Investigating stereotype structure with empirical network models

Sayans-Jiménez, P.; van Harreveld, F.; Dalege, J.; Rojas Tajada, A.J.

DOI
10.1002/ejsp.2505
Publication date
2019
Document Version
Final published version
Published in
European Journal of Social Psychology

EJSP

RESEARCH ARTICLE

Investigating stereotype structure with empirical network models

Pablo Sayans-Jiménez*,†, Frenk van Harreveld‡, Jonas Dalege‡ & Antonio J. Rojas Tejada*,†

* Department of Psychology, University of Almería, Almería, Spain
† Centre for the Study of Migrations and Intercultural Relations (CEMyRI), University of Almería, Spain
‡ Department of Social Psychology, University of Amsterdam, Amsterdam, The Netherlands

Correspondence
Dr. Pablo Sayans-Jiménez, Department of Psychology, Faculty of Psychology, University of Almería, Almería 04120, Spain.
E-mail: psj242@ual.es

Received: 13 April 2017
Accepted: 1 May 2018

https://doi.org/10.1002/ejsp.2505

Keywords: stereotype structure, intergroup attitudes, empirical network, stereotype content model

Abstract

In this work we present empirical network models as a new approach in the investigation of stereotype structure. We will argue that empirical network models can provide more insight into stereotype structure because they do not suffer from the inherent constraints of factor analysis and multidimensional scaling (e.g., group features interpreted homogeneously only on the basis of their shared variance, impossibility to adequately represent cognitive schemas, difficulties to make inferences on the basis of dimensions potentially overlapping). In the present research we show how empirical network models can represent stereotypes as dynamic cognitive structures clustered in different substructures. These structures will be based on both the stereotype content and the co-occurrence of features in each group target. Additionally, this research shows how using empirical networks can contribute to broadening the interpretation of stereotypes representing them in the framework of prejudice or intergroup attitudes.

Over the last years, the application of empirical network models in the area of psychology has provided novel perspectives on structural properties of psychopathological disorders (e.g., Cramer, Waldorp, van der Maas, & Borsboom, 2010; Fried, Epskamp, Nesse, Tuerlinckx, & Borsboom, 2016), the structure of attitudes (Dalege et al., 2016), and the impact of attitudes on behaviors (Dalege, Borsboom, van Harreveld, Waldorp, & van der Maas, 2017). Given the unequivocal importance of insight into stereotype structure when predicting various psychosocial variables (e.g., Brambilla & Riva, 2016; Brambilla, Sacchi, Rusconi, Cherubini, & Yzerbyt, 2012; Cameron & Trope, 2004; Cuddy, Fiske, & Glick, 2007; López-Rodríguez & Zagefka, 2015; Quadflieg et al., 2011), we present empirical network models as a valuable alternative approach in the investigation of stereotype structure.

Using the stereotype content model (SCM; Fiske, Cuddy, Glick, & Xu, 2002; Fiske, Xu, Cuddy, & Glick, 1999) as a framework, we will show that empirical network models are better equipped than common factor models to deal with the inherent complexity and dynamics of stereotype structure (e.g., overlapping or conflicting components, differential predictive capability of components, dynamic influence between components: e.g., Abele & Wojciszke, 2014; Brambilla, Rusconi, Sacchi, & Cherubini, 2011; Brambilla, Sacchi, Pagliaro, & Ellemers, 2013; Brambilla et al., 2012; Goodwin, Piazza, & Rozin, 2014; Landy, Piazza, & Goodwin, 2016; Leach, Ellemers, & Barreto, 2007; Sayans-Jiménez, Rojas, & Cuadrado, 2017). The SCM is used because of its impact on the stereotype literature (Fiske et al., 1999, 2002) and the fact that its proposed structure has been established in multiple countries and cultures (e.g., Cuddy et al., 2009; Durante et al., 2013).

The value of empirical networks lies in their ability to overcome some of the methodological and conceptual constraints associated with common factor procedures. Methodologically, common factor models (e.g., Brown, 2006) identify the way in which variables can be grouped on the basis of shared variance, but they require all variables to be interpreted as virtually homogeneous indicators of the same latent variable. Furthermore, once the common variance among variables is identified, it is not possible to interpret the individual relationships among each pair of variables unless these relationships are considered as measurement errors (i.e., because they are not attributable to common/reliable variance) or method effects. Equally important, when common factor models are applied, they can produce an infinite number of nearly equivalent models based on trivially small fit variations (Raykov & Penev, 1999), but with very different theoretical interpretations (e.g., first order, higher order, or bi-factor models; see Van Bork, Epskamp, Rhemtulla, Borsboom, & van der Maas, 2017). This may contribute to misinterpretations in the absence of strong and solid pre-specified theories. As a consequence, in the context of the SCM, it has been argued that stereotype structure is best represented by a two-factor structure (e.g., Fiske et al., 2002), three-factor structure (e.g., López-Rodríguez, Cuadrado, & Navas, 2013), second order factor structure (interpersonal perception traits, Srivastava, Guglielmo, & Beer, 2010), or bi-factor structure (Sayans-Jiménez, Cuadrado, Rojas, & Barrada, 2017).

