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Perceived group cohesion versus actual social structure: A study using social network analysis of egocentric Facebook networks

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ABSTRACT

Research on group cohesion often relies on individual perceptions, which may not reflect the actual social structure of groups. This study draws on social network theory to examine the relationship between observable structural group characteristics and individual perceptions of group cohesion. Leveraging Facebook data, we extracted and partitioned the social networks of 109 participants into groups using a modularity algorithm. We then surveyed perceptions of cohesion, and computed group density and size using social network analysis. Out of six linear mixed effects models specified, a random intercept and fixed slope model with group size as a predictor of perceived group cohesion emerged as best fitting. Whereas group density was not linked to perceived cohesion, size had a small negative effect on perceived cohesion, suggesting that people perceive smaller groups as more cohesive. We discuss the potential of social network analysis, visualization tools, and Facebook data for advancing research on groups.

1. Introduction

Groups are crucial units across social settings, and accomplishing tasks in groups has many advantages over working individually (Guerrero and Bradley, 2013; Kerr and Tindale, 2004; Laughlin et al., 2006). Such advantages of groups, however, are more likely to arise in cohesive groups, as consistently demonstrated by meta-analyses (e.g., Beal et al., 2003; Chiocchio and Essiembre, 2009; Evans and Dion, 1991; Gully et al., 1995).

Despite cohesion being considered a central group property across both social psychology and sociology (Friedkin, 2004), the link between perceived group cohesion and structural properties of groups is not fully explored. Seminal work by Lawler and colleagues demonstrated that certain (power) structures within networks generate cohesion via positive social exchanges (e.g., Lawler and Yoon, 1996, 1998). Relatedly, Molm and colleagues demonstrated the importance of network structure for the emergence of reciprocity and trusting bonds (e.g., Molm, 2010; Molm et al., 2000). Since this work has primarily focused on exchange relationships between dyads (that are embedded in networks), or experimentally-induced groups (Lawler et al., 2000; Molm et al., 2007), it is not entirely clear to what extent perceived group cohesion is associated with relational structures of a range of existing social groups within networks. In social psychology research, the study of group cohesion is typically limited to experimentally-induced (task) groups who interact for a very short period of time (for a review, see McGrath et al., 2000). While some studies do manipulate the size of such task groups (Carron and Spink, 1995), they are unable to convincingly induce complex webs of social relationships that are often found in people's real-life social networks. Such networks typically contain a range of different groups (i.e., friends, family, and acquaintances)

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that are likely to not only differ in group size, but also in the extent to which group members are interconnected (i.e., group density). In the field of social network research, different structural measures (e.g., size, density, node connectivity) were posited to predict cohesion (Friedkin, 2004). However, structural predictors of cohesion tend to be studied in larger collectives (Moody and White, 2003) or in simulated networks (Friedkin, 1981). It is yet unclear whether theories of structural cohesion also apply to small and real-life groups. Therefore, this study aims to investigate whether structural group properties (i.e., group size and density) predict perceived cohesion in small, real-life groups.

To address this research question, we propose to leverage social network theory and methods. Social network analysis maps the structure of social relationships and provides measures of how people (in a group) are connected to one another (Wölfer et al., 2015). With advances in technology and readily available data on individuals' social environments online, social network analysis offers tools for extracting social networks, partitioning these into meaningful groups, and analyzing their structural properties. The present paper contributes to the social science literature by integrating individual perceptions of group cohesion with innovative social network methods and empirically examining the distinction between perceived cohesion and structural group characteristics. We show how social network analysis of existing egocentric network data (i.e., Facebook friendship data) can be leveraged as an efficient, behavior-based, and unobtrusive way of measuring structural group characteristics that might be linked to individual perceptions of group cohesion. Finally, we discuss implications for our understanding of cohesion in an increasingly connected world and for the intersection of individual perceptions and observed group constructs more broadly.

2. Theoretical background and hypotheses

Many researchers studying group dynamics would agree that cohesion is a key feature of (successful) groups. Cohesion broadly refers to the "stickiness" of a group and to the extent that group members are motivated to advance the group's continuity or well-being (for a recent review, see Casey-Campbell and Martens, 2009; Greer, 2012; Salas et al., 2015). A useful differentiation that is often drawn in cohesion research concerns the distinction between the task dimension and the social dimension of group cohesion (Salas et al., 2015). Task cohesion refers to group members' commitment to working well together in order to achieve goals (Carron et al., 1985). Social cohesion refers to the attractiveness of a group that is based on group members' social relationships (Lott and Lott, 1965; Seashore, 1954). Here, we specifically focus on social cohesion.

While we agree that group cohesion is a multidimensional construct, in this study, we focus on social cohesion for two reasons. First, social cohesion is most relevant for the aims of this study, as we investigate social groups that tend to be held together by the social bonds between group members (e.g., friends, and family). Such groups are characterized by the liking, trust, and attraction between group members. Second, social cohesion is theoretically closest to conceptual approaches by social network theorists (Friedkin, 1984; Moody and White, 2003), who consider cohesion to be based on the relationship structure that underlies groups. A group is argued to be more cohesive when its members are better connected to one another via direct and indirect relationship ties. Such connectedness tends to occur via bi-directional ties and allows for reciprocal exchange of support, advice and approval which can flow not only back to the initial sender of support, but also to any another actor who is embedded in the network (Molm, 2010). This is a crucial condition for generalized exchange and the emergence of trust and strong, affective bonds within a network (Molm et al., 2007). This relational focus is consistent with the instrument that we use to assess perceived group cohesion in this study (Wongpakaran et al., 2013), which taps into group members' relationships to one another (e.g., "The members of this group like and care about each other"). Next, we elaborate how structural properties of groups relate to the social dimension of group cohesion from a social network analysis stance.

2.1. The structural predictors of group cohesion: applying social network analysis

Broadly defined, social network analysis is a set of theories and methodological tools for analyzing and understanding the structure and relationships within social networks (e.g., Borgatti et al., 2009). In research on groups, the so-called "nodes" of a network are typically the people and the "edges" are the relationships between people.

Groups have structural properties that could be predictive of perceived group cohesion. Some social network researchers proposed that group cohesion may depend on the extent to which individuals are connected to one another (Cartwright, 1968; Festinger, 1950; Friedkin, 1984, 1993; Moody and White, 2003; Moreno and Jennings, 1937). The closer a social network is to completeness (i.e., the closer the group is to having realized all possible connections), the stronger the cohesion. In social network analysis terms, this is sometimes referred to as *structural cohesion* or *density* (Friedkin, 1981; Hanneman and Riddle, 2005; Wasserman and Faust, 1994). The rationale behind this is that with increasing numbers of (indirect) ties that bind people together, individuals are discouraged from leaving the group, which prevents the group from dissolving (White and Harary, 2001). With higher density, information can spread via shorter and quicker paths to reach every group member, which creates more homogeneity in attitudes (Friedkin, 1993; Reagans and McEvily, 2003), as well as in behavior (Haynie, 2001). Groups that have a lot of cross-connections between individuals are better at imposing collective sanctions and rewards which promotes the coordination of group activities and the emergence of shared norms (Coleman, 1988).

