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Are the different layers of a social network conveying the same information?

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Abstract

Comprehensive and quantitative investigations of social theories and phenomena increasingly benefit from the vast breadth of data describing human social relations that is now available within the realm of computational social science. Such data are, however, typically proxies for one of the many interaction layers composing social networks, which can be defined in many ways and are composed of communication of various types (e.g., phone calls, face-to-face communication, etc.). As a result, many studies focus on one single layer, corresponding to the data at hand. Several studies have however shown that these layers are not interchangeable, despite the presence of a certain level of correlation between them. Here, we investigate whether different layers of interactions among individuals lead to similar conclusions with respect to the presence of homophily patterns in a population—homophily represents one of the widest studied phenomenon in social networks. To this aim, we consider a data set describing interactions and links of various nature in a population of Asian students with diverse nationalities, first language and gender. We study homophily patterns, as well as their temporal evolution in each layer of the social network. To facilitate our analysis, we put forward a general method to assess whether the homophily patterns observed in one layer inform us about patterns in another layer. For instance, our study reveals that three network layers—cell phone communications, questionnaires about friendship, and trust relations—lead to similar and consistent results despite some minor discrepancies. The homophily patterns of the co-presence network layer, however, does not yield any meaningful information about other network layers.

Keywords: Social networks; Multilayer networks; Temporal homophily

1 Introduction

Mining and analyzing social networks in various contexts yield important insights towards a better fundamental knowledge and understanding of human behavior [1]. Data on social networks have allowed researchers to investigate social theories and effects such as homophily, influence, triadic closure, etc. Data also help design data-driven models of human interactions, which can be used to describe the many processes taking place in a given population, such as information spreading, coordination, consensus formation, or spread of infectious diseases [2]. Accurate descriptions of social interactions are therefore crucial to shed light on the most relevant mechanisms at work in these processes, and for instance to understand the factors determining if a rumor will spread, or what are the best measures to contain the spread of a disease.

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Within a given population, however, several networks of social interactions can be defined: e.g., friendship relations, patterns of communications, co-presence, face-to-face interactions. These different types of relations form a multilayer network [3, 4], for which each layer can be explored using possibly different methods. Friendship relations are typically mined through surveys, physical interactions and proximity by diaries or more recently using wearable sensors [5, 6], and communication patterns are extracted from mobile phone call records [7–9]. In recent times in particular, technological developments have allowed researchers to gather increasing amounts of digital data on face-to-face contacts, phone communication patterns and online relationships, at widely different scales in terms of population size, space and time resolution. These data have been widely used to investigate the structure of social networks, the patterns of social interactions and social theories, such as the strength of weak ties [7], homophily patterns (the tendency of individuals to have social links with similar individuals, with respect to gender, nationality, social class, etc. [10]) [11–16], mechanisms of link formation and persistence [11, 12, 17], social strategies linked to limited attention capacity [8], etc.

In recent years, a number of data gathering efforts has moreover managed to access simultaneously more than one layer of interactions in various population groups, leading to multilayer network data [18, 19]. The issue then arises of how to deal with the resulting increased complexity of the data sets, as different types of ties are not interchangeable [20]. In fact, it has been shown in a number of cases that these layers are correlated but not equivalent [4, 21–28]. For instance, a comparison between face-to-face contacts measured by sensors and friendship relations obtained through surveys has shown that the distribution of contact durations are broad both for pairs of friends and pairs of non-friends, even if the longest contacts occur between friends [24]. In addition, a comparison between proximity events and online social links has shown that a simple thresholding procedure retaining only the strongest proximity links is not enough to determine online friendship [23]. Furthermore, a recent study of communication, online links, and proximity events has highlighted that these layers differ and cannot be reduced to a single channel of interaction [28]. Several approaches have thus been put forward to manage multilayer social networks, such as block-modelling for multiple relations [29], stochastic actor-oriented models dealing with more than one layer [30], or dimensional reduction based on structural similarities of layers to define composite network measures [31].

In most cases however, studies of social networks are still based on data describing one specific layer of the multilayer network characterizing social interactions, and consider this layer as a proxy of "the" social network of the population under study, despite the well-accepted and known differences between the "social networks" defined through different proxies [3]. Indeed, many authors have argued that close relationships correspond to both higher frequencies of face-to-face contacts and phone communication [9, 11, 14, 16, 32, 33]. It is, for instance, often assumed that the most important relationship of an individual can be captured by his/her mobile phone records, and that the "best friend" of an individual is the person he or she is in most contact with. Some evidence to support this assumption has come from surveys [32, 34] or from comparison between surveys and mobile phone records [9], which are, however, rarely available for the same population.

It is thus important to gather and investigate data sets containing multiple layers of social interactions, to better ground such assumption and assess the extent of its validity. It is worth highlighting that the number of data sets offering multiple layers of interactions,

enriched with metadata describing individual characteristics, remains extremely limited. Moreover, it is crucial to investigate whether, given that the layers of interactions are correlated but not equivalent, socially relevant patterns and theories can be reliably assessed from one layer only. If it is indeed the case, then for a given population the data that is most conveniently accessible or that offers the best resolution can safely be used to explore such issues. Here, we focus on homophily along a range of individual characteristics, as one of the most explored patterns structuring social networks [10]. A recent study has shown some notable differences in the strength of homophilous patterns in different communication channels in a population of European students [4]. We investigate this particular issue in a diverse population of Asian students of various nationalities in a university of Singapore, for which we have access to phone communication records, co-presence events, and friendship and trust relations over one full calendar year. Detailed metadata about gender, nationality, first spoken language, academic performance and psychological traits are also available, allowing us to assess homophily and its temporal evolution along multiple traits and multiple layers of social relationships. We put forward a methodology to systematically compare homophily patterns across layers, as observed through different indicators and with respect to different attributes, and apply this methodology to our dataset. In this case, we show that patterns of homophily in the co-presence layer do not inform us on the patterns in other layers, while the patterns observed in the communication network and in the networks of friendship and trust obtained from surveys, although not equal, are informative of each other.

2 Data and methods

We consider data collected in a Singapore university during one full academic year—three consecutive terms separated by short breaks—and concerning 35 participating students, of which 15 students were from one cohort class and 20 students from another cohort class, studying in the same campus and staying at the same on-campus hostel. Each cohort class varied between 45 to maximum 50 students based on the university policy. There were no inclusion criteria for this study. The data consists in several types of relationship between students, as well as in metadata about each student.

Each participant was given a mobile phone (models included Samsung Galaxy S3, Samsung Nexus, and Sony Xperia, all having equivalent features and supporting the state-of-the-art Android system at that time, namely 4.2/4.3 Jelly Bean) to use for the duration of the study. This smartphone was preinstalled with a specially developed software capable of recording and sending phone usage data and colocation information to a server located in the university premises, as described in [35]. Raw data collected by the software consists therefore in all call events between participating students, with timestamp and duration of the call, and timestamped colocation events Specifically, co-presence events were detected by periodic Bluetooth scanning at 5-minute intervals. If two participants were discovered in co-presence, there would be one co-presence event registered for each participant, thus a total of two co-presence events for the dyad [35]. Automated location data collection by each phone was turned off each night from 12:00 a.m. to 7:00 a.m. for energy saving.

All 35 participants reported in this paper completed all components of the study. Participants were also reminded to always carry the phone with them and use it as their own at the beginning of each term in order to get meaningful data. All participants agreed to participate in this study on a voluntary basis, where each participant was compensated

with SGD$30 for participation and completion of all survey questions. Besides the 35 participants who completed the study, there were another two students who participated but withdrew from the study (one discontinued after 1 day of participation, and the other one pulled out from the study at the end of the first term because of school transfer).

The resulting data is conveniently represented as 2 temporal networks, the communication and the co-presence ones, in which nodes represent students and events correspond to a phone call communication or to a co-presence event. Each communication event is directed, represented by the calling node, the receiving node, the starting time and the duration of the call. Each co-presence event is instead undirected, represented by two nodes, a starting time and a duration.

Each temporal network can be aggregated on any arbitrary time window. We have considered on the one hand communication and co-presence aggregated over the full study (one year), and on the other hand shorter periods of four months corresponding to the university terms: Term 1 (T1: May to August), Term 2 (T2: September to December) and Term 3 (T3: January to April). Each aggregated communication network relates nodes, representing students, by directed links: a directed link is drawn from student i to student j if i placed at least one call to j during the aggregation time window. Each directed link can be weighted in two different ways: (1) the weight can be either the number of calls $n^c_{i\to j}$ from i to j, or (2) the total duration $d^c_{i\to j}$ of these calls. We also consider an undirected version of these communication networks in which the weight of a link between i and j is simply the sum of the weights from i to j and from j to i, $w^s_{ij} = w_{i\to j} + w_{j\to i}$ (with $w = n^c$ or d^c).

As already mentioned, the co-presence networks are undirected. Moreover, in order to discard classroom activities that are imposed by the university schedule and not driven by personal relationships, we consider in the co-presence aggregated networks only co-presence events taking place either after 9:00 p.m. each day for the week days or during weekends. For each pair of students (i, j), a link is drawn if they have been detected at least once in co-presence, and the corresponding weights are defined, as in the communication network, either as the number n^{cp}_{ij} of such events, or by their total duration d^{cp}_{ij}. Table 1 shows the properties of both networks under study for these time windows. Figure 1 displays the yearly aggregated communication and co-presence networks.