To the contrary, empirical network models (e.g., Schmittmann et al., 2013) can perform more refined analyses without losing their ability to cluster variables in substructures (Golino and Epskamp (2017) show how empirical networks can perform more accurate estimations of the number of substructures or factors than the common variance procedures). In addition to their clustering ability, empirical network models can estimate all the individual partial correlations between every pair of variables allowing for more dynamic and flexible interpretations of the substructures. In the resulting network, the distance between variables is the inverse of the strength of their relationship (i.e., the stronger the relationship, the closer the variables are represented) allowing for more densely interconnected groups of variables to be represented as substructures inside the network. Moreover, empirical network models provide new additional statistical indicators, centrality indices, that will inform about node connectivity and their relative importance within the network (see Epskamp, Borsboom, & Fried, 2017).

Conceptually, the contrast between empirical network models and common factor procedures resides in how they explain the correlation among variables. Whereas common factor models require the assumption of an underlying latent factor, empirical network models do not require the existence of latent factors. In these latter models co-occurrence can be explained by the mutual interactions between variables. Applying this approach to the structure of stereotypes can provide new insights into the ways in which group features are activated. For example, instead of assuming that a social category activates the perceived competence of a group, and that this perceived competence activates a set of features related to this content (in factor analysis, latent factor account for the variance and the covariance of observable variables, see Brown, 2006), the application of empirical network models enables us to assume that the presence of the social category activates some features linked to a specific group and that they (affected by specific contexts and goals) can activate other related features without the need to assume any latent construct. In the specific case of stereotypes, it could be said that latent constructs are a statistical artifact that facilitates measurement, but we do not need to assume necessarily that these latent constructs (e.g., perceived competence, warmth or morality and sociability) are the actual structure of stereotypes.

Application of empirical network models to the structure of stereotypes

In examining stereotype structure, researchers generally rely on multidimensional scaling (e.g., Ashmore & Tumia, 1980; Bruckmüller & Abele, 2013; Jones & Ashmore, 1973; Rosenberg, Nelson, & Vivekananthan, 1968) and factor analysis (e.g., Fiske et al., 1999; Landy et al., 2016; López-Rodríguez et al., 2013; Sayans-Jiménez et al., 2017). This research has generated important insights into the study of the way stereotypes are grouped in different latent dimensions, but its main utility does not serve to study stereotype structure but to scale stereotypes (multidimensional scaling) or to scale people (factor analysis and multidimensional scaling). That is, to measure the amount of a construct that a group feature represents (e.g., the amount of social or intellectual desirability of different personality traits was studied in Rosenberg et al., 1968) or which characteristics people are perceived to "have" (e.g., the amount of perceived competence or warmth of different groups has been frequently studied in the framework of the SCM, e.g., Cuddy et al., 2009; Durante et al., 2013; Fiske et al., 1999, 2002).

Despite the undeniable contributions provided by common factor models, empirical network models may provide important additional information. Specifically, empirical network models overcome factor analysis and multidimensional scaling constraints because: (i) they are better able to reproduce the way in which stereotypes are actually structured in the brain, (ii) they allow for more flexible and accurate detection of substructures and hence offer better explanations for overlap between substructures, (iii) they overcome the issue of model equivalence, (iv) empirical network models can provide dynamical explanations capturing the influence between stereotypes (e.g., morality-related stereotypes can influence stereotypes related to other features; see Landy et al., 2016). Altogether, these advantages allow for more comprehensive models, integrating stereotype content with intergroup emotional reactions (IER; i.e., complex reaction to a situation or event that includes differentiated cognitions and feelings, see Mackie, Devos, & Smith, 2000), intergroup behaviors or group evaluations. Below we will discuss these advantages in more detail.