Group density and group size are linked both theoretically and mathematically (Wasserman and Faust, 1994), such that larger groups tend to be lower in density. Group density is defined as the number of observed connections divided by the number of possible connections in a group. As group size increases linearly, the potential number of possible ties increases super-linearly. To maintain the same level of density, larger groups on average need to realize many more connections between their group members (i.e., mean degree). This mathematical association is reflected in the equation for calculating group density:

$$D = \frac{L}{n(n-1)} \tag{1}$$

where

D = density
L = observed number of connections in a group
n = group size

The observed number of connections in a group, which is denoted by L, can be obtained by multiplying group size n by the mean degree d, which is the average number of ties per group member. This equation algebraically reduces to:

$$D = \frac{d}{n-1} \tag{2}$$

where

D = density
d = mean degree
n = group size

This mathematical link between group size, density and mean degree can also be explained theoretically. Maintaining social relationships requires cognitive and emotional resources, which explains why people can maintain only a limited number of meaningful relationships (Dunbar, 1992). As groups grow larger, people need to maintain many more connections to maintain the same group density. However, due to cognitive and time limits, group members cannot keep up with the increased number of additional social connections that they would need to maintain. In this study, we account for the link between density and size in two ways. First, we do not include them in the same analyses, because they create problems of multicollinearity. Second, we run ancillary analyses controlling for the effect of mean degree.

Some theoretical arguments for the link between density and perceived cohesion can be applied to group size as well. The argument that faster transmission of information facilitates social cohesion via the emergence of shared attitudes and norms (Coleman, 1988; Friedkin, 1993) was shown to also be relevant for group size given that interaction and communication are easier in smaller groups (Carron, 1990). It is worth noting that fast dissemination of information is not restricted to small groups, and can well occur in larger groups in the presence of major hubs in a network (i.e., nodes that have a greater than average number of ties to others). Such central individuals are well connected to others, and can diffuse information quickly even when groups are large (e.g., Goldenberg et al., 2009). However, assuming that these central individuals maintain their ties with a limited time and energy budget, even hubs will diffuse information to all network members faster when the group is smaller.

This is in line with group dynamics research, where smaller groups were found to breed more trust, commitment, and cohesion (Soboroff, 2012). The underlying reason may be that smaller groups have more opportunities to interact and to communicate with every single member (Carron and Spink, 1995). In addition, a meta-analysis on group performance found the relationship between cohesiveness and group performance to be mediated by group size (Mullen and Copper, 1994). That is, smaller groups are more cohesive, and perform better as a result. Even though these theoretical considerations primarily stem from research on experimentally-induced groups, we theorize that they apply to real-life social groups as well: the smaller the group, the more "visible" every single group member is, and the more chances group members have to interact, and form close ties to one another which in turn increases group cohesion.

The rationale outlined above leads us to conclude that group cohesion increases with increasing density, and decreasing size. However, to the best of our knowledge, the relationship between these structural group properties and individual perceptions of cohesion has not been investigated to date. Hence, the question remains whether group density and group size, as measured by means of social network analysis, are also related to people's subjective judgments of group cohesion.

We opted to approach this question using Facebook friendship data. This has several theoretical and methodological advantages. Firstly, on Facebook people usually "befriend" others that belong to their real-life social networks (Bryant and Marmo, 2009; Dunbar, 2010). The decision to add someone as a Facebook friend and the resulting social tie has been shown to be based on social attraction and the wish to maintain the social relationship (Stern and Taylor, 2007). Recent research shows that the structure of Facebook networks reflects the structure of real-life social networks (Dunbar et al., 2015). Moreover, Facebook networks span a wide range of social relationships, such as friends, family, and acquaintances, allowing the study of a range of important social groups within real life networks (Bryant and Marmo, 2009).

Facebook data extraction facilitates an efficient way of mapping social networks, because individuals are not required to manually draw all existing social connections. The traditional self-report method of gathering social network data has been shown to be experienced as tiresome and unenjoyable by participants, which leads to biased responses (Stark and Krosnick, 2017). Furthermore, Facebook data extraction does not rely on participants' (possibly biased) memory, and thus facilitates a more accurate measure of group density and size.

2.2. Social network structure vs. individual perceptions

The central question of this paper is whether structural properties of groups predict individual perceptions of cohesion. The relevance of social perception versus reality is a longstanding debate (e.g., Jussim, 1991; Snyder and Swann Jr, 1978), and the view that perception rather than reality governs human action is famously summarized in the Thomas theorem, which states that: “If men define situations as real, they are real in their consequences”. According to this view, people's perceptions construct their reality, and guide their behaviors irrespective of how erroneous those perceptions may be. While we agree that individual perceptions of groups - however erroneous they are - will guide individual behavioral tendencies, the successful realization of these intended behaviors depends on the actual group structure, and is more likely to be successful if perception and reality are aligned. This is because the group structure (i.e., group size and density) provides an opportunity structure that facilitates and constrains realizable behavioral options.

Individual perceptions could be aligned with structural properties, because it pays off to implicitly understand group structure (Rico et al., 2008). Group members need to communicate well to coordinate their activities (Lehmann-Willenbrock et al., 2013), anticipate and meet the needs of others (Van Doesum, Van Lange and Van Lange, 2013), and adapt their behavior to ensure the welfare of the group (Hogg and Reid, 2006). These interactive behaviors are more likely to be successful when individuals have an accurate understanding of the social structure underlying their groups. If individual group members understand who is connected to whom and via which paths, they can navigate the group more effectively and are better able to promote the wellbeing of the group (Rico et al., 2008). Being implicitly aware of the roles of individual group members and how they are embedded by their social interconnections helps coordinate participation in the group (Dourish and Bellotti, 1992). Thus, it is instrumental for group members to pay attention to how their groups are structured.

One key structural feature concerns the relationship constellation within a group, which can be measured in terms of group density. If group members are indeed aware of the web of social relationships within their groups and the implications this has for cohesion within these groups, then they are likely to judge denser groups as more cohesive. This rationale leads us to propose the following hypothesis:

H1. Group density is positively related to perceived group cohesion.