In addition, questionnaires were used to assess self-reported relations among students. Each participant indicated his/her friendship tie-strength with all other participants by answering individually the following two questions: (Q1) "How strong is your relationship with this person?" and (Q2) "How would you feel asking this friend to loan you $100 or more?". For each question, a 9-point scale was used where 1 indicates for Q1 that they barely know each other (resp., for Q2 that they would never ask), while 9 indicates they are close to each other (resp., for Q2, that they would feel comfortable). These questionnaires were answered by the students at the start of the study (T0) to establish baseline values, and subsequently at the end of every term (T1, T2, T3). At each such time, we obtain therefore two questionnaire networks (one for each question asked). Both networks are fully-connected, directed, and weighted, where the weight $W_{i\to j}$ of an edge from student i to student j ranges from 0.1 to 1.0 (9 points) indicating the reported strength of the friendship (Q1) or trust (Q2) relationship of i towards j.

Finally, several attributes are available for each student: (1) his/her so-called cohort class (the students were divided into two cohort classes of approximately 50 students), (2) gen-

Table 1 Properties of the communication and co-presence networks

(a) Aggregation period: 1 year

Network properties	Communication	Co-presence
Number of nodes	33	35
Number of edges	282	435
Average degree	8.5	24.85
Average clustering coefficient	0.45	0.858
Edge weight—total number	2125	14,249
Edge weight—average number	64.4	407.1
Edge weight—total duration (s)	93,580	11,966,878
Edge weight—average duration (s)	2835.8	341,911.0

(b) Aggregation period: 4 months (Term)

Network properties	Communication			Co-presence		
	T1	T2	T3	T1	T2	T3
Number of nodes	33	33	33	35	34	31
Number of edges	162	150	129	347	292	145
Average degree	9.81	9.09	7.81	19.82	17.17	9.35
Average clustering coefficient	0.30	0.34	0.23	0.80	0.80	0.65
Edge weight—total number	766	822	555	5387	7057	1791
Edge weight—average number	23.2	24.9	16.8	153.9	207.5	57.8
Edge weight—total duration (s)	29,969	37,553	26,550	3,981,721	6,412,726	1,493,623
Edge weight—average duration (s)	908.1	1138	804.5	113,763.4	188,609.5	48,181.3

der, (3) nationality, (4) first spoken language (all students can be considered bilingual to a certain extent, with some participants being fluent in three or more languages), (5) academic performance measured by the participants' grade point average (GPA) in each term. Table 2 summarizes the demographic composition of participants in terms of gender and nationality. Self-reported data about psychological factors such as loneliness, classroom community, and adaptation to college life were also collected by means of a questionnaire at the end of each term. For each psychological factor surveyed, a numerical index was used (see [35] for details): *(i)* The UCLA loneliness scale (LS) ranges from a minimum of 20 to a maximum of 80, where a higher score indicates a greater sense of loneliness; *(ii)* the classroom community scale (CC) consists of 20 items that measure the individual sense of community in a learning environment, leading to a total score ranging between 0 and 40, with a higher score indicating a greater sense of community; *(iii)* the student adaptation to college questionnaire (SACQ) was applied to measure college adjustment, with higher scores indicating better adjustment.

For each attribute, the population under study was divided into two groups. For gender and cohort class, the division is straightforward. For nationality, the participants were divided into two groups—Singaporeans and foreigners—although several nationalities are represented (see Table 2). With respect to the first spoken language, in order to avoid confounding effects with respect to nationality, we focus only on Singaporean students, whose first language is either English or Chinese. For academic performance (GPA) and the psychological indices, again the participants were segregated into two groups to facilitate the analysis of the results: first group with above-the-median values, and the other group with below-the-median values.

2.1 Measuring homophily

Homophily in a social network can be assessed in a number of ways. It is possible for instance to investigate the fraction of ties between individuals with similar versus different

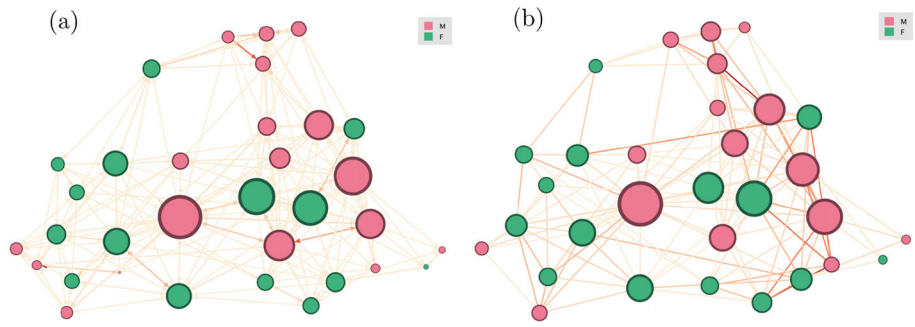

Figure 1 Graphical representation of yearly aggregated networks. (**a**) Communication network. (**b**) Co-presence network. Nodes are colored by gender ("M" for male and "F" for female), and their size depends on their degree. Edges are colored by aggregated duration. For the co-presence network, only edges present as well in the communication network are shown. As a result, two nodes become isolated and are not represented

Table 2 Demography table: Number of participants by nationality and gender

Nationality	Gender		Total
	Male	*Female*	
Singaporean/permanent resident (PR)	7	15	22
Indian	2	0	2
PRC Chinese	4	1	5
Malaysian	4	0	4
Vietnamese	2	0	2
Total	19	16	35

characteristics, but also higher-order structures such as triads [36], and even temporal patterns or motifs [15]. Given the weighted nature of the networks at hand—with possibly broad distributions of weights as often encountered in human interaction networks, taking into consideration edge weights is crucial [4].

Here, we consider the following metrics to describe and quantify homophily in each network, and for each node attribute A:

- *Dyadic homophily*: we first consider homophily at the basic dyad level, i.e., considering the basic elements forming the network, that is the edge. We compute the total fraction of weights carried by edges between nodes with the same value of the attribute A (directed networks being converted to their undirected versions):

$$D = \frac{\sum_{i,j/A_i=A_j} w^s_{ij}}{\sum_{i,j} w^s_{ij}}. \tag{1}$$

- *Triadic homophily*: closed triangles describe the smallest non-trivial structure in a social network. For a given attribute A, that can take only two values, triangles can either be formed by three individuals with equal value of the attribute, or by a group of 2 individuals different from the third. We therefore compute the ratio of the weights of triangles formed by individuals with the same attribute value to the total weight carried by triangles:

$$T = \frac{\sum^{\Delta}_{i,j,k/A_i=A_j=A_k} (w^s_{ij} + w^s_{ik} + w^s_{jk})}{\sum^{\Delta}_{i,j,k} (w^s_{ij} + w^s_{ik} + w^s_{jk})}, \tag{2}$$

where the sums $\sum^{\Delta}$ are conditioned on ijk being a closed triangle. To compute this index, we convert directed networks to their undirected versions.

- *Social preference*: for each node i, we can rank his/her neighbors j according to the value of the corresponding edge weight $w_{i\to j}$. As it was found in [9] that a large fraction of communication is typically allocated by each individual to a small number of top-ranked alters, it is indeed of interest to check if the individual and these top-ranked alters share common attributes. We focus here on comparing the attributes of i and of his/her first-ranked neighbor and compute the fraction of individuals for which these attributes are equal (we have performed the same test for the second-ranked neighbors, but omit the results in order to avoid accumulating too many indicators). An agent whose strongest contact has the same attribute shows indeed homophilic behaviour, so the fraction of such agents gives an indication of the existence of homophily in the population. We can moreover compute these fractions separately for all nodes i with a given value of the attribute A. For instance, we can compute separately the fraction of male students and of female students for whom the strongest link is towards a male student, therefore enabling to detect whether homophilic trends are different for individuals with different characteristics.
- *Temporal motifs*: as put forward in [15], the availability of time-resolved data makes it possible to investigate homophily in temporal patterns of interactions by considering events concerning the same set of nodes and close enough in time. As in [15], we consider sets of events separated by at most 10 minutes and involving the same 2 or 3 individuals, and investigate the similarity (or difference) of their attributes. For the sake of simplicity and given the lack of statistics for motifs involving more than 2 nodes in our data, we limit the evidence shown to reciprocal and repeated calls (within the time-window of 10 minutes) between two nodes: we consider all such patterns and compute the fraction involving nodes with equal attributes.

Null model: The measure of the above-defined quantities is not enough in itself to assess the presence of homophily in the data. For instance, if a population is divided into two groups, with one group much larger than the other, then one would observe more links within the larger group than between the two groups even if links were created totally at random. One thus needs to compare the data with a baseline corresponding to a null hypothesis of absence of homophily. To this aim, a well known and often used way to assess homophily is to compare the values obtained in the data with those obtained in a proper null model. Several possibilities have been considered in the literature. For instance, one can consider an ensemble of random networks in which each individual has the same number of links as in the real data i.e., an ensemble of networks with fixed degree sequence, sampling this ensemble by simply reshuffling links at random [37]. Such a procedure was used for instance in [4, 13]. In this ensemble however, structures and correlations in the network are not fixed (they are indeed destroyed by the reshuffling procedure), while they might be relevant, in particular in social contexts. For instance, the number of triangles is not fixed in this ensemble, so that this procedure is not suited to test for triadic homophily. One possibility would then be to use as null model an ensemble of random graphs in which, for each node, its degree and the number of triangles to which it belongs are fixed, as defined in [38]. Such a null model however still disregards higher order structures and correlations such as communities or groups of individuals. To deal with this issue, several authors have used, instead of ensembles of random networks