First, empirical network models parallel the way in which stereotypes are connected and structured in memory. Stereotypes have been defined as the most characteristic and distinctive features associated to groups or their members (Stangor, 2016). These associations between stereotypes are deemed to be located in semantic memory, in the same structure (i.e., the lateral temporal lobe) that form the basis for semantic knowledge (Amodio, 2014). In the semantic space similar concepts are closely represented because they share highly associated features (Tyler & Moss, 2001), and "a symmetric association between two features can be interpreted as a kind of correlation between those features" (Sloman, 1996, p. 4). In the same manner, in empirical network models the features associated with a group or its members will conform to a network where each feature is (more or less) related to the others (e.g., perceived honesty of a group is likely to be related to perceived sincerity, or sociability to friendliness in the same way).

Second, the flexibility of empirical network models allows for the detection of different stereotype structures depending on the group target. Essentially, the assorted co-occurrence of features of different dimensions should be assumed as a natural consequence of social categorization. For instance, some groups can be indissolubly considered as trustworthy and competent (e.g., doctors), or others can be considered to be inseparably competent and likeable but not moral (e.g., insurance brokers). However, the SCM (e.g., Cuddy et al., 2009; Fiske et al., 1999, 2002), and its derived models (e.g., Brambilla et al., 2011, 2012, 2013), are based on the existence of two (or three) underlying dimensions along which the most common traits for describing people have to be distributed (i.e., structured): competence and warmth (competence, morality, and sociability). That is, stereotypes can only be grouped on the basis of their shared content. Furthermore, these dimensions, according with the multidimensional scaling performed by Rosenberg et al. (1968), were proposed to be orthogonal (Fiske et al., 1999, 2002). These assumptions lead to a double constraint that is probably very useful for scaling stimuli or people along these dimensions (i.e., to estimate the amount of competence, morality, or sociability), but also likely to restrict the examination of the way in which stereotypes are interrelated conforming to their structure. Since empirical network models do not require to constraint the features to belong to an exclusive substructure, they capture the real structure of group features and can provide insight into the overlap between different contents (e.g., *kind* is moral and sociable, whereas *honest* is exclusively moral; Goodwin et al., 2014).

The third constraint of traditional approaches concerns the shared variance among dimensions, something that has not been thoroughly addressed by the SCM, and the production of nearly equivalent models with great theoretical differences when applying common factor models (see Van Bork et al., 2017). Empirical network models do not have this problem because they identify the single best-fitting network that represents the data (Epskamp, Waldorp, Mõttus, & Borsboom, 2018).

Fourth, the aforementioned flexibility of empirical network models provides the key to a more dynamic representation of stereotype structure, allowing the researcher to take into account the potential dynamic influence between features (i.e., nodes). Over the last few years empirical network models have been shown to be a promising technique in this respect. For instance, Cramer et al. (2010) have shown how the network approach can provide adequate solutions to the study of comorbidity of depression symptoms. Additionally, centrality indices provide further information related to the connectivity of each node, like their direct and indirect strength to affect the network, or their capability to connect or disrupt the relationships among other pair of nodes. These indices have already shown their degree of informativeness when using attitudinal networks for predicting behaviors (Dalege, Borsboom, van Harreveld, Waldorp, & van der Maas, 2017).

Finally the empirical network models have proved their utility for studying attitudes, their structure, their connectivity, their capability to predict behaviors, and attitudinal change (Dalege et al., 2016; Dalege, Borsboom, van Harreveld, & van der Maas, 2017; Dalege, Borsboom, van Harreveld, Waldorp, et al., 2017). For this reason, we think that, in the SCM framework, their application can help us to represent and to study broader structures integrating stereotypes, IER, behaviors, and/or evaluations.

In conclusion, we argue that empirical network models are well suited to investigate stereotype structure and may provide additional insight to common factor methods (or multidimensional scaling). The current research presents the application of empirical network models to the analysis of the stereotypes and their structure.

Overview

Two studies were designed in order to investigate the utility of network models for exploring the structure of stereotypes. In the first study, community analyses are performed in a set of group features to detect possible substructures within each network. Based on previous studies on stereotype content (Brambilla et al., 2011, 2012; Fiske et al., 1999; Goodwin et al., 2014; Landy et al., 2016; Leach et al., 2007) these substructures are expected to match with the different dimensional components of stereotype content (i.e., competence, morality, and sociability, or warmth and competence). Network analysis can thus also shed more light on the debate whether the warmth dimension actually consists of two dimensions: morality and sociability features might be clustered in different substructures with strong connections between them. In addition, based on the results of the studies of Landy et al. (2016) sociability and competence related features can also be expected to show connections. In Study 2 network models are applied to the same set of group features, and also to IERs, and a global evaluation (representing the valence and its intensity that is reported to be associated to a specific object), all of them directed toward a low valued group (one of those employed in Study 1). This second study has two objectives: (i) to examine if stereotype structure estimated for one of the group targets (Roma People) replicates in a different sample and (ii) to show how its stereotype structure is represented together with IER and a global evaluation measurement, broadening the focus of study and integrating stereotype structure with intergroup attitudes.

