participants were asked to list all unrelated individuals "for whom you have contact details and with whom you consider that you have some kind of personal relationship (friend, acquaintance, someone you might interact with on a regular basis at school, work or university)." The participants were also asked to list all their known relatives. For all individuals listed, participants were asked to provide both landline and mobile phone numbers. In each survey, for both kin and friends/acquaintances, the participants were asked to indicate the emotional intensity of the relationship by providing an emotional closeness score, measured on a 1–10 scale, where 10 is someone "with whom you have a deeply personal relationship."

At t_1, all participants lived in the same large UK city. At month 4 of the study, the participants took their final examinations at school ("A-levels") and left the school. Of the 24 participants who completed all three questionnaires, 6 participants stayed in the home city and worked, not going to university; 8 went to university in the city (which has two large universities); and the remaining 10 went to university elsewhere in England.

As compensation for participating in the study, participants were given a mobile phone, with an 18-mo contract from a major UK mobile telephone operator. The line rental for the mobile phone was paid for and included 500 free monthly voice minutes (to landlines or mobiles) and unlimited free text messages. For each participant, we obtained itemized, electronic monthly phone invoices that listed all outgoing calls (recipient phone number, time,

and duration of calls). The electronic portable document format invoices were parsed into machine-readable form. The questionnaire data and the call dataset form the main basis for our analysis. This study was approved by the Human Ethics Review Committee of the University of Liverpool (the institution at which the data collection phase of this project was originally initiated) and informed consent was obtained from all participants prior to data collection.

Constructing Egocentric Call Networks. For each participant in the study (ego), we used the list of kin and friends/acquaintances (alters) generated in response to the three social network questionnaires and combined it with the electronic phone invoices to construct a set of egocentric call networks. If an alter was listed as having multiple phone numbers, a mobile and a fixed line number, a call by the ego to either number was recorded as a call between ego and the alter. Phone numbers appearing on the invoices but not listed in the questionnaire responses were treated as unique alters; however, service numbers (such as those with 0800 prefixes) were filtered out. All alters appearing in the phone records that were believed to be nonservice numbers were used in the calculation of the signatures, independently of being recalled or not by the egos at the time the questionnaires were completed (percentages for the number of alters not recalled are directly related to call frequency; details in *SI Text*). The 18-mo observation period of electronic phone invoices was divided into three consecutive intervals of 6 mo each (I_1, March–August; I_2, September–February; I_3, March–August). For each ego in each of the three intervals, we counted the total number of calls made to each alter. Using the alter-call counts per interval, we ranked the egos from most called to least called and calculated their social signatures, depicting the total fraction of calls to an alter as a function of the alter's rank.

Analyzing Social Signatures. We quantify the variation between the sets of alters an ego calls in two time intervals with the Jaccard coefficient

$$J(I_i, I_j) = \frac{|A(I_i) \cap A(I_j)|}{|A(I_i) \cup A(I_j)|},$$ **[1]**

where $A(I_i)$ and $A(I_j)$ are the sets of alters called by the ego in two time intervals I_i and I_j, respectively. Then $J = 1$ if the sets are the same, and $J = 0$ if the sets have no common alters. For a pairwise comparison of the social signatures between two different egos or two different time intervals for a single ego we measure the JSD (32), defined as

$$JSD(P_1, P_2) = H\left(\frac{1}{2}P_1 + \frac{1}{2}P_2\right) - \frac{1}{2}[H(P_1) + H(P_2)],$$ **[2]**

where P_1 and P_2 are the two social signatures where $P_i = \{p_i(r)\}$ such that $p_i(r)$ is the fraction of calls to the alter of rank r in signature i. Additionally, $H(P)$ is the Shannon entropy,

$$H(P) = -\sum_{r=1}^{k} p(r) \log p(r),$$ **[3]**

where $p(r)$ is as above and k is the maximum rank, i.e., the total number of alters called. The Jensen–Shannon divergence is a generalized form of the Kullback–Leibler divergence (KLD) such that $JSD(P_1, P_2) \in [0, \infty)$, and JSD $(P_1, P_2) = 0$ if the distributions are identical. We chose JSD over KLD due to its capacity to deal with zero probabilities $p(r) = 0$. The maximum number of alters called by an ego in a given time interval, k, varies depending on the ego and the interval; therefore, if $k_2 > k_1$ is the larger number, we assign $p_1(r_1) = 0$ for $k_1 > r_1 \geq k_2$; i.e., zero pad the series of fractions of calls such that they are of the same length. Additionally, for validating the pairwise comparison results, we also calculated the ℓ^2 norm for pairs of social signatures defined as $\ell^2 = \sqrt{\sum_{r=1}^{k} |p_1(r) - p_2(r)|^2}$.

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