that keep only a specific set of properties of the original network, a null model in which the network structure is kept completely intact, but in which each possible permutation of the attributes among the nodes is equally probable: this null model is sampled by randomly reshuffling the attributes among nodes, equivalently to the permutations used in QAP procedures [39–41]. Homophily has been measured in this way for instance with respect to gender in school children [13], with respect to academic performance in students [42], for temporal motifs in communication networks [15] and with respect to gender in online relationships, using dyadic and triadic measures [36]. We consider here this standard null model and reshuffling procedure to sample it. In addition, we show in the Supporting Information (SI) (Additional file 1) an example of results obtained when considering instead as null model an ensemble of random graphs with fixed degrees and numbers of triangles for each node [38]. In each case, we sample the null model by performing 100 reshuffling and compute the homophily indices for each. The empirical value is then compared to the resulting distribution (shown in figures as a boxplot, with the box extremities representing the 25th and 75th percentiles of the distributions, and whiskers at the 5th, 10th, 90th and 95th percentiles). It is considered that the data reveals an absence of homophily if the data point falls within the box ("No"), and that we have respectively weak ("W"), strong ("S") and very strong ("VS") degrees of homophily if the data point lies respectively between the 75th and the 90th percentiles, between the 90th and the 95th percentiles, and above the 95th percentile. In addition, we find in few cases evidence for heterophily, i.e., the tendency to have less homophilic dyads, triads or motifs with respect to the null model. Similarly to the homophily patterns, we consider that we have respectively weak ("W_{het}"), strong ("S_{het}") and very strong ("VS_{het}") degrees of heterophily when the data point lies respectively between the 10th and the 25th percentiles, between the 5th and the 10th percentiles, and below the 5th percentile of the null model distribution. (Note that the use of these percentile values is obviously somewhat arbitrary—even if the ones we use are quite usual—, but we remind that the main goal of our paper will be to assess whether homophily patterns are exhibited consistently across different layers of the social network: the main requirement is thus to have a consistent way of measuring homophily in the different layers.)

Finally, and for the sake of simplicity, we will also envision a coarser classification of patterns, in which we group the cases "W", "No" and "W_{het}" together (and as no evidence for homophily nor heterophily), and we consider as evidence for homophily (resp. heterophily) both "S" and "VS" cases (resp. "S_{het}" and "VS_{het}").

2.2 Networks comparison

The data at hand defines different types of relationship among students: specifically, communication, co-presence, friendship and trust relations. It is worth noting that these data are available with different temporal resolutions throughout the 12-month study period. To enable a meaningful comparison of these networks, we resort to two distinct metrics:

- The *Pearson correlation coefficient* between the weights of links between individuals within the two considered networks. If one of the network is directed and the other undirected, we first convert the directed one into its undirected counterpart: for each pair of nodes (i,j), the resulting weight is the sum of the weights on the directed edges $i \to j$ and $j \to i$.

- The *cosine similarity* for each node i, which measures the similarity between this node and its neighborhoods in the two networks. If $w_{ij,1}$ and $w_{ij,2}$ denote the weights on the links from i to j respectively in networks 1 and 2, the cosine similarity of i is defined as

$$\mathrm{sim}_{1,2}(i) = \frac{\sum_j w_{ij,1} w_{ij,2}}{\sqrt{\sum_j w_{ij,1}^2}\sqrt{\sum_j w_{ij,2}^2}}. \tag{3}$$

  We compute the distribution of $\mathrm{sim}_{1,2}(i)$ for a pair of networks and compare it with two null models: in the first one, we keep the link structure and reshuffle the weights on the links; in the second, we reshuffle the links while keeping the degree of each node fixed [37].

While these measures give us an idea of the topological similarity of networks, our goal here is also to provide a way to estimate whether homophily patterns are exhibited consistently across different networks. To this aim, we tabulate for each network and each homophily index used—dyadic homophily, triadic homophily, etc.—the occurrences corresponding to an absence of homophily, weak, strong, or very strong evidence of homophily (or heterophily). We then compute the number of concordant and discordant cases for each pair of networks. For instance, we track the number of indices for which no evidence of homophily is found in one network, while strong evidence is uncovered in the second network. This gives us a first indication with respect to whether homophily patterns are similar across two networks. Moreover, we compare these numbers to a null model defined as follows: for each network and each homophily index, we reshuffle the "No", "W", "S", "VS", "W_{het}", "S_{het}", "VS_{het}" cases, keeping their number fixed, and compute again the number of concordant and discordant indices. If the empirical number of concordant cases falls outside the confidence interval of the resulting distribution for the null model, it indicates that the number of concordant cases obtained is not just due for instance to a large majority of "No" cases. Thus, it is a strong indication that the homophily patterns between networks are similar enough so that information on homophily can be obtained from either.

Note that this comparison procedure can be performed independently of the way in which homophily (or lack thereof) is assessed, as long as this way is consistent across layers. Note also that it can be applied to arbitrary numbers of layers, of attributes and of homophily indicators.

3 Results

3.1 Description of network characteristics

We first present an overview of some descriptive characteristics of the data under investigation.

Figure 2 shows the normalized number of calls events as a function of the hour of the day, summed over all days of data collection, and as a function of the day of the week, summed over all weeks. As expected, communication events display clear daily and weekly patterns, with almost no calls at night, an increase during the day, and a peak around 6–7 p.m. around the end of class time. It is worth adding that all participants dwelled on campus from Monday to Friday as part of their residential program requirements. Fewer calls were placed during weekends, with instead more calls on Fridays and Mondays. We show in the SI the timelines for co-presence events. Interestingly, we observe in this case a

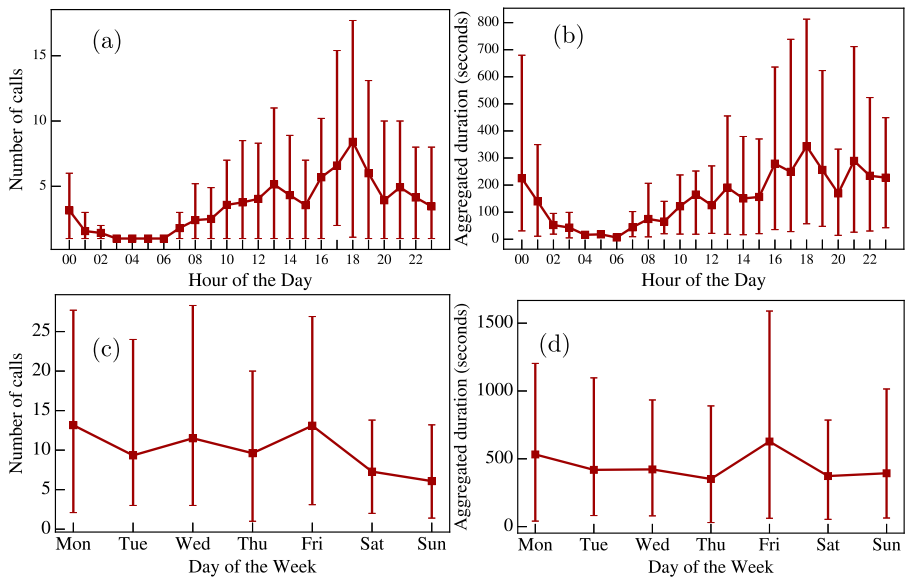

Figure 2 Timelines of communication events. (**a**) Number of calls between participants on an hourly basis throughout the day. (**b**) Aggregated duration of calls on an hourly basis throughout the day. (**c**) Number of calls on a daily basis throughout the week. (**d**) Aggregated duration of calls on a daily basis throughout the week. Each data point is normalized by the number of individuals present at that time and the error bars go from the 10th to the 90th percentile of the distribution of values over different individuals and different days or weeks

peak on Thursdays, which may be attributed to the fact most Singaporean students leaved the campus on Friday evenings. During weekends, co-presence peaks in the evenings, especially on Sunday when students come back to stay on campus in preparation for school the next day. Finally, we show in the SI the full timeline of numbers and aggregated durations of communication and co-presence events at a weekly resolution.

As expected in this type of networks, edge weights (number and aggregated durations of events) show broad distributions spanning several orders of magnitude (see Supporting Information). On the other hand, node degree distributions are narrow as the population under investigation is of relatively small size (35 students). We note that, even considering yearly aggregation, the networks are far from being fully connected, especially for the communication network: each student had on average communicated only with less than 10 other students, and the maximal degree is 22, in line with results on limited communication capacities observed in larger systems [8]. Finally, Fig. 3 displays the distribution of weights in the questionnaire networks. Most links carry the minimum possible weight in all cases, but this tendency decreases over time in both questions (see Sect. 2 for the exact phrasing), while the fraction of strong friendships tends to increase, and the distribution tends towards a bimodal shape.