Study 1

In this study, empirical network models are applied to a set of group features in relation to four different outgroups, which were selected because they have been investigated frequently in stereotype research: morality, sociability, and competence (Abele & Wojciszke, 2014; Brambilla & Leach, 2014). More specifically, we selected a group that was unequivocally highly valuated (firefighters), unequivocally lowly valuated (Roma People; see Urbiola, Willis, Ruíz-Romero, & Moya, 2014; Navas & Cuadrado, 2003), ambivalent (see Glick & Fiske, 2001) with high perceived competence and low perceived morality and sociability (multimillionaires), and ambivalent with low perceived competence and high perceived morality and sociability (people with Down syndrome). The set of group features includes competence, morality, and sociability related contents, therefore, according to the SCM, it is expected that community detection shows how the different group features conform to clusters based on their content. Finally, centrality indices will show the connectivity and the relative importance (within the network conformed to the set of group features) of each feature to represent each specific group.

Method

Participants. The survey was administered by trained staff at the place of residence of each respondent in two provinces of the southeast of Spain. CSA, a consultancy company of marketing and social research, collected the data of sub-samples 1 and 2. Nine hundred and nine people participated and were divided into three sub-samples of 300, 300, and 309 people. Incidental quota sampling was performed based on the age and gender composition of the Spanish population (*a priori* fixed quotas). The gender quota was 50% for women and 50% for men. The ranges for age quota were 30–32% for ages between 18 and 35 years old, 38% for ages between 36 and 55 years old, and 30–32% for 56 and older. One sub-sample was asked about their stereotypes toward Roma People (Sub-sample 1, $n = 300$, 150 women with an average age of 46.51 [$SD = 17.82$], and 150 men with an average age of 46.51[$SD = 17.82$]), another sub-sample about their stereotypes toward professional firefighters (Sub-sample 2, $n = 300$, 150 women with an average age of 46.51 [$SD = 17.82$], and 150 men with an average age of 46.44 [$SD = 18.05$]), and the third sub-sample was subsequently asked about their stereotypes toward people with Down syndrome and multimillionaires (Sub-sample 3, $n = 309$, 153 women with an average age of 45.43 [$SD = 16.45$], 153 men with an average age of 46.61 [$SD = 17.09$], and three people with no informed gender). None of the participants belonged to any of these groups.

According to Bühlmann and van de Geer (2011) an accurate estimation in a multiple regression framework needs $(p(p{-}1)/2) \times 5$ observations, with p being the number of variables. Therefore, this study needs sample sizes with more than 180 participants and all the four sub-samples meet this requirement to perform accurate estimations of the 32 partial correlation coefficients that have to be estimated in each sub-sample.

Measures. Three sets of items were administered: a questionnaire including competence, morality, and sociability scales; another one including additional psychosocial variables beyond the scope of the present article (evaluation of group features, stereotypes toward “people in general,” items regarding IER and intergroup behaviors, a semantic differential, a test of adult attachment, and two items related to intergroup contact and social distance); and the third one containing socio-demographic data items (i.e., sex, age). In this study, only stereotype variables were used.

Competence, morality, and sociability scales. Three items representing each kind of content were used to assess whether participants perceived the groups as competent (i.e., intelligent, skillful, capable), moral (i.e., sincere, honest, trustworthy), and sociable (likeable, warm, friendly). These features were based on those used in Brambilla et al. (2011) and were applied in Spanish. All the items assessing these features were presented jointly in random order following the same instructions:

> In this task you have to imagine a large group of people representing all types you think exist in the Roma ethnic group (or professional firefighters group/people with Down syndrome group/multi-millionaire people group) [...] Try to guess about how many people in this group of non-familiar Roma ethnic people (or professional firefighters group/people with Down syndrome group/multi-millionaire people group), representing all types of people in this group, have the qualities displayed below.

For all items the answer categories were: *none* (1), *almost none* (2), *few* (3), *half* (4), *many* (5), *almost all* (6), and *all* (7). The purpose of the instructions was that the scale would not make specific individual features of outgroup members personally known to participants salient.