Group size is another structural property that helps infer group cohesion and that individuals might be aware of. To recognize a number of individuals as a group requires at least knowing which members this group consists of. Indeed, a lot of social network research relies on individuals recalling and reporting who is member of which group in their personal social networks (Wellman, 2007). If people have an accurate representation of who belongs to the group, they also have an accurate representation of group size without having to stop and count. This is because group size –as opposed to density-is easily inferred and does not require any additional information beyond knowing who is member of a group. Similarly, if people are not required to recall groups themselves, but they are asked to judge groups that are presented to them (e.g., in form of a list of names or a social network illustration), they automatically receive information on the size of the group. Thus, group size is a readily available structural feature in people's memory and perception of groups (Brashears and Quintane, 2015). Building on the notion that individuals use heuristics to store and recall social network information (Brashears, 2013), we suggest that group size qualifies as such a heuristic to infer group cohesion. It requires minimum mental effort to recall the size of a group, but it can give valuable information on other group properties. Considering that group size is negatively related to group cohesion (Dunbar and Spoors, 1995; Brian Mullen and Copper, 1994; Zhou et al., 2005), it is generally accurate for people to apply the simple heuristic that smaller group are more cohesive. Therefore, we suggest the following hypothesis:

H2. Group size is negatively related to perceived group cohesion.

3. Method

3.1. Participants and design

One hundred and nine participants (37 men, 72 women) were recruited on campus of a large European University. In order to be able to participate in the study, individuals were required to have an active Facebook account, and be at least 18 years old. The mean age in our sample was 21.62 years (SD = 3.20), and participants had had their Facebook profiles for an average of 4.85 years (SD = 1.53). Participation was rewarded with a monetary compensation of €3.50 or course credit. In addition, participants were provided with the opportunity to receive an illustration of their personal social network (for an example, see Fig. 1). These illustrations were created in Gephi by applying the ForceAtlas 2 algorithm (Jacomy et al., 2014) and the Fruchterman and Reingold (1991) algorithm with standard settings. Participants did not see this illustration until the completion of the study, in order to avoid the illustration influencing their perceptions of cohesion within their groups (McGrath et al., 1996).

3.2. Materials

3.2.1. Perceived cohesion scale

We used a perceived cohesion scale originally developed by Bollen and Hoyle (1990) for sociological research on cohesion in large reference groups, such as colleges or cities. For the present study, we used an adapted version for small groups (Chin et al., 1999). The

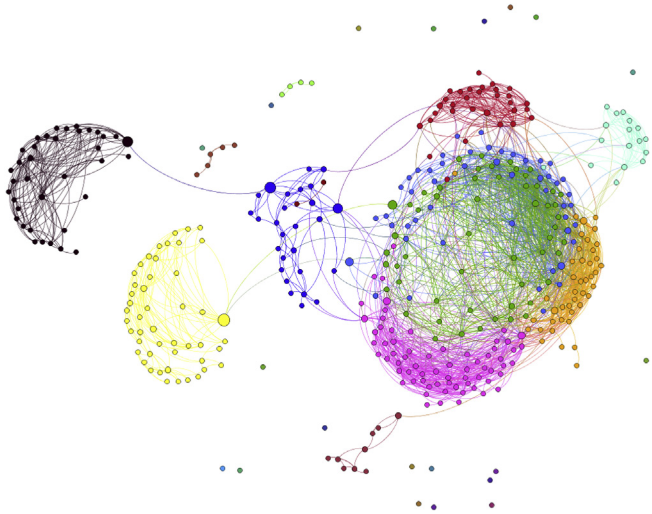


Fig. 1. Illustration of a social network graph partitioned into subgroups (marked by different colors). This visualization was obtained using the ForceAtlas 2 algorithm and Fruchterman Reingold algorithm with standard settings in Gephi. Subgroups are identified by Gephi's modularity algorithm. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

scale consists of six items and measures perceived cohesion on two dimensions: sense of belonging (e.g., "I see myself as part of this group") and feelings of morale (e.g., "I am content to be part of this group"). All items are coded on a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree). Reliability in our sample was high (unweighted $\alpha = 0.95$, pooled across all groups).

3.2.2. Group cohesiveness scale

We used a group cohesiveness scale (Wongpakaran et al., 2013) that consists of seven items scored on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree), e.g., "Members of this group feel accepted by the group" or "The members feel a sense of participation". Reliability in our sample was high (unweighted $\alpha = .90$ pooled across all groups) and the correlation with the perceived cohesion scale was moderate ($r = 0.63$). At the bottom of the group cohesiveness scale, we included an open-ended question in order to identify the type of group, i.e., "Think of a possible label for this subgroup, e.g. family, friends from home, university students, sports team etc. How would you name this group?".

3.2.3. Facebook questionnaire

We selected seventeen items concerning Facebook use and attitudes relevant to this study from a survey developed by Ross and colleagues that assesses Facebook use, attitudes and privacy precautions (Ross et al., 2009). Items were scored on a 6-point scale, with six attitude items ranging from 1 = strongly agree to 6 = strongly disagree, e.g. "I feel out of touch when I haven't logged on to Facebook for a while". Six frequency of use items ran from 1 = more than once daily to 6 = less than once per year, e.g. "How often do you send private Facebook messages?". Two items measured whom participants communicated with by posting on their Facebook walls, and by sending private messages, for instance "Family", "Current friends" or "People from the past". Another item asked why people liked Facebook, e.g. "It is how I communicate with my current friends". Finally, two open-ended questions measured how many minutes per day people spend on Facebook (in minutes), and how long people have had their Facebook profile (in years). In addition to these Facebook questionnaire items, we added socio-demographic questions on age, gender, nationality, sexual orientation, and occupation.

3.3. Social network tools

3.3.1. NetGet

We used NetGet (Rieder, 2013) to extract participants' Facebook friendship data. The application requires participants to log on to their Facebook accounts, and allows for extraction of Facebook friend names and connections between them, as well as friends' genders, age ranks and wall post counts. These network data can be downloaded into a Graph Modeling Language (GML) file, which can be imported into social network analysis software (e.g., Gephi). The NetGet application does not store any personal information, and the server erases the network data files regularly.

3.3.2. Gephi

The open-source software Gephi allows for basic social network analyses and visualizations of egocentric networks (Bastian et al., 2009). We used the modularity function in Gephi (known as the Louvain method) to partition participants' social network graphs into subgroups (Blondel et al., 2008). The underlying algorithm detects clusters (or modules) of nodes that are highly connected with each other, while having fewer connections to other clusters. This algorithm iterates over all nodes in the network until no moving of nodes from one group to another will improve modularity. Depending on the starting point of the iterations, slightly different clusters might be detected. For the present study, we set the algorithm to start at a random node, and we chose a default resolution of 1. Higher resolution leads to fewer and larger subgroups, while lower resolution extracts more and smaller subgroups. For our purposes, we excluded communities with $N < 3$ from analyses, in part due to the necessity for calculating the network metrics.