3.1.1 Comparison between successive terms

Table 3 and Fig. 4 illustrate the temporal evolution of the different networks at the term level. The communication networks aggregated in the second and third terms are very strongly correlated, while they are only moderately correlated with the first term network. On the other hand, the co-presence networks in different terms show weak correlations. For both networks, the cosine similarity distribution extends over a quite broad range

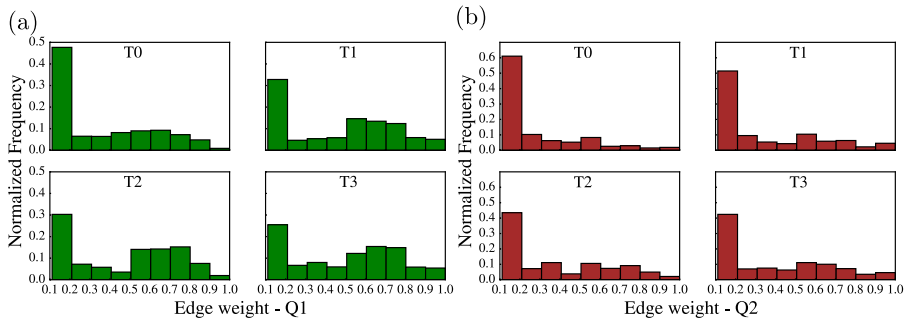

Figure 3 Histograms of weights for the networks defined by the two questionnaires. (**a**) Q1. (**b**) Q2

Table 3 Pearson correlation coefficients between term-aggregated networks

(a) Communication vs. communication ($p = 0$ for all entries)

	Duration-T1	Duration-T2	Duration-T3	Number-T1	Number-T2	Number-T3
Duration-T1	1.0	0.57	0.59	0.89	0.49	0.59
Duration-T2	0.57	1.0	0.89	0.6	0.9	0.88
Duration-T3	0.59	0.89	1.0	0.52	0.77	0.9
Number-T1	0.89	0.6	0.52	1.0	0.56	0.57
Number-T2	0.49	0.9	0.77	0.56	1.0	0.9
Number-T3	0.59	0.88	0.9	0.57	0.9	1.0

(b) Co-presence vs. co-presence

	Duration-T1	Duration-T2	Duration-T3	Number-T1	Number-T2	Number-T3
Duration-T1	1.0 ($p = 0.0$)	0.4 ($p = 0.0$)	0.44 ($p = 0.0$)	0.93 ($p = 0.0$)	0.37 ($p = 0.0$)	0.2 ($p = 0.04$)
Duration-T2	0.4 ($p = 0.0$)	1.0 ($p = 0.0$)	0.41 ($p = 0.0$)	0.32 ($p = 0.0$)	0.91 ($p = 0.0$)	0.3 ($p = 0.002$)
Duration-T3	0.44 ($p = 0.0$)	0.41 ($p = 0.0$)	1.0 ($p = 0.0$)	0.48 ($p = 0.0$)	0.43 ($p = 0.0$)	0.87 ($p = 0.0$)
Number-T1	0.93 ($p = 0.0$)	0.32 ($p = 0.0$)	0.48 ($p = 0.0$)	1.0 ($p = 0.0$)	0.35 ($p = 0.0$)	0.3 ($p = 0.002$)
Number-T2	0.37 ($p = 0.0$)	0.91 ($p = 0.0$)	0.43 ($p = 0.0$)	0.35 ($p = 0.0$)	1.0 ($p = 0.0$)	0.44 ($p = 0.0$)
Number-T3	0.2 ($p = 0.04$)	0.3 ($p = 0.002$)	0.87 ($p = 0.0$)	0.3 ($p = 0.002$)	0.44 ($p = 0.0$)	1.0 ($p = 0.0$)

(c) Questionnaire vs. questionnaire ($p = 0$ for all entries)

	Q1-T0	Q1-T1	Q1-T2	Q1-T3	Q2-T0	Q2-T1	Q2-T2	Q2-T3
Q1-T0	1.0	0.65	0.58	0.51	0.62	0.55	0.52	0.43
Q1-T1	0.65	1.0	0.81	0.77	0.47	0.71	0.7	0.63
Q1-T2	0.58	0.81	1.0	0.77	0.37	0.6	0.73	0.59
Q1-T3	0.51	0.77	0.77	1.0	0.28	0.52	0.63	0.73
Q2-T0	0.62	0.47	0.37	0.28	1.0	0.58	0.49	0.34
Q2-T1	0.55	0.71	0.6	0.52	0.58	1.0	0.71	0.59
Q2-T2	0.52	0.7	0.73	0.63	0.49	0.71	1.0	0.65
Q2-T3	0.43	0.63	0.59	0.73	0.34	0.59	0.65	1.0

(Fig. 4), and show larger values than in the two null models considered, with lowest median value for the similarities between the non-successive terms T1 and T3. Finally, for each type of questionnaire question, the correlation between the weights decrease as the time between questionnaires increases. In particular, the network constructed from the questionnaire answered at the start of the study shows the weakest correlation with successive questionnaires, which may be attributed to the fact that the students did not know each other well at that stage. Cosine similarities between different terms take very large values, much larger than in the null model with reshuffled weights (Fig. 4).

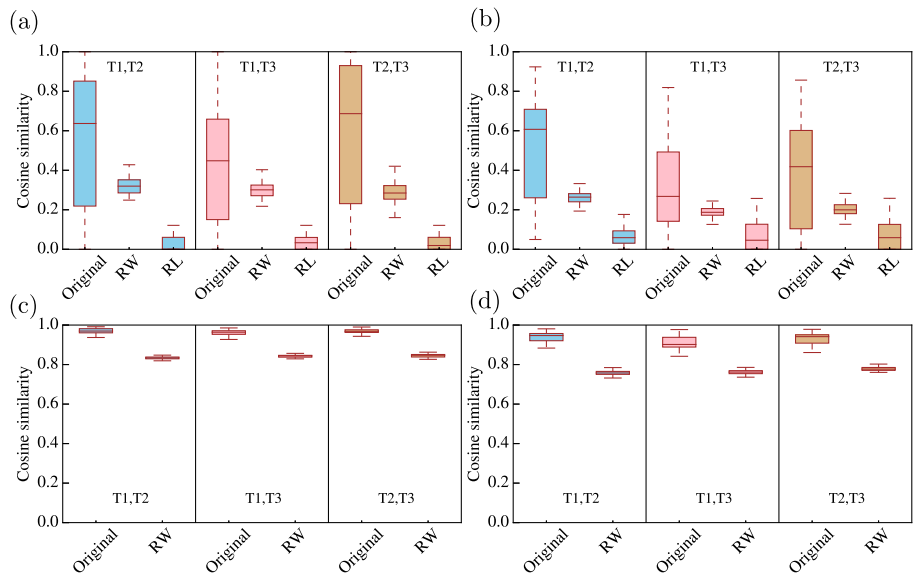

Figure 4 Boxplots of the cosine similarity distributions within the networks aggregated in different terms (T1, T2, T3), compared with the same distributions for networks with reshuffled weights (RW) or links (RL). (**a**) Communication networks—weights given by aggregated call durations. (**b**) Co-presence networks—weights given by aggregated durations. (**c**) Questionnaire—Q1. (**d**) Questionnaire—Q2. For the questionnaire cases the RL and RW procedures are equivalent as the networks are fully connected

3.1.2 Comparison between the communication, co-presence, friendship and trust networks

We found no significant correlation between the weights of edges in the yearly- or term-aggregated communication and co-presence networks, showing that these networks correspond potentially to quite different interaction patterns (the cosine similarities between these networks show also quite low values). On the other hand, both communication and co-presence weights show weak but significant correlations with the weights resulting from the two questionnaires Q1 and Q2. The values of the cosine similarities of neighborhoods of nodes (i) between communication and questionnaires, and (ii) between co-presence and questionnaires, display moreover values much larger than in the null models with reshuffled weights or edges. Finally, in each term, the weights reported in Q1 and Q2 are strongly correlated (but distinct), and the cosine similarities of neighborhoods of nodes in the two questionnaire networks are close to 1 (see Supporting Information).

To explore in more details the comparison between pairs of networks, we consider the properties of links either *(i)* common to two networks or *(ii)* present only in one of two networks. Figure 5 displays the complementary cumulative distribution function (CCDF) of edge weights for links common to the communication and co-presence networks, as well as the CCDF of weights for links present in only one of the two networks. Note that many links are present only in the co-presence network, while few are present only in the call network, which is not surprising given the much denser nature of the co-presence network. A clear difference is observed between the distributions of co-presence weights, with broader distributions for links common to both networks than for links present only in the co-presence networks: students who communicated by phone calls also tended to spend more time in co-presence, but a broad distribution is obtained even for the links between students who did not communicate by phone. On the other hand, no clear dif-

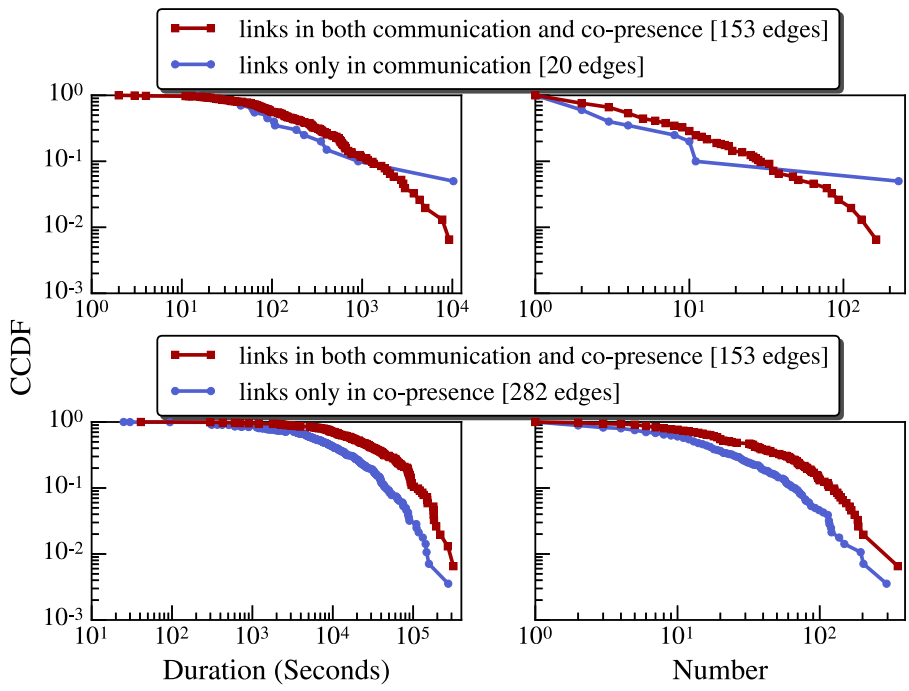

Figure 5 CCDF of weights of links common to communication and co-presence networks, compared to the CCDF of weights of links present only in one of these networks. Top plots: CCDF of the weights in the communication network. Bottom plots: CCDF of the weights in the co-presence network

ference is observed in the communication weights between pairs of students who were at least once in co-presence and pairs who were not, maybe because of the lack of statistics for the latter: very few pairs of students indeed communicated but were never detected in co-presence.