Procedure. Respondents' anonymity and confidentiality were guaranteed. All subjects gave their written informed consent. It was established that participants were participating voluntarily, that they were over 18, and that they know they could stop participating at any time. Since participants from Sub-samples 1 and 2 participated in larger questionnaires they were rewarded with five euros.[1] The variables were presented always in the same order: stereotypes, related psychosocial variables, and socio-demographic variables. This procedure was approved by the Human Research Bioethical Committee of the University of Almería, Spain.

Data analysis. Networks were estimated using the R package qgraph (Epskamp, Cramer, Waldorp, Schmittmann, & Borsboom, 2012). The GeLasso-procedure with the L_1 regularization with the optimal sparsity level defined via Extended Bayesian Information Criteria (EBIC; Epskamp, 2016) was applied to the responses on the stereotype items using the R-package qgraph (Epskamp et al., 2012). The EBIC tuning parameter was set to 0.5 (which is the default option in qgraph). This procedure estimates networks based on partial correlations and it involves the GLASSO regularization technique (based on the true network structure and sample size) aiming to control spurious correlations (Epskamp, 2016; Friedman, Hastie, & Tibshirani, 2008; Tibshirani, 1996). As a result, the network shows (i.e., using different edges thickness and colors) the regularized partial correlation among each pair of features after controlling the effect of the rest of the features in the network. Each node in the network represents one of the nine features used to measure stereotypes. Community detection was performed using Exploratory Graph Analysis (i.e., detection of the number of the clustered substructures in the network; for a detailed description of substructure detection process see Golino & Epskamp, 2017). The use of the walktrap algorithm (Pons & Latapy, 2005) allows us to detect how many dense subgraphs (communities or cluster) there are in the partial correlation matrix.[2] Edge-weights accuracy was estimated using nonparametric bootstrap to estimate the 95% confidence interval of each edge (see Epskamp et al., 2017).

Centrality plots were created to represent the values of the centrality indices: strength, closeness, and betweenness. These indices provide information about the importance of each node (i.e., features) within the network (see Dalege, Borsboom, van Harreveld, & van der Maas, 2017; for a detailed description of these indices). Strength (or degree) is the sum of all correlation magnitudes of each node with the rest of the nodes (Cramer et al., 2010). The closeness of a node provides information about its distance (i.e., direct or indirect influence) from all other nodes in the network. This index is obtained through the inverse of the mean of all the shortest paths between a given node and the rest of the nodes in the network. The higher the closeness, the shortest is the distance between the node and the remaining nodes in the network. These indicators reflect how each node is connected to the rest of elements in the network. Highly connected nodes (high indicators of strength and/or closeness) will be more difficult to change than those with weaker connections, but change in such nodes will also result in more change throughout the rest of the network (Dalege et al., 2016).

Finally, betweenness informs about the power of each node to disrupt information flow in the network. This indicator takes into account the number of times the node is situated on the shortest path between two other nodes. Therefore, nodes situated between two sets of clustered nodes will show higher betweenness. This information is of great importance for studying which nodes will transmit the influence from one cluster of features to another (e.g., which nodes connect features related to warmth to features related to competence). Centrality stability estimations are performed estimating network models based on subsets of the data. The centrality stability is quantified using the correlation stability coefficient (CS-coefficient, see Epskamp et al., 2017). CS-coefficient values "should not be below 0.25, and preferably above 0.5" (Epskamp et al., 2017, para. 19).

The positioning of the nodes in the network shown in this article is based on Fruchterman and Reingold's (1991) algorithm, which places strongly connected nodes close to each other. The nodes are colored according to the detected communities. Casewise deletion was used for handling missing data.

Results

Fourteen incomplete cases where removed from Sub-sample 3. The descriptive statistics were calculated for all stereotype ratings (see Table 1). The obtained empirical scores were as expected. That is, Roma People were evaluated the least positive of all groups, on all the items, and firefighters were most positively evaluated (on all items). People with Down syndrome were evaluated less positively on competence than on morality and sociability, while multimillionaires were rated lower in morality and sociability than in competence. All items showed statistically significant differences (Bonferroni adjustment to the significance level was applied; $\alpha = .008$) among groups ($p < .001$) with the exception of the six following cases: Roma People–

[1]To test if the financial compensation generated any effects on the stereotype responses we compared the means of each group feature between Sub-sample 1 (rewarded with five euros) and the sample of the Study 2 (not rewarded), both referred to Roma People. Intelligent t (702.92) = 1.11, $p = .27$; Skillful t (844) = 2.14, $p = .03$, Capable t (845) = 0.67, $p = .5$, Sincere t (846) = −0.57, $p = .57$, Honest t (848) = −0.53, $p = .6$, Trustworthy t (846) = −1.32, $p = .19$, Likeable t (672.45) = −3.36, $p < .001$, Warmth t (846) = −0.06, $p = .95$, Friendly t (847) = 0.18, $p = .86$. We only found statistical differences between both groups in the skillful ($d = .16$) and likeable ($d = .23$) features, therefore it cannot be assumed that the financial compensation had any general effect on people's answers.