3.4. Instructions and procedure

The study took place at the psychology laboratory of a large European university and was approved by the ethics committee at that university. There was no deception involved at any point in the study. Upon participants' arrival, the experimenter checked eligibility and led participants to separate cubicles, where they read and signed the informed consent form. Using the NetGet application, the experimenter assisted participants with extracting their Facebook friendship data onto a flash drive. Then participants filled in the Facebook questionnaire in an online survey tool (Qualtrics). In the meantime, the experimenter imported participants' Facebook friendship data (GML file) into Gephi and ran the modularity function to partition their social network graphs. Next, the experimenter copied friend names that were identified to belong to the same subgroups and pasted them into templates of the two cohesion scales (i.e., perceived group cohesion and group cohesiveness). This means that participants were asked to complete one perceived group cohesion scale and one perceived cohesiveness scale per subgroup (for a screenshot of the Qualtrics questionnaire, see Fig. 2). The display order of the subgroups was randomized in Qualtrics. Once participants finished the Facebook questionnaire, they were instructed to fill in their cohesion questionnaires, while the experimenter prepared a visualization of participants’ social networks. After participants filled in the subgroup questionnaires, they were debriefed, and either paid a monetary compensation or assigned course credits. Finally, the experimenter showed and explained participants their personal social network graph. Upon request, participants received a .pdf file of their social network graphs via email.

3.5. Analytical strategy

We chose multilevel modeling as an analytical approach in order to account for the hierarchical structure of our data. More specifically, we collected measures on multiple groups of the same participant, which causes group data to be nested within participants (Tabachnick and Fidell, 2013). Thus, we treated group data as level 1 and participant data as level 2. This allowed for testing the effects of density and size on perceived group cohesion, while accounting for interdependence of group measures within participants (Bolker et al., 2009; Snijders and Bosker, 2012). We estimated all models using both cohesion scales as dependent variables, which yielded similar patterns of results. Given the lens of this paper, we are reporting only the results using the Group Cohesiveness Scale (Wongpakaran et al., 2013) as dependent variable. This scale is more closely aligned with social cohesion conceptualized as the group dynamics, attraction and trust between group members, than the Perceived Cohesion Scale (Bollen and Hoyle, 1990) which captures group belonging of a single individual.

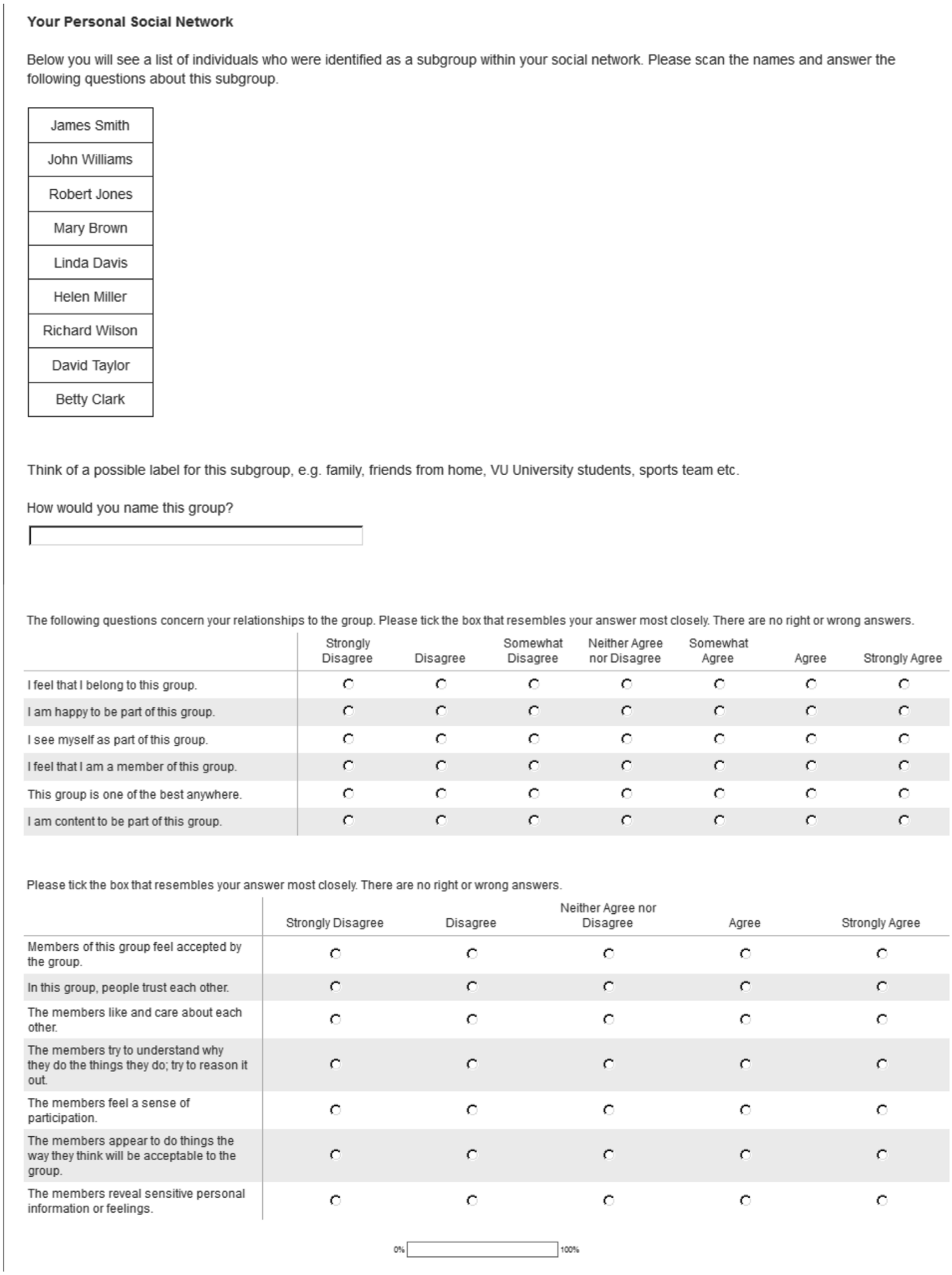
To test our hypotheses, we used the MIXED procedure in SPSS 21.0 (Peugh and Enders, 2005) with Maximum Likelihood Estimation. We first ran a null model with perceived group cohesion as dependent variable and we allowed the intercept to vary randomly across participants. Next, we fitted a set of six linear mixed effects models entering density (Models D1–D3) or size (Models S1–S3) as predictors. More specifically, we first tested the effects of density on perceived group cohesion by running a fixed intercept fixed slopes model with density as predictor (Model D1). In the subsequent model, we allowed the intercept to randomly vary (Model D2), and in the third model (Model D3), we also allowed slopes to vary randomly across participants. To test the effects of size on perceived group cohesion we fitted three models following the same procedure. That is, entering size as predictor of perceived group cohesion, we first fixed both intercept and slope (Model S1). Next, we allowed the intercept to vary (Model S2), and finally we allowed both intercept and slope to vary (Model S3). For random slope models (Models D3 and S3) we specified unstructured covariance matrices. Since density and size had a high collinearity ($r(871) = -0.706$, $p < .001$), we did not add them as predictors to the same models.