We also compare the communication links and weights for the various weight categories in the questionnaires as shown in Fig. 6. As the questionnaire weight w increases, the fraction of links with that weight that are also present in the communication network increases strongly, from almost 0 for low weights to 60–70% for the strongest weights. This result confirms earlier findings that stronger friendship relations correspond to more probable communication. Interestingly, however, the average number or duration of these communications does not depend on the questionnaire weight category, except for the largest weight category, for which larger average number and duration of communications are observed: the pairs of closest friends have more frequent and longer communication patterns with respect to other pairs of students. It is also worth highlighting that no such clear tendency is observed when comparing questionnaire weights and co-presence patterns: the fraction of links corresponding to co-presence barely increases with the questionnaire weight, and the corresponding average co-presence duration (or number of events) does not show any clear trend (not shown).

3.2 Homophily patterns in yearly-aggregated networks

We first present a brief study of the homophily patterns for the globally aggregated networks. We focus here mostly on the communication network, data for the co-presence network being shown in the Supporting Information. Figure 7 gives a first indication of

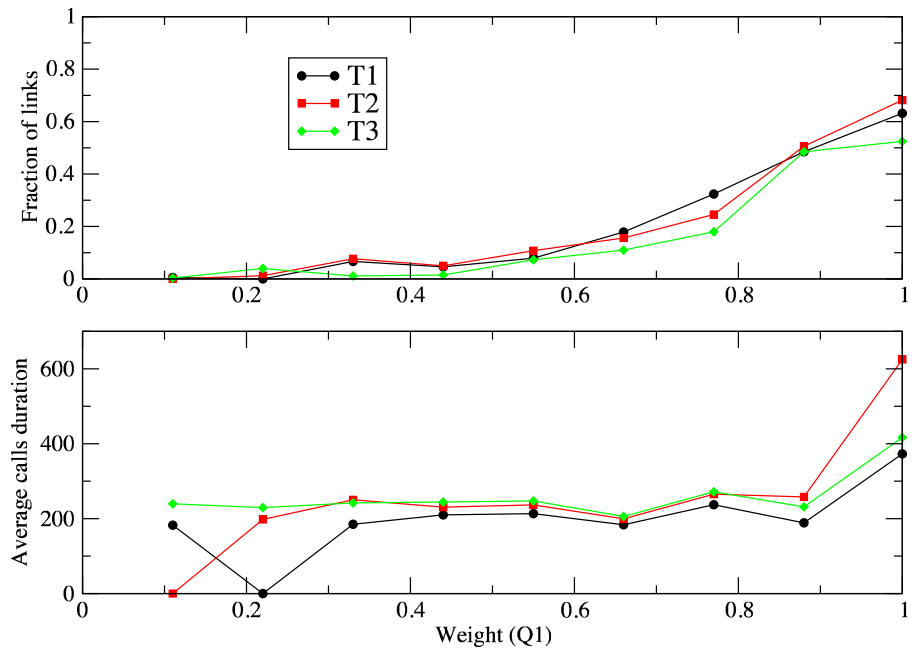

Figure 6 Communication between individuals as a function of friendship. Top plot: fraction of links corresponding to a communication as a function of their weight in Q1. Bottom plot: average aggregated duration of communication along a link (i.e., weight of the link in the communication network) as a function of its weight in Q1

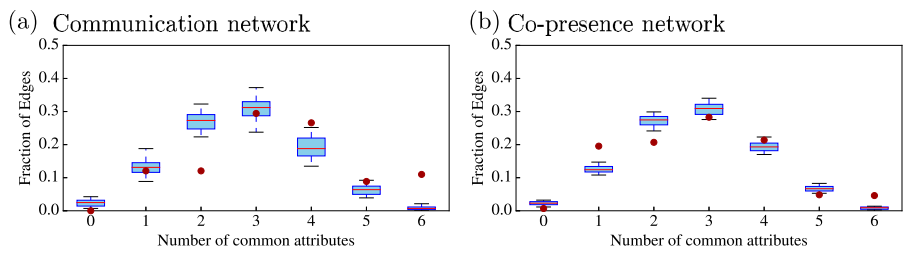

Figure 7 Distribution of the number of common attributes on an edge, compared with a null model with reshuffled attributes. Attributes: Cohort class, Age, Gender, Nationality, GPA and First Language. Boxplot: Whiskers—5th, 10th and 90th, 95th percentiles; box—25th and 75th percentiles

the presence of homophily in the communication and co-presence networks, by comparing the distribution of the number of shared attributes for individuals connected by a link with the same distribution in the null model in which attributes are reshuffled across nodes. Here, we consider the following six attributes: cohort class, age, gender, nationality, GPA, and first spoken language. Large values of the number of shared attributes are over-represented with respect to the null model: in particular, a much larger fraction of links connect nodes sharing all these attributes than in the null model, while the fraction of links connecting nodes with no common attribute is smaller than in the null model.

Figure 8 goes further by showing the CCDF of edge weights in the communication network, separately for edges between individuals with similar and different values for these six attributes. All distributions are broad: both weak and strong links are observed in each case, showing that one cannot separate these easily in two groups and guess from the

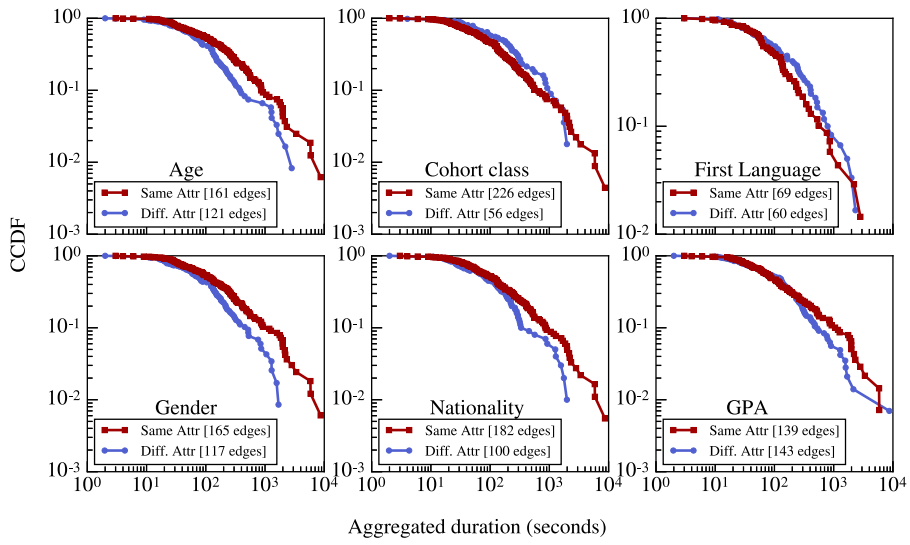

Figure 8 Complementary cumulative distribution function (CCDF) of the edge weights in the yearly aggregated communication network, for edges linking nodes with either the same attribute or different values. Results are shown separately for different attributes

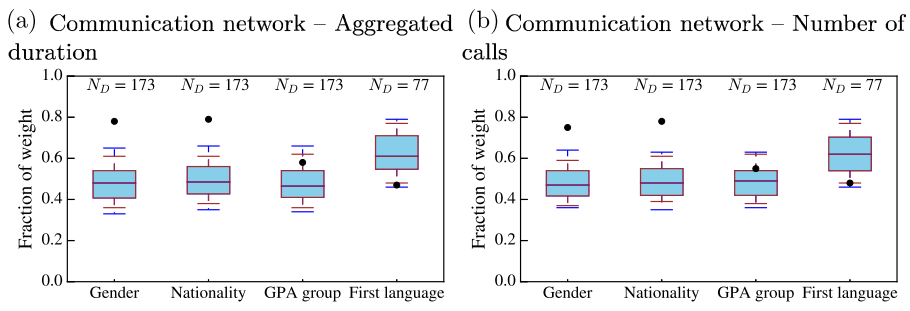

Figure 9 Dyadic homophily—yearly-aggregated communication network. Data (black dots) are compared with the distribution (boxplots) obtained for a null model in which attributes are reshuffled among nodes. N_D gives the number of dyads on which the measure is performed. Boxplot: Whiskers—5th, 10th and 90th, 95th percentiles; box—25th and 75th percentiles

weight of a link if the two connected individuals share an attribute. On the other hand, the distributions tend to be broader for edges linking nodes with the same value for several attributes, and the largest weights link nodes with same nationality, gender, age and class.

Figures 9 and 10 show the homophily patterns with respect to gender, nationality, first spoken language and GPA uncovered by investigating the fraction of weight carried respectively by links and triangles between individuals with the same attribute, as described in the Methods section. Very strong homophily patterns are found with respect to gender and nationality, not only at the dyadic level but also for triangles: gender and nationality homophily determine which triangles, and not only which links, carry more weight in the network. Homophily with respect to GPA is on the other hand absent or at most very weak, while heterophilic patterns are observed for the first language.