[2]Walktrap algorithm detects the number of dense subgraphs by utilizing the lengths of random walks between nodes in the network. In the walktrap algorithm a given number of steps have to be set that the random walks take. To select the optimal number of steps, we used the modularity of the detected clusters, which is a common measure of optimal partitioning of a network (e.g., Clauset, Newman, & Moore, 2004; Fortunato, 2010; Newman, 2004, 2006).

Table 1. Descriptive statistics for all the items in the three sub-samples

	Sub-sample 1 (Roma People) *M* (*SD*)	Sub-sample 2 (firefighters) *M* (*SD*)	Sub-sample 3: Down syndrome people *M* (*SD*)	Sub-sample 3: Multimillionaire people *M* (*SD*)
Competence				
Skillful [Habilidosas]	2.11 (0.96)	5.01 (1.08)	3.82 (1.05)	4.22 (1.21)
Intelligent [Inteligentes]	2.46 (0.78)	4.43 (1.10)	4.00 (1.32)	4.48 (1.12)
Capable [Capacitadas]	2.28 (0.89)	5.79 (1.02)	4.09 (1.28)	4.46 (1.12)
Morality				
Sincere [Sinceras]	2.50 (0.86)	5.32 (1.12)	5.30 (1.18)	2.83 (1.11)
Honest [Honestas]	2.64 (0.74)	5.61 (0.95)	5.28 (1.15)	2.99 (1.05)
Trustworthy [De Confianza]	2.44 (0.99)	5.19 (1.26)	4.68 (1.35)	2.85 (0.99)
Sociability				
Likeable [Simpáticas]	2.17 (0.85)	4.86 (0.97)	5.27 (1.09)	3.78 (1.04)
Warmth [Cariñosas]	2.24 (0.87)	4.80 (1.06)	5.57 (1.00)	3.29 (1.16)
Friendly [Amistosas]	2.15 (0.88)	4.99 (0.99)	5.44 (0.98)	3.68 (1.13)

Note: *M* = Mean; *SD* = standard deviation.

firefighters (likeable, $t[598] = -2.47$, $p = .014$), gypsy ethnic people–Down syndrome people (intelligent, $t[590.071] = -0.01$, $p = .99$; capable, $t[605] = -1.12$, $p = .26$), gypsy ethnic people–multimillionaire people (skillful, $t[605] = 1.08$, $p = .28$; trustworthy, $t[607] = 0.97$, $p = .33$), and firefighter–Down people syndrome (honest, $t[607] = 0.42$, $p = .68$). Only in Sub-sample 1 did we find high values of skewness and kurtosis in items referring to morality (see Appendix).

Group features employed in this study belonged to the three most salient dimensions (i.e., contents) representing groups or their members, but their relationships vary depending on the group target. In this vein, community detection has identified different substructures varying in number and composition (see Figure 1). First, in the Roma People network three dense substructures were found. Each substructure matches with the dimensions generally distinguished on stereotypes (i.e., competence, morality, and sociability) within the SCM framework. Second, the features about firefighters clustered in two substructures. While the first one encompasses features related to competence and morality content, the second one presents the features regarding sociability. Third, attributes about people with Down syndrome were clustered according to competence and warmth (warmth includes morality and