4. Results

4.1. Preliminary analyses

The average number of Facebook friends in our sample was 420.61 (SD = 263.56), and participants’ networks consisted of an average of 8 groups (SD = 2.68) with around 52.61 friends (SD = 56.82) on average. The mean density of these groups was .45 (SD = 0.25). Based on the group labels provided by the participants, we coded the groups into different categories, namely, friends, family, class mates, colleagues, acquaintances, other, inactive groups and missing or undefined groups. Among the clearly defined groups, class mates formed the largest part of the network (23.6%), followed by friends (16.3%), family (9.6%), colleagues (7.7%), and acquaintances (5.2%). Considering perceived group cohesion as measured by the Group Cohesiveness Scale (scores ranged from 1 to 5), family groups unsurprisingly showed the highest perceived cohesion, namely 3.89 (SD = 0.71), followed by friends (M = 3.42, SD = 0.64), colleagues (M = 3.46, SD = 0.59), class mates (M = 3.31, SD = 0.74), and acquaintances (M = 2.81, SD = 0.93). The density was highest among colleagues (M = 0.53, SD = 0.25), followed by friends (M = 0.46, SD = 0.27), class mates (M = 0.44, SD = 0.22), family (M = 0.40, SD = 0.24), and acquaintances (M = 0.39, SD = 0.24).

A group that sticks out due its rather large fraction of the network (24.7%), as well as its relatively high perceived cohesion (M = 3.31, SD = 0.77) and density (M = 0.46, SD = 0.26) was a mixed group that we labeled “other”. It contained sports groups,



Your Personal Social Network

Below you will see a list of individuals who were identified as a subgroup within your social network. Please scan the names and answer the following questions about this subgroup.

James Smith
John Williams
Robert Jones
Mary Brown
Linda Davis
Helen Miller
Richard Wilson
David Taylor
Betty Clark

Think of a possible label for this subgroup, e.g. family, friends from home, VU University students, sports team etc.

How would you name this group?

The following questions concern your relationships to the group. Please tick the box that resembles your answer most closely. There are no right or wrong answers.

	Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
I feel that I belong to this group.							
I am happy to be part of this group.							
I see myself as part of this group.							
I feel that I am a member of this group.							
This group is one of the best anywhere.							
I am content to be part of this group.							

Please tick the box that resembles your answer most closely. There are no right or wrong answers.

	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
Members of this group feel accepted by the group.					
In this group, people trust each other.					
The members like and care about each other.					
The members try to understand why they do the things they do; try to reason it out.					
The members feel a sense of participation.					
The members appear to do things the way they think will be acceptable to the group.					
The members reveal sensitive personal information or feelings.					

0% 100%

Fig. 2. Screenshot of a personalized perceived group cohesion questionnaire. All names are fictional and merely serve illustrative purposes.

travel groups, flat mates, or people from respondents' home town. We grouped them together, because none of them were further specified as belonging to the existing categories (e.g., friends or acquaintances), and none of these single groups appeared frequently enough to justify keeping them in their separate categories. Given our focus on social cohesion, we tested our hypotheses excluding colleagues from the main analyses, since they are better classified as a task cohesion group. Descriptive statistics per group are displayed in Table 1. Following recommendations for multilevel modeling (Enders and Tofighi, 2007; Peugh, 2010; Snijders and Bosker, 2012), we centered all independent variables around the grand mean for subsequent analyses.

Table 1
Descriptive statistics of dependent and independent variables by groups.

	Frequency	%	Perceived Group Cohesion	Density	Mean Size	Mean Degree
Class mates	232	29.8	3.31 (0.74)	.44 (.22)	56.84 (51.08)	19.74 (17.98)
Friends	142	18.3	3.42 (0.64)	.46 (.27)	55.80 (57.17)	16.90 (17.17)
Family	84	10.8	3.89 (0.71)	.40 (.24)	34.08 (31.12)	9.43 (8.15)
Acquaintances	45	5.8	2.81 (0.93)	.39 (.24)	60.24 (63.75)	14.87 (15.40)
Other [a]	216	27.8	3.31 (.77)	.46 (.26)	53.80 (64.39)	15.15 (17.03)
Inactive groups [b]	37	4.8	3.04 (0.56)	.45 (.29)	58.70 (65.38)	16.24 (18.83)
Missing or labeled as no group [c]	22	2.8	3.14 (0.42)	.33 (.25)	62.73 (50.62)	14.82 (13.92)
Total	778	100	3.35 (0.76)	.44 (.25)	53.80 (56.29)	16.25 (16.77)

Note: Standard deviations are in parentheses.
[a] This category contains sports group, travel groups, flat mates or people living in respondents' home town, but were not specified as friends.
[b] This category contains groups that were labeled as no longer active, such as “Ex-friends”, “People I don't talk to anymore”, or “Group from previous life”.
[c] Missing values or participants indicated to not recognize the group.

4.2. Model selection

As recommended by (Burnham and Anderson, 2004), we used both the Akaike Information Criterion (AIC) and Schwarz's Bayesian Information Criterion (BIC) to guide our model selection. We first computed difference scores between the model with the lowest AIC (Model S3) and all other models. Next, we computed Akaike weights, which indicate the likelihood of a model given the set of model candidates. The same procedure was applied to compute BIC difference scores and BIC weights. Table 2 provides an overview of AIC and BIC analyses of all competing models. A more detailed explanation of model comparison and model selection based on AIC and BIC can be found in Appendix A. Model S2 emerged as the best fit according to the AIC. Including size in a random intercept fixed slope model (Model S2) improved AIC as compared to the null model. Following recommendations of Burnham and Anderson (2004), this can be interpreted as considerable support for a model containing an effect of group size. However, it should be noted that in terms of BIC, which is more conservative, Model S2 did not show better fit than the null model. We bootstrapped parameter estimates of Model S2 for further inspection by drawing 1984 stratified resamples. To bootstrap the confidence interval, we applied a Bias-Corrected Accelerated method. This is a non-parametric procedure - unlike the reported p values it thus does not require a normality assumption (Davison and Hinkley, 1997). The fixed slope estimate of size was -0.001, and bootstrapping resulted in a bias-corrected and accelerated 95% confidence interval of -0.002 to -0.0005. The bootstrapping procedure thus suggests that size is negatively associated with perceived group cohesion. This finding is mirrored by the (asymptotic) parameter estimates for group size, which were statistically significant in both Model S2 and Model S3 which include size as a fixed effect (see Table 3). Taken together, these findings show support for our hypothesis that group size is negatively related to individual perceptions of cohesion (H2).