Figure 11 investigates the social preference homophily patterns of each group of individuals. Both male and female students show a clear homophily pattern in their preferred

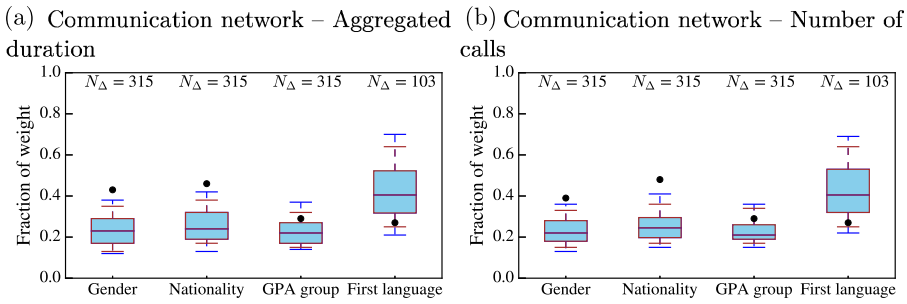

Figure 10 Triadic homophily—yearly-aggregated communication network. Data (black dots) are compared with the distribution (boxplots) obtained for a null model in which attributes are reshuffled among nodes. N_Δ gives the number of triads on which the statistics is made. Boxplot: Whiskers—5th, 10th and 90th, 95th percentiles; box—25th and 75th percentiles

communication partner. Similarly, both Singaporean and Foreigners display homophilous social preference. On the other hand, homophily with respect to GPA shows contrasting trends: individuals with an above median GPA do not show homophily in their preferred communication partner, while individuals who have low GPA (below median) do (more so in terms of aggregated duration of communication than in terms of number of calls). For first spoken language, a weak tendency toward heterophily is observed for non-Chinese speaking students.

Finally, Fig. 12 exhibits strong homophily patterns observed in reciprocal and repeated call motifs, both for gender and nationality. Only weak homophily is further observed with respect to GPA. In the first spoken language case, we also observe some tendency toward homophily, in contrast with the other indexes described above.

With respect to these attributes, various homophily patterns are thus observed when aggregating over the whole dataset of one year without taking into account the timing of communication events, but also when considering sequences of calls separated by short time windows.

3.3 Evolution of homophily in communication across terms

We now turn to the study of how homophily patterns evolve across the year in the group of students. To this aim, since questionnaire networks were collected once in each term, and also to work with sufficient statistics, we consider term-aggregated networks of communication. We show here the results corresponding to homophily patterns in dyads, while figures for triadic homophily and social preference are shown in the Supporting Information. Gender homophily as revealed by the weight carried by dyads with the same gender is very strong in all terms, and exhibits a clear increasing trend (Fig. 13(a) and (b)). The same increasing trend is observed in the weight carried by homophilic triads, even if the evidence for homophily is only weak with respect to the null model in the first term. In terms of social preference patterns, homophily increases for males, from absent or weak in the first two terms to very strong in the last term, while it is very strong in all terms for females (see Supporting Information).

Homophily with respect to nationality is also very strong and stable across terms as measured by dyads. It weakens, however, in the third term as measured by triads. In terms of social preference, interesting distinct patterns are found: homophily decreases strongly

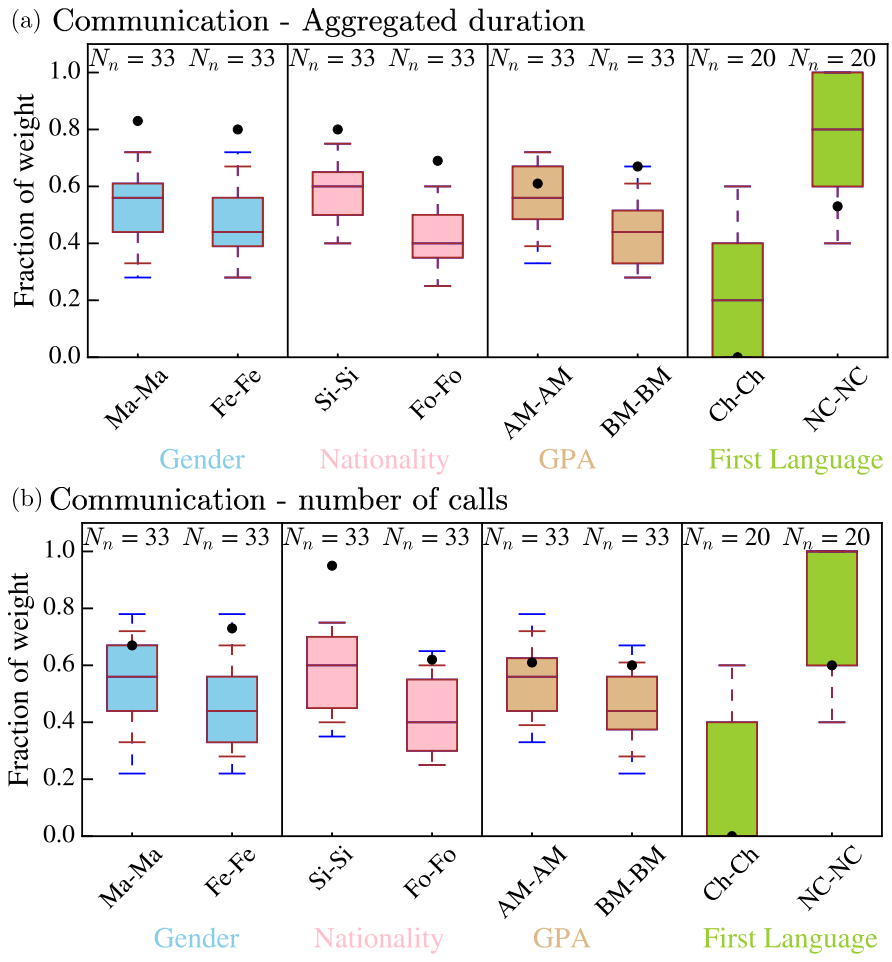

Figure 11 Homophily in social preference—yearly-aggregated communication network. Ma: Male; Fe: Female; Si: Singaporean; Fo: Foreigner; AM: Above Median; BM: Below Median; Ch: Chinese; NC: Non-Chinese. Data (black dots) are compared with the distribution (boxplots) obtained for a null model in which attributes are reshuffled among nodes. Boxplot: Whiskers—5th, 10th and 90th, 95th percentiles; box—25th and 75th percentiles

and becomes weak or absent in the third term for Singaporean students, but instead remain very strong and in fact increase for foreigners (see Supporting Information).

The tendency toward homophily with respect to GPA remains rather weak across all terms with respect to all indicators, except in the first term for triads and in the third term for dyads. On the other hand, several instances of heterophilic tendencies are found with respect to the first spoken language. Finally, we find no clear tendency toward homophilous behavior of students with respect to their scores in the three psychological questionnaires (see Supporting Information). Some tendency toward heterophilous behavior is even observed in some cases, in particular in the social preference of the students with loneliness index below median.

3.4 Comparison between homophily in various networks

As discussed in the introduction, an important issue, besides the evidence for homophily (or the lack thereof) in each layer of interaction or relations available for analysis, is whether the same or different conclusions are reached when investigating these different

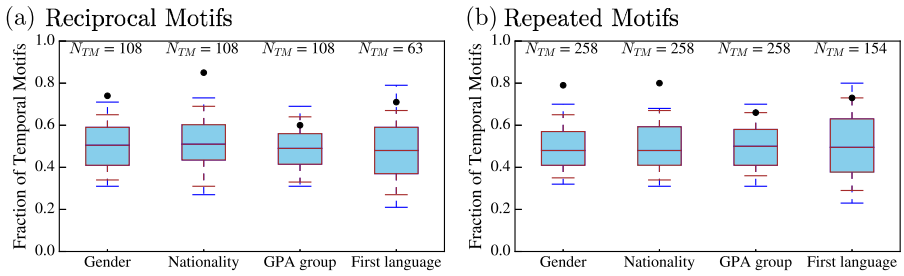

Figure 12 Homophily in temporal motifs—yearly-aggregated communication network. Motif types—reciprocal and repeated events. Data (black dots) are compared with the distribution (boxplots) obtained for a null model in which attributes are reshuffled among nodes. N_{TM} gives the number of temporal motifs in the network. Boxplot: Whiskers—5th, 10th and 90th, 95th percentiles; box—25th and 75th percentiles

layers. As made clear from the comparison reported above, there are indeed significant correlations between communication and friendship or trust networks, and the students linked in the communication network tend also to have spent more time in co-presence. However, these networks are very distinct both in terms of structure and weights.

In order to investigate if the layers are similar enough in terms of the homophily patterns they exhibit, it is possible to thoroughly compare the results provided in the previous section for the communication network and in the Supporting Information for other networks. Examples of such comparisons are given in Figs. 13 and 14: in these figures, we can visually check if a given indicator shows homophily in each term for different networks. For instance in Fig. 13, we notice that there is dyadic homophily in all terms for gender and nationality in the communication network, while in the co-presence network there is homophily only in the first term for nationality, and in the first and third terms for gender. Such a visual investigation, also found for instance in [4], is however limited to only one type of indicator in each figure (e.g., one figure for dyadic homophily, one for triadic, etc.), and only a few attributes. Overall, a systematic side-by-side comparison of the figures showing whether homophily is present, for all pairs of layers and all possible indicators of homophily, would be difficult and tedious to carry out and would not improve the holistic analysis of homophily. A first improved visual way enabling a more holistic comparison of homophily across layers is given by Table 4 (see also Supporting information). In this Table, we summarize the evidence for homophily or heterophily in the different layers and terms, with respect to all the considered attributes. The use of colors highlights cases in which the same answer is obtained in different layers (e.g., gender and nationality homophily in communication and in both questionnaire networks). On the one hand, however, this Table is still not easy to apprehend globally, and on the other hand, one needs to draw a separate table for each type of homophily measure.