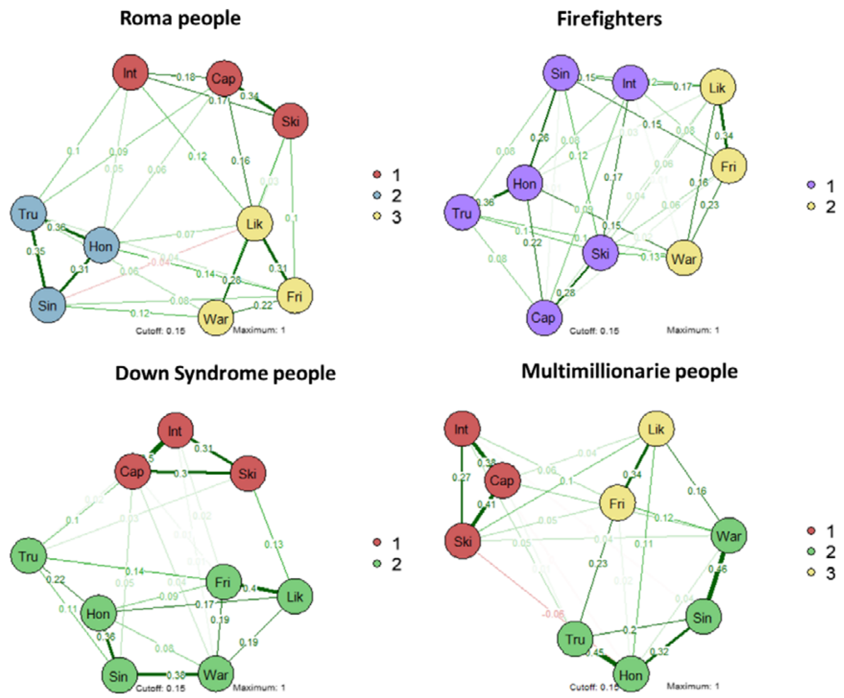

Fig. 1: Empirical network models or each group target. Each node represents an attribute associated with the social target. The edges represent the relationship among attributes. The thicker the edge is, the greater is the relationship between attributes. Attributes clustered in the same substructure as a result of community analysis are colored the same. Positive relationships are represented in green while negative are red. Ski: Skillful; Int: intelligent; Cap: capable; Sin: sincere; Hon: honest; Tru: trustworthy; Lik: likeable; War: warmth; Fri: friendly. The numbers included in the legend of each graph denote the number of subclusters and their respective color indicate which nodes belongs to which subcluster. [Colour figure can be viewed at wileyonlinelibrary.com]

sociability). Finally, attributes associated with millionaires conform to three substructures matching the content of the features with the exception of the feature *warmth* which is incorporated in a cluster together with morality-related features.

Although the features have been clustered in highly correlated (i.e., dense) substructures, the obtained networks also reveal individual connections among nodes belonging to different clusters. Partial correlation magnitudes can be seen in Figure 1 and correlation estimations and their 95% bootstrapped confidence intervals can be seen in Table 2. The firefighter group network is the one that shows the highest level of interconnections among all the nodes. In this network it can be seen how even though there are two substructures both are represented close to each other. With respect to the remaining social groups the substructure confirmed a competence cluster clearly separated from the rest, but with individual connections to morality and sociability clusters. Additionally, individual connections among morality and sociability related features are visible in all networks.

Centrality indices were estimated from each network and plotted all together to facilitate their comparison among groups (Figure 2). Strength indicators show the extent to which each node can influence the rest of the nodes of the network. In the Roma group it can be seen that likeable, honest, and trustworthy are the features with high levels of strength. In case of firefighters, *honest* stands out because of its strength in contrast to the rest of the nodes. Regarding the group of people with Down syndrome, the feature *capable* is the one with the highest strength in contrast to *trustworthy*, which shows less of a direct influence within the network as compared to the rest of the nodes. Finally, the network for the representation of the multimillionaire group shows that while skillful and likeable have the lesser strength, the rest of the features have a similar direct influence within their network.

Regarding closeness indicators, two different patterns can be seen depending on the group. On one hand, in the network representing the attitudes toward firefighters *sincere* and *honest* are the nodes with the largest direct and indirect influence within the network. On

Table 2. Partial correlations [95% bootstrapped confidence intervals] of the network representing stereotypes in Study 1