All models including density showed poor model fit as indicated by AIC and BIC, and none of the (asymptotic) parameter estimates pointed to a significant effect of density on perceived group cohesiveness (all $p > .44$ in Models D1-D3). This finding leads us to reject hypothesis H1. Table 3 provides an overview of all models and their parameter estimates.

Table 2
Results of AIC and BIC analysis for seven competing models.

Model	No. Par_i	AIC_i	Δ_i (AIC)	w_i (AIC)	BIC_i	Δ_i (BIC)	w_i (BIC)
Null	3	1763.28	2.34	0.18	1777.25	0	0.73
D1	3	1787.15	26.21	0	1801.12	23.87	0
D2	4	1764.76	3.82	0.08	1783.39	6.14	0.03
D3	6	1767.47	6.53	0.02	1795.40	18.15	0
S1	3	1784.33	23.39	0	1798.30	21.05	0
S2	4	1760.94	0	0.57	1779.57	2.32	0.23
S3	6	1763.66	2.72	0.15	1791.60	14.35	0

Note: No.Par_i = number of estimated parameters for model i; Δ_i (AIC) = [AIC_i- AIC_{min}]; w_i (AIC) = rounded Akaike Criterion weights; Δ_i (BIC) = [BIC_i- BIC_{min}]; w_i (BIC) = rounded Bayesian Information Criterion weights. Models D1, D2 and D3 had density as predictors. Models S1, S2 and S3 had size as predictors.

Table 3
Parameter estimates of seven models predicting perceived group cohesion.

	Null Model	D1	D2	D3	S1	S2	S3
Fixed Effects							
Intercept	0.005 (0.04)	0.0002 (0.03)	0.005 (0.04)	0.006 (0.04)	0.000 (0.03)	0.006 (0.04)	0.009 (0.04)
Density		0.06 (.11)	0.08 (0.11)	0.08 (0.11)			
Size					- 0.001 (0.005)	- 0.001* (0.00049)	−0.001* (0.00048)
Random Effects							
Intercept	0.07*** (0.02)		0.07*** (0.02)	0.07*** (0.02)		0.07*** (0.02)	0.07*** (0.02)
Density				0.05 (0.04)			
Size							−0.0003* (0.0001)
Residuals	0.51 (0.03)	0.58 (0.03)	0.51 (0.03)	0.51 (0.03)	0.58 (0.03)	0.51 (0.03)	0.50 (0.03)

Note: Standard errors are in parentheses. $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

4.3. Ancillary analyses

The average number of social ties in participants' networks exceeded the number of meaningful relationships that people are posited to be able to maintain (Dunbar, 2010, 2016). This suggests that some groups might not be meaningful to our participants (anymore). To account for tie mortality, we excluded all groups that participants labeled as inactive or that participants did not recognize as a group (anymore). Rerunning the above analyses without these groups did not significantly change the pattern of results.

Recent research on cognitive processing of social network ties suggests that kin ties might be processed differently from non-kin ties. The kinship label was shown to serve as a compression heuristic when recalling social network information, because it contains rich additional information on how people are connected to one another (Brashears, 2013). This is further supported by evidence showing that kin ties are processed faster than non-kin ties (Machin and Dunbar, 2016), and that kin ties are processed in other brain regions than non-kin ties (Wlodarski and Dunbar, 2016). To account for this, we ran additional analyses separating kin and non-kin groups. This did not improve the results for non-kin groups. For kin groups, results show that the effect of size points in the reverse direction. This effect, however, was not statistically significant (p-values ranged from 0.10 to 0.29). Appendix B displays the parameter estimates, and Appendix C shows the AIC and BIC analyses. These ancillary analyses suggest that the effect of size might differ for non-kin and kin groups. While there is some evidence that smaller non-kin groups are judged as more cohesive, the effect for kin groups is not significant.

5. Discussion

This study set out to explore the relationship between structural group properties and people's subjective perceptions of cohesion. Drawing from social network theory, we put forth arguments for the notion that group-level network characteristics predict subjective perceptions of cohesion. We showed how social network analysis of online data can be leveraged as an efficient approach for measuring predictors of group cohesion. We argued that subjective perceptions of cohesion would align with the social structure that underlies groups (i.e., density and size), given that it is likely beneficial for group members to implicitly understand the relationship constellation (i.e., density) within their group in order to coordinate behaviors and promote the welfare of the group. Furthermore, group size is an easily accessible structural feature of groups, which individuals might use as a heuristic to infer group cohesion.

Several findings accrue from this study. First, we did not find support for our hypothesis that group density is positively linked to individual perceptions of cohesion. However, group size did play a role in people's subjective evaluations of group cohesion, albeit a small one. In this context, it should also be noted that while model selection with AIC indicated that inclusion of size improved fit, model selection with BIC, which is more conservative, did not. When evaluating the estimates, bootstrapping revealed a robust fixed effect of size on group cohesion in the predicted direction, suggesting that people perceive groups in their social networks to be more cohesive if they are smaller. This effect was reversed for kin groups, which were perceived as more cohesive with increasing size, albeit not significantly so.

5.1. Theoretical implications

The positive link between structural group size and perceived cohesion is in line with previous findings that suggest smaller groups to be more cohesive than larger ones (Dunbar and Spoors, 1995; Brian Mullen and Copper, 1994; Zhou et al., 2005). Previous research demonstrated that people compress social information by using mental short cuts (Brashears, 2013; Brashears and Quintane, 2015; Kilduff et al., 2008). Following this rationale, our findings suggest that people may rely on the simple, and generally correct heuristic that smaller (non-kin) groups tend to be more cohesive. It might be particularly difficult for individuals to assess cohesion in large groups that consist of many weak ties (e.g., high school cohort). With increasing group members and decreasing relevance of the group, individuals may be less aware of all existing social connections between group members. Group size is a rather prevalent structural feature of groups, which can readily be applied as a heuristic to infer group cohesion when the exact relationship constellation is unclear.