We thus perform one more summarizing step in order to reach more easily interpretable results: for each pair of networks, we count the number of cases in which one network gives a certain answer while the other network gives another answer, where by "case" we mean "one homophily measure on one attribute for one term". We tabulate these numbers for each pair of networks and show the full tables in the Supporting Information. In Table 5, we show the outcome of a simplified counting procedure in which we group "No", "W" and "W_{het}" as evidence for "No homophily nor heterophily pattern" on the one hand and "S" and "VS" (resp. "S_{het}" and "VS_{het}") as evidence for homophily (resp. heterophily) on the

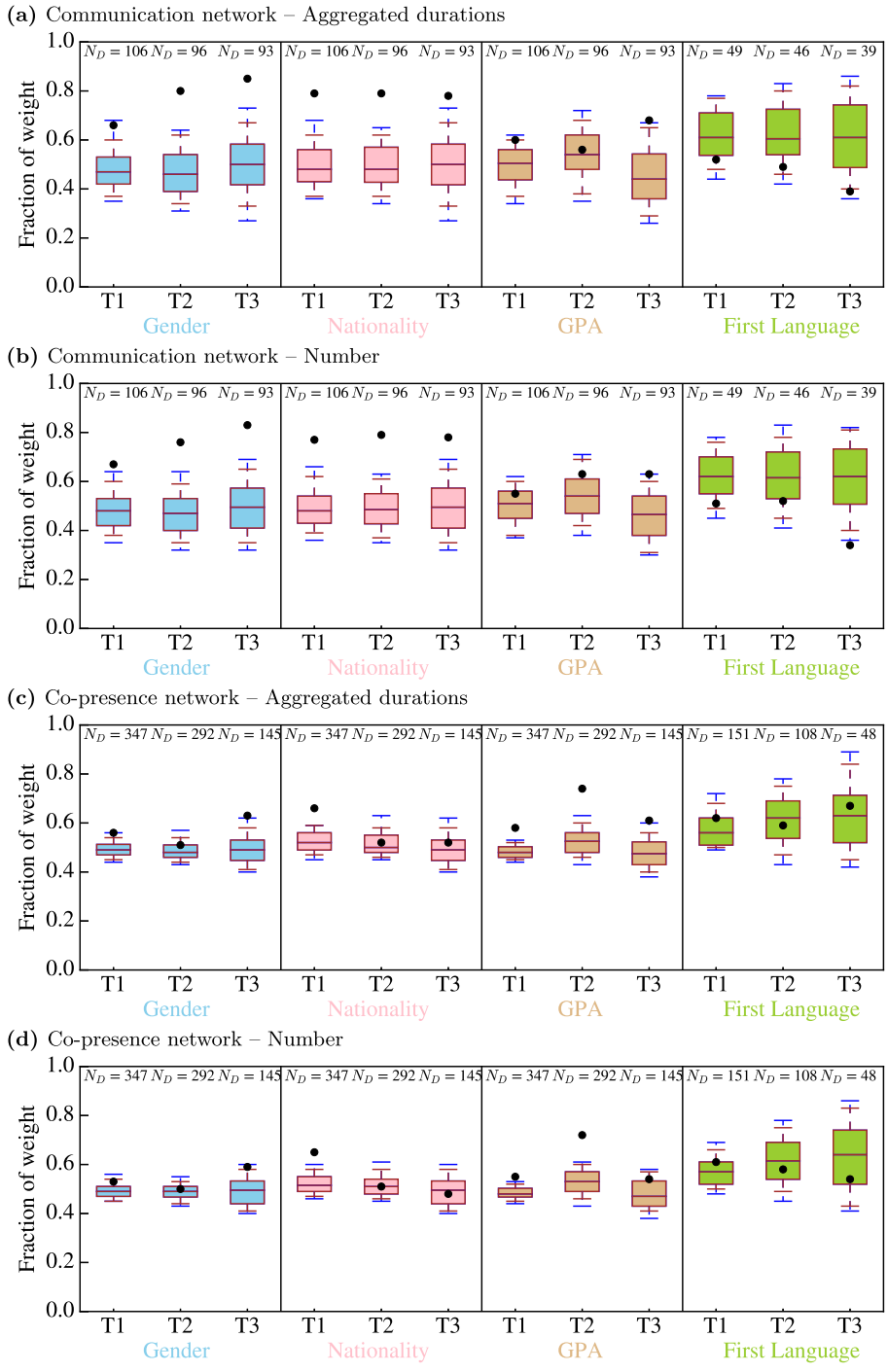

Figure 13 Homophily in dyads with respect to several attributes—term aggregated communication and co-presence networks. Data (black dots) are compared with the distribution (boxplots) obtained for a null model in which attributes are reshuffled among nodes. N_D gives the number of dyads on which the measure is performed. Boxplot: Whiskers—5th, 10th and 90th, 95th percentiles; box—25th and 75th percentiles

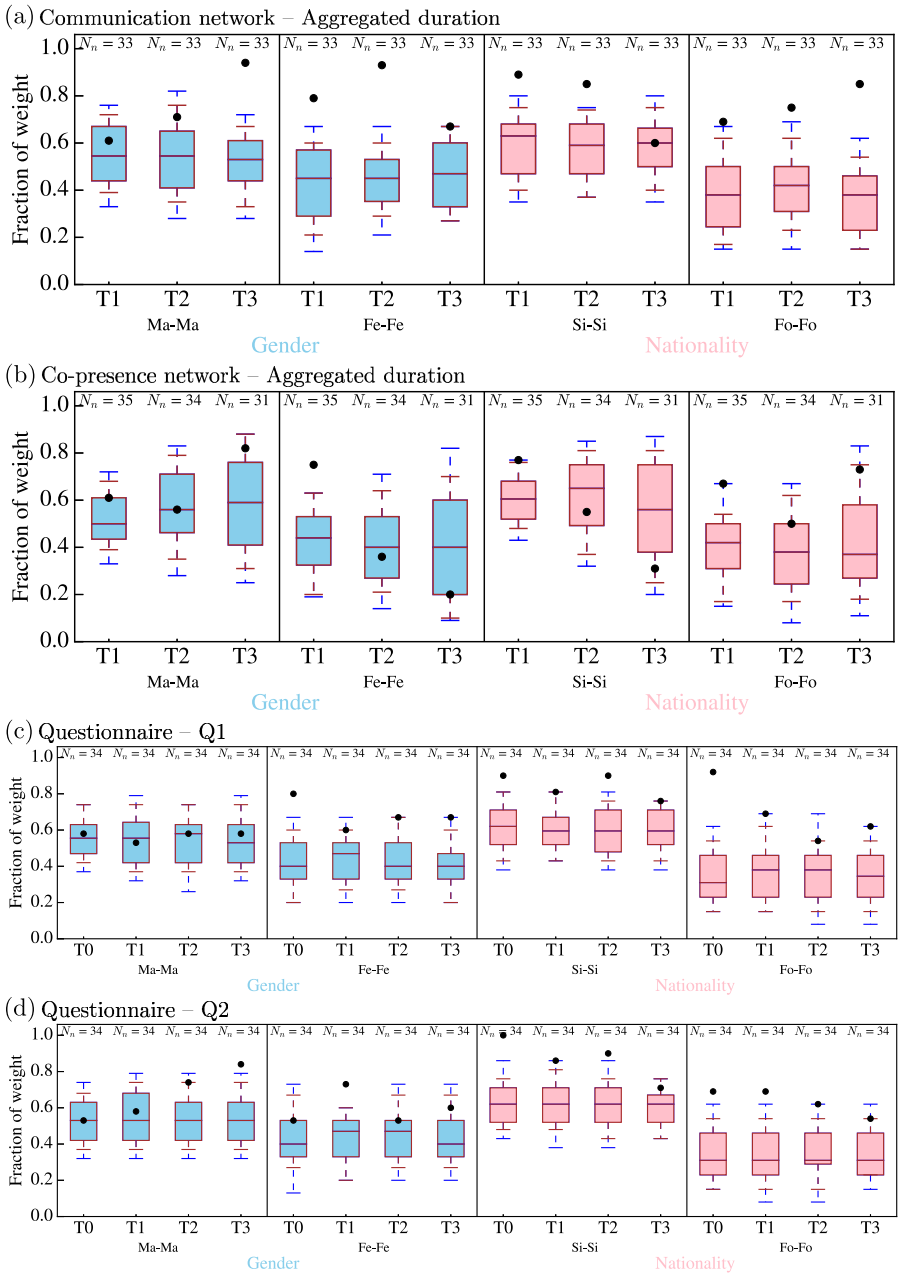

Figure 14 Concordant vs. discordant cases: Homophily in social preference in gender and nationality—term-aggregated networks. Ma: Male; Fe: Female; Si: Singaporean; Fo: Foreigner. Data (black dots) are compared with the distribution (boxplots) obtained for a null model in which attributes are reshuffled among nodes. Boxplot: Whiskers—5th, 10th and 90th, 95th percentiles; box—25th and 75th percentiles

other hand. Note that this methodology could easily be adapted to answer more detailed comparisons, for instance by separating attributes into different groups (e.g., considering only homophily with respect to psychological indices), or on the opposite to include an arbitrary number of homophily indicators and of attributes.