	Roma ethnic people	Firefighters	Down syndrome people	Multimillionaires
Cap–Fri	.00 [−.07: .11]	.01 [−.05: .12]	.02 [.00: .12]	.00 [−.06: .12]
Cap–Hon	.06 [.00: .17]	.25 [.11: .37][a]	.00 [.00: .12]	.00 [−.14: .01]
Cap–Lik	.16 [.02: .27][a]	.04 [−.05: .16]	.00 [−.15: .02]	.04 [.00: .15]
Cap–Sin	.00 [−.07: .06]	.00 [−.06: .13]	.03 [.00: .12]	.00 [−.05: .09]
Cap–Tru	.09 [.00: .18]	.10 [.00: .23]	.11 [.00: .19]	.00 [−.04: .13]
Cap–War	.00 [−.05: .13]	.00 [−.09: .13]	.02 [.00: .12]	.05 [.00: .16]
Hon–Fri	.14 [.01: .24][a]	.00 [−.12: .05]	.06 [.00: .19]	.00 [−.04: .12]
Hon–Lik	.05 [.00: .14]	.02 [.00: .15]	.19 [.07: .32][a]	.11 [.00: .22]
Hon–Tru	.38 [.24: .50][a]	.38 [.24: .51][a]	.23 [.10: .34][a]	.51 [.41: .61][a]
Hon–War	.00 [−.08: .08]	.15 [.01: .28][a]	.09 [.00: .21]	.00 [−.03: .15]
Int–Cap	.18 [.05: .31][a]	.11 [.00: .23]	.50 [.36: .61][a]	.39 [.27: .51][a]
Int–Fri	.00 [−.11: .07]	.06 [.00: .19]	.02 [−.02: .10]	.05 [.00: .15]
Int–Hon	.05 [.00: .17]	.05 [.00: .17]	.00 [−.10: .02]	.00 [−.09: .03]
Int–Lik	.11 [.00: .24]	.20 [.05: .32][a]	.00 [−.03: .09]	.00 [−.10: .08]
Int–Sin	.00 [−.13: .04]	.15 [.02: .28][a]	.00 [−.04: .08]	.00 [−.12: .00]
Int–Ski	.18 [.05: .31][a]	.18 [.06: .30][a]	.30 [.17: .43][a]	.26 [.13: .40][a]
Int–Tru	.10 [.00: .22]	.00 [−.14: .05]	.00 [−.03: .11]	.04 [.00: .18]
Int–War	.00 [−.12: .05]	.00 [−.06: .14]	.03 [.00: .11]	.00 [−.04: .09]
Lik–Fri	.34 [.20: .47][a]	.40 [.25: .51][a]	.42 [.28: .56][a]	.33 [.21: .44][a]
Lik–War	.29 [.16: .42][a]	.15 [.01: .28][a]	.18 [.07: .33][a]	.15 [.03: .26][a]
Sin–Fri	.07 [.00: .19]	.15 [.00: .28]	.00 [−.17: .05]	.00 [−.08: .05]
Sin–Hon	.32 [.20: .43][a]	.28 [.10: .39][a]	.36 [.24: .49][a]	.30 [.13: .42][a]
Sin–Lik	−.04 [−.18:00]	.11 [.00: .24]	.00 [−.16: .02]	.00 [−.08: .07]
Sin–Tru	.37 [.22: .50][a]	.05 [.00: .19]	.09 [.00: .25]	.22 [.11: .34][a]
Sin–War	.11 [.00: .23]	.00 [−.12: .09]	.42 [.31: .56][a]	.50 [.39: .60][a]
Ski–Cap	.35 [.24: .45][a]	.31 [.16: .43][a]	.31 [.21: .44][a]	.40 [.27: .51][a]
Ski–Fri	.08 [.00: .20]	.07 [.00: .18]	.00 [−.11: .06]	.05 [.00: .16]
Ski–Hon	.00 [−.08: .09]	.00 [−.09: .11]	.00 [−.12: .01]	−.05 [−.14: .00]
Ski–Lik	.04 [.00: .19]	.04 [.00: .17]	.12 [.01: .25][a]	.08 [.00: .20]
Ski–Sin	.00 [−.10: .04]	.13 [.00: .24]	.00 [−.05: .06]	.00 [−.09: .04]
Ski–Tru	.00 [−.05: .05]	.10 [.00: .23]	.03 [.00: .15]	.00 [−.1: .03]
Ski–War	.13 [.00: .25]	.13 [.00: .25]	.00 [−.07: .04]	.06 [.00: .16]
Tru–Fri	.03 [.00: .13]	.00 [−.04: .14]	.12 [.01: .28][a]	.21 [.08: .33][a]
Tru–Lik	.00 [.00: .09]	.00 [−.12: .06]	.00 [−.09: .07]	.02 [.00: .16]
Tru–War	.06 [.00: .16]	.10 [.00: .23]	.00 [−.15: .07]	.00 [−.15: .01]
War–Fri	.22 [.07: .35][a]	.23 [.09: .35][a]	.23 [.10: .35][a]	.11 [.02: .22][a]

Note: Ski, skillful; Int, intelligent; Cap, capable; Sin, sincere; Hon, honest; Tru, trustworthy; Lik, likeable; War, warmth; Fri, friendly.
[a]Reliable correlations.