In line with previous research on the social processing of kin and non-kin groups (Brashears, 2013; Machin and Dunbar, 2016; Wlodarski and Dunbar, 2016), we found divergent effects for different group types: While non-kin groups were perceived as more cohesive when they were smaller, this was not the case for kin groups. This finding provides further support for the notion that kin groups are processed and perceived differently from non-kin groups. Compared to all other groups, kin groups were perceived as most cohesive irrespective of structural group properties. It may be the case that the kin label is such a prominent indicator of cohesion that it overrides other heuristics that are based on structural indicators such as size and density.

Concerning the link between density and perceived group cohesion, the present findings challenge some previous research (Friedkin, 1981, 1984; 1993; Moody and White, 2003). If people had an accurate representation of the density of their groups, then we would expect them to perceive denser groups as more cohesive. The results of our study reveal a different picture. It appears that participants in our study did not judge members of denser groups to trust and like each other more. This suggests that people's understanding of the web of social relationships within their groups may be limited, possibly because individuals rely on their personal attraction to the group or single group members in assessing cohesion. People's perceptions of social networks are not always accurate. For instance, previous research showed that people's memory of who was present during a social encounter was shown to be erroneous (Freeman et al., 1987). Not only did people not remember those who were present, but they also falsely reported people who were not present. Furthermore, recent research showed that perceptions of network density are malleable and can be temporarily distorted as the result of experiencing social distress (O'Connor and Gladstone, 2015). Our findings too highlight the possible drawback of relying on individual perceptions when studying group processes from a social network perspective.

An alternative explanation for our null findings concerning density may lie in the nature of Facebook friendship networks. Facebook networks accumulate relationships from the past, which are no longer actively maintained, but kept for means of possible reconnection in the future (Ramirez and Bryant, 2014). Indeed, with a friend average of 420.61 (SD = 263.56), social networks in our sample greatly exceeded the proposed cognitive limit of 150 meaningful relationships (Dunbar, 1992), which suggests that not all these ties can be actively maintained (Dunbar, 2016). If people collect Facebook friends from the past that are no longer active, it is possible that groups which used to be cohesive are still ‘frozen’ at high levels of density, even though group members are no longer in contact at the time of data extraction. As an aggregation of inactive Facebook friends and friend groups may have added noise to our initial findings, we removed the groups that participants judged as inactive and reran our analyses. This adjustment, however, did not change the results, thus strengthening our conclusions.

Future research could address this issue by collecting additional information on contact frequency (i.e., the frequency of private messages exchanged, wall posts, and comments on the same threads) to detect inactive ties more accurately. An interesting question for future investigations is whether inactive ties should be treated as noise or whether they deserve to be studied in their own right. While it may be the case that people accumulate many Facebook connections that are not actively maintained, these ties might still be meaningful and potentially beneficial in the future.

Despite these considerations, we argue that Facebook data extraction is a powerful tool for studying groups. Facebook data offer a closer representation of people's social networks, including not only colleagues, but also family, friends and acquaintances (Gilbert and Karahalios, 2009). In 2016, 78% of all adults in the US had a Facebook account making it the most popular social media platform (Facebook Inc., 2016). Among the younger population in Western countries almost everyone has a Facebook account, which they use actively to maintain social relationships (Bryant and Marmo, 2009). This is also reflected in our sample considering that participants spent an average of 74.19 min (SD = 67.85) on Facebook daily. Thus, with an increasing importance of social media in maintaining social relationships, it is indispensable to study social relationships in the setting where many social interactions take place nowadays, which is the online world.

The social network approach we use in the present study does not rely on individual perceptions or memory, which are potentially flawed (Baumeister et al., 2007; Bernard et al., 1984; Podsakoff and Organ, 1986; Wellman, 2007). Social network analysis of existing data on social groups can offer a more objective and efficient alternative for studying groups in experimental settings. Nowadays, people leave traces of their social relationships not only on social media websites, but also in terms of other forms of electronic communication (e.g., email communication among members of a work team).

5.2. Limitations and future research directions

This study has several limitations that hint at future research opportunities. First, we used a student sample, which may limit the generalizability of our findings (Sears, 1986). Our sample represents a very specific group, namely Western, Educated, Industrialized, Rich, and Democratic (WEIRD) people (Henrich et al., 2010). Nevertheless, we believe that given our research design and research question, the benefits of using a student sample outweigh the costs. Among many students in the Netherlands there is a social norm to leave the parental home (Billari and Liefbroer, 2007), which means that students will often have social networks that are located in different cities and that potentially emerged to serve different functions. The younger generations are not only among the heaviest Facebook users, but they also primarily use Facebook to maintain social relationships. For such active users, Facebook data provide networks that span different spheres of life and different types of groups. However, it should be borne in mind that errors exist in Facebook data as opposed to ‘real’ group data. Some individuals might not be on Facebook or might choose to be more restrictive in which individuals they befriend online as opposed to offline. This would lead to unidirectional error whereby group memberships would be underestimated. While this could indeed be the case, respondents did not verbally communicate that people from their real-life network were missing, and they readily identified the groups discovered in their Facebook network.

A related concern is a possible perceptual bias introduced by the survey measures. In the survey, a list of Facebook friends was brought up, respondents then assigned a label to the list of friends (e.g., “high school friends”), and they then answered the cohesion questions. Given this setup, it is unclear whether respondents answered the cohesion questionnaire based on the list of friends they saw or on the group label they assigned, which could also include group members that were not actually listed. This possible bias is of particular concern for our findings if non-Facebook members were included in respondents' answers to the cohesion questionnaire, because non-Facebook members do not appear in the structural group measures (i.e., size and density). While we are unable to empirically account for this limitation, we believe that the exclusion of non-Facebook members is of minor concern in the age group that we studied. Facebook use is widespread in the Netherlands, and with 89% of Facebook users in the age group of 20–39 years, our respondents and their peers seem to be particularly well represented on Facebook (Van der Veer, Boekee and Peters, 2017). However, this biased recall might be present for older Facebook friends, namely those aged 40–64 (77% Facebook users) and those aged 65–79 (68% Facebook users). We expect the underrepresentation of these age groups on Facebook to primarily affect the representation of family ties within our respondents’ Facebook networks, and this might explain why the effects of group structure on individual perception followed a different pattern for family groups than it did for non-kin groups.

A second limitation concerns the fact that we studied static social networks with bi-directional, unweighted ties. In other words, we observed networks at one point in time, and relationships between people were measured dichotomously. This means that a tie between two individuals was either present or absent, but not weighted in strength. Moreover, due to the befriending procedure on Facebook, every tie is bidirectional and we cannot draw any conclusions regarding unidirectional ties or tie strength. Relying on such a cross-sectional research design does not allow us to make causal inferences. For example, it is not clear whether perceptions of groups are a consequence of attributes of how groups were formed or whether individuals’ perceptions also shape the attributes and formations of these groups. In order to fully study cohesion and make causal inferences we would require an experimental and/or longitudinal design. Nevertheless, while cross-sectional, our study does benefit from assessing properties from groups via multiple methods (self-reports and Facebook network data) and we believe this is a useful contribution to the further study of groups.