A first assessment of the results gathered in Table 5 indicates that concordant cases (on the diagonals) are far more numerous than discordant ones. It is, however, important to

Table 4 Summary of the dyadic homophily patterns found in the different networks, with respect to the various attributes considered

Attribute	Weight	Communication			Co-presence			Weight	Questionnaires			
		T1	T2	T3	T1	T2	T3		T0	T1	T2	T3
Gender	Volume	S	VS	VS	S	No	VS	Q1	VS	S	S	VS
	Number	VS	VS	VS	W	No	S	Q2	S	VS	VS	VS
Nationality	Volume	VS	VS	VS	VS	No	No	Q1	VS	VS	VS	VS
	Number	VS	VS	VS	VS	No	No	Q2	VS	W	S	W
GPA	Volume	W	No	VS	VS	VS	VS	Q1		VS	W	W
	Number	No	W	S	VS	VS	W	Q2		VS	No	W
First language	Volume	W_{het}	W_{het}	S_{het}	No	No	No	Q1	No	No	No	No
	Number	W_{het}	W_{het}	VS_{het}	No	No	No	Q2	No	No	W_{het}	No
Loneliness	Volume	W_{het}	W_{het}	No	S_{het}	No	No	Q1	VS	No	No	No
	Number	W_{het}	No	No	W_{het}	No	No	Q2	W_{het}	No	No	No
SACQ	Volume	W_{het}	W_{het}	W	W	S_{het}	W_{het}	Q1	VS	W_{het}	No	No
	Number	No	No	W	S	W_{het}	W_{het}	Q2	W	No	No	No
Classroom community	Volume	W_{het}	W_{het}	No	W	No	No	Q1	No	No	No	W
	Number	W_{het}	No	No	W	W	No	Q2	W_{het}	W	No	No

deepen our analysis as this overall observation might simply be due to the large number of indicators showing an absence of homophilous patterns. Indeed, if we consider a large number of attributes and a large number of indicators, and only few of them show evidence for homophily, then many concordant cases will be automatically observed, even if the few cases of homophily are very different in distinct network layers. To check if this is indeed the case, we resort to a comparison with the following null model: for each layer and each homophily indicator (dyadic, triadic or social preference), we reshuffle at random the answers ("VS", "S", "W", "No", "W_{het}", "S_{het}" and "VS_{het}") across terms and attributes, and compute for each reshuffling the number of concordant and discordant cases. We present in Table 5 the confidence intervals (C.I.) defined by the 5th and 95th percentiles of this null model, we emphasize in boldface the cases in which the empirical numbers are outside the C.I. and we color in particular the cells in which the numbers of concordant cases are above the C.I.

For the comparison between the two questionnaire networks, as well as between the communication network and the questionnaire networks, the numbers of concordant cases with and without homophily are both much larger than the upper bound of the confidence intervals of the null model, while the numbers of cases in which one network shows homophily while the other does not are smaller than the lower bound of the C.I. These three networks have therefore overall similar homophily patterns, despite discrepancies occurring in a number of specific cases.

On the other hand, comparisons involving the co-presence network lead mostly to numbers of concordant and discordant cases within the C.I. of the null model. This means that, even if the co-presence network displays a similar "amount" of evidence for homophilous behavior with respect to the other layers of the social network, the homophily patterns are no more similar than random, given this amount. Hence, the co-presence homophily patterns do not inform us about which specific attributes and which specific indicators exhibit homophily patterns in the other networks.

Table 5 Comparison of homophily in networks. Each table corresponds to a pair of networks and gives at row X and column Y the number of cases in which an indicator gives a result X in the first network and a result Y in the second. The intervals correspond to the confidence intervals of the null model described in the text, and empirical numbers are emphasized in boldface if they lie outside this interval

(a) Communication vs. co-presence

		Co-presence		
		HOM	NO	HET
Communication	HOM	**16** [5–13]	30 [30–38]	**0** [1–5]
	NO	**17** [18–26]	89 [83–91]	**11** [6–10]
	HET	0 [0–3]	5 [2–6]	0 [0–1]

(b) Questionnaire—Q1 vs. Q2

		Q2		
		HOM	NO	HET
Q1	HOM	**18** [4–10]	**14** [19–26]	0 [0–4]
	NO	**18** [24–30]	**102** [90–97]	8 [6–9]
	HET	0 [0–3]	6 [4–8]	2 [0–2]

(c) Communication vs. Q1

		Q1		
		HOM	NO	HET
Communication	HOM	**23** [6–12]	**22** [31–38]	1 [1–4]
	NO	**9** [19–25]	**102** [85–93]	6 [3–7]
	HET	0 [0–2]	4 [3–6]	1 [0–1]

(d) Communication vs. Q2

		Q2		
		HOM	NO	HET
Communication	HOM	**26** [6–12]	**20** [31–37]	**0** [1–5]
	NO	**10** [22–29]	**97** [81–88]	**10** [5–9]
	HET	0 [0–3]	5 [2–6]	0 [0–1]

(e) Co-presence vs. Q1

		Q1		
		HOM	NO	HET
Co-presence	HOM	9 [3–10]	24 [21–28]	0 [0–4]
	NO	23 [20–27]	93 [91–99]	8 [4–8]
	HET	0 [0–4]	11 [6–12]	0 [0–2]

(f) Co-presence vs. Q2

		Q2		
		HOM	NO	HET
Co-presence	HOM	**13** [4–11]	**18** [20–28]	2 [0–4]
	NO	23 [23–30]	93 [86–95]	8 [5–9]
	HET	0 [0–5]	11 [5–12]	0 [0–2]

4 Discussion

The increased availability of data providing proxies for human behavior and social relationships, often in digital form, has led to a surge in the number of studies of social theories and effects. Most such studies are, however, based on the analysis of one specific layer (e.g., phone call communications) of the population social network, which is best represented as a multilayer network. It is now well established that the various network layers bear some level of correlations but are far from being equivalent. However, it is still unclear to what extent one can infer general conclusions from the study of only one layer. In this paper, we have considered this issue—with a particular focus on homophily patterns—through the lens of a dataset providing data on several layers of the same population, namely a communication layer, a co-presence layer, and two questionnaires describing friendship and trust relationships. The population under scrutiny is formed of first-year students in an Asian university. Notably, the diversity of students in the population allows us to investigate homophily patterns along several dimensions: gender, nationality, first spoken language, GPA and psychological indices assessed by questionnaires. It is worth adding that most studies about homophily reported in the literature are concerned with populations having a homogeneous composition in terms of nationality and first language [4, 11–16].

In terms of direct comparison between networks, we found no correlation between the weights of links in the co-presence and communication network, but significant correlations between communication or co-presence and questionnaires networks. We also found a clear correlation between communication (number and call volume) and reported friendship strength, confirming results of other authors with other types of population [9, 11, 14, 16, 32, 33]. This latter point stands in stark contrast with the absence of correlation between the amount of co-presence and friendship strength.

The strongest uncovered evidence of homophily is with respect to gender and nationality in several indicators and layers, while weaker evidence concerns homophily with respect to academic performance as measured by the GPA. No homophily was found with respect to the first spoken language nor psychological indices (similarly to [4], even if for different indices).

Most importantly, we have put forward here a systematic way of comparing homophily patterns with respect to a heterogeneous group of attributes in the different layers of a social network. This methodology is based on counting the numbers of concordant and discordant indicators of homophily in each pair of networks. As a large number of concordances might simply be due to a scarcity of indicators showing homophily, a crucial point is to compare these numbers with a null model in which the results of the indicators are reshuffled within each network and type of indicator. If the observed number of concordant (resp. discordant) cases lies above (resp. below) the confidence interval of this null model, it means that both networks yield an overall concordant picture of the homophily patterns in the studied social network, in a way that is not simply due to an overall lack of homophily. On the other hand, if the observed number of concordant cases falls within the confidence interval of the null model, we can conclude that one cannot extract information about homophily patterns in one network from the patterns in the other network.

In the specific case under study, we found that the communication and questionnaire layers lead to similar conclusions in many cases—even if some minor discrepancies are observed—and more than expected from the null model. This means that the communi-

cation layer allows us to obtain information about homophilous trends in the friendship and trust networks of this social network. On the other hand, the co-presence network cannot be used to assess homophily patterns occurring in the other layers.

Our work has several limitations that are worth mentioning. First, from the experimental viewpoint, it could be argued that providing the participants with a new device might have influenced some user behaviors in the early stages of the study. For instance, participants might spend time exploring the features of the new device. However, it is unlikely that the target behaviors of interest (i.e., chatting on mobile phone, co-presence activity) had been changed. In supporting this, the communication networks in different terms showed moderate to strong correlations. Moreover, the co-presence networks in different terms were also significantly correlated with each other. Another obvious limitation is the fact that our study is based on one single dataset of a specific population of limited size. The population was, however, largely isolated, and data is available for a whole year, allowing the analysis of the evolution of the homophily patterns along the year, as well as the comparison with the evolution in the other layers. Moreover, we could not reliably use messaging data, although messages nowadays represent a fair amount of communication between individuals. Furthermore, we did not have access to any online social network on which messages are also exchanged. The co-presence data had limited spatial resolution owing to the particular choice of the Bluetooth technology. It might be that with another technology yielding a higher spatial resolution, data on face-to-face interactions would lead to different conclusions, and correspond to a larger similarity of homophily patterns with the communication and questionnaire networks.

To conclude, we note that the methodology put forward to assess the similarity of homophily patterns in different layers of a social network is general and can be applied to any dataset composed of several layers of interactions or relationships between individuals, and to any set of attributes for which homophily patterns are of interest. We therefore hope that the present study will stimulate further similar dataset collections and investigations into this crucial issue.

Additional material

Additional file 1: Supporting information: Tables and graphs. Comparison between term-aggregated networks; Homophily patterns in the yearly aggregated co-presence network; Evolution of homophily patterns in triads and social preference in the communication network; Summary tables of homophily patterns for triads and social preferences; Detailed tables of the numbers of concordant and discordant cases for each network pair. (PDF 2.6 MB)
Additional file 2: Dataset. (TGZ 84 kB)

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List of abbreviations
CC, classroom community; CCDF, complementary cumulative distribution function; C.I., confidence interval; GPA, grade point average; LS, loneliness scale; QAP, quadratic assignment procedure; S, strong; SACQ, student adaptation to college questionnaire; VS, very strong; W, weak.

Availability of data and materials
All data is provided as Additional file 2.

Competing interests
The authors declare that they have no competing interests.

Authors' contributions
WQY designed the network smartphone study and data collection. AB and RB conceived and designed the study of homophily for the social network, with consultations from WQY. AM performed the statistical data analysis. AB, AM, and RB wrote the manuscript. WQY reviewed the manuscript. All authors read and approved the final manuscript.

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