Third, we extracted groups using a modularity algorithm that detects clusters within a social network. One concern associated with using such a modularity algorithm is that actors within the network can only belong to one group. This may seem to be at odds with the social reality of people simultaneously occupying several social roles within an ego network (i.e., multiplexity). It remains unclear to what extent our respondents would have perceived specific Facebook friends to belong to more than one group within their network (e.g., a sports team member who is also a university friend). While the modularity algorithm selects the best-fitting group for individual actors based on the web of binary connections that best tie actors to a cluster, it is well-possible that an actor is almost as equally well connected to other clusters. This is not captured by our data. However, previous research shows that overlap of different roles, known as multiplexity, is most likely to occur in stronger ties (Marsden and Campbell, 1984), and that it is unlikely in family ties (Verbrugge, 1979). Given that Facebook networks primarily consist of weak ties (Hofstra et al., 2017), multiple group memberships likely only affected a fraction of the alters in our sample. Nevertheless, future research could investigate the role of multiplexity and multiple group memberships in the perception of group cohesion.

An additional concern associated with using a modularity algorithm may be that it is unclear whether the extracted groups in fact reflect real-life groups. The extracted groups are merely based on how densely connected people are in a network. Where these friends met, how and how often they have contact with each other, or any similar relevant information was not included to determine which friends belong to the same group. In order to check whether the algorithm extracted meaningful groups, we did ask participants to think of a label that describes the group best. During the debriefing participants indicated that –with few exceptions-they recognized the extracted groups as actual groups that they have in real life. Another concern may be that the modularity algorithm extracted larger groups of lower density that contained several more densely connected subgroups. If this was the case, then participants would not have been able to assign labels. Yet, our analyses show that participants were generally able to assign meaningful labels to the extracted groups. Excluding the few groups that participants did not recognize as groups did not change the results. This leads us to conclude that the algorithm generally extracted groups that reflected the real life social groups of our participants.

The question of respondent fatigue deserves some attention, given that repeatedly completing the same set of cohesion scales may have impaired attention, especially for participants with a large number of groups. Yet, although we could not directly control for possible respondent fatigue in our analyses, many participants reported to the experimenter that they enjoyed answering questions about their friends and learning about their own social networks upon completion of the study. Participants were generally engaged and motivated, which was reflected in the fact that a majority of participants left their email addresses to be informed about the results of the study. This observation combined with the fact that the entire process of data collection (i.e., network data extraction and completion of questionnaires) took less than 30 min, suggests that respondent fatigue was not a major concern. Moreover, the order in which groups were presented to participants was randomized. Thus, even if participants with an increased number of groups had experienced some fatigue, the effect of fatigue would have been randomized across groups of different sizes and densities, and therefore unlikely to influence the results.

Finally, it is unclear how the social networks emerged, even though emergence is now a widely-shared assumption about group cohesion (e.g., Salas et al., 2015). The underlying idea is that cohesion is a dynamic state that varies as groups go through different processes (Marks et al., 2001). Since we captured social networks at one time point, in the present study we could not account for how groups emerged over time, and how cohesion potentially evolved. While researchers increasingly call for cohesion to be studied as an emergent state (Santoro et al., 2015), currently there are few studies using longitudinal measurements, probably due to practical constraints. Especially in fast-changing, dynamic or complex settings, self-report measures may be difficult, if not impossible, to employ. Even though in the present study we investigated static networks, the methods we present could well be applied to investigate dynamic networks. Future research could extract social network data at several time points, and weigh ties according to contact frequencies and duration. This would account for cohesion as a dynamic and emergent phenomenon, which has thus far been practically challenging (Santoro et al., 2015).

Appendix D. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.ssresearch.2018.04.004.

Appendix A

Model Selection based on AIC and BIC

Based on Akaike weights, the random intercept fixed slope model with size as predictor (Model S2) emerged as superior. Based on the evidence ratio, calculated as w_{S2} (AIC)/w_{null} (AIC), Model S2 was 3.2 times more likely to be the best model compared to the null model. Furthermore, Model S2 was 3.8 times more likely than Model S3, which was the next best model. However, according to the BIC, which punishes complex models more than the AIC, Model S2 did not perform better than the null model. The BIC evidence ratio showed that the likelihood for the null model was 3.17 times higher than the likelihood of Model S2.

Appendix B

Parameter Estimates of Seven Models Predicting Perceived Group Cohesion (only Family Groups)

	Null Model	D1	D2	D3	S1	S2	S3
Fixed Effects							
Intercept	0.02	0.00	0.02	0.02	0.00	0.02	0.02
	(0.08)	(.08)	(0.08)	(0.10)	(0.08)	(0.08)	(0.08)
Density		−0.23	−0.22	−0.12			
		(.31)	(0.31)	(0.41)			
Size					0.003	0.004	0.003
					(0.002)	(0.002)	(0.002)
Random Effects							
Intercept	0.12		0.12	0.20		0.13	0.12
	(0.08)		(0.08)	(0.18)		(0.08)	(0.07)
Density				0.18			
				(0.96)			
Size							−0.002
							(0.001)
Residuals	0.37	0.49	0.37	0.50	0.48	0.34	0.33
	(0.08)	(0.08)	(0.08)	(0.17)	(0.07)	(0.08)	(0.08)

Note: Standard errors are in parentheses. $^*p < .05$; $^{**}p < .01$; $^{***}p < .001$.

Appendix C

Results of AIC and BIC Analysis for Seven Competing Models (only Family Groups)

Model	No. Par_i	AIC_i	Δ_i (AIC)	w_i (AIC)	BIC_i	Δ_i (BIC)	w_i (BIC)
Null	3	181.98	0.38	.26	189.27	0	.43
D1	3	184.51	2.91	.07	191.81	2.54	.12
D2	4	183.50	1.9	.12	193.22	3.95	.06
D3	6	191.66	10.06	0	206.24	16.97	0
S1	3	183.21	1.61	.14	190.50	1.23	.23

S2	4	181.60	0	.31	191.33	2.06	.15
S3	6	183.97	2.37	.10	198.56	9.29	0

Note: No.Par_i = number of estimated parameters for model *i*; Δ_i (AIC) = [AIC_i- AIC_{min}]; w_i (AIC) = rounded Akaike Criterion weights; Δ_i (BIC) = [BIC_i- BIC_{min}]; w_i (BIC) = rounded Bayesian Information Criterion weights. Models D1, D2 and D3 had density as predictors. Models S1, S2 and S3 had size as predictors.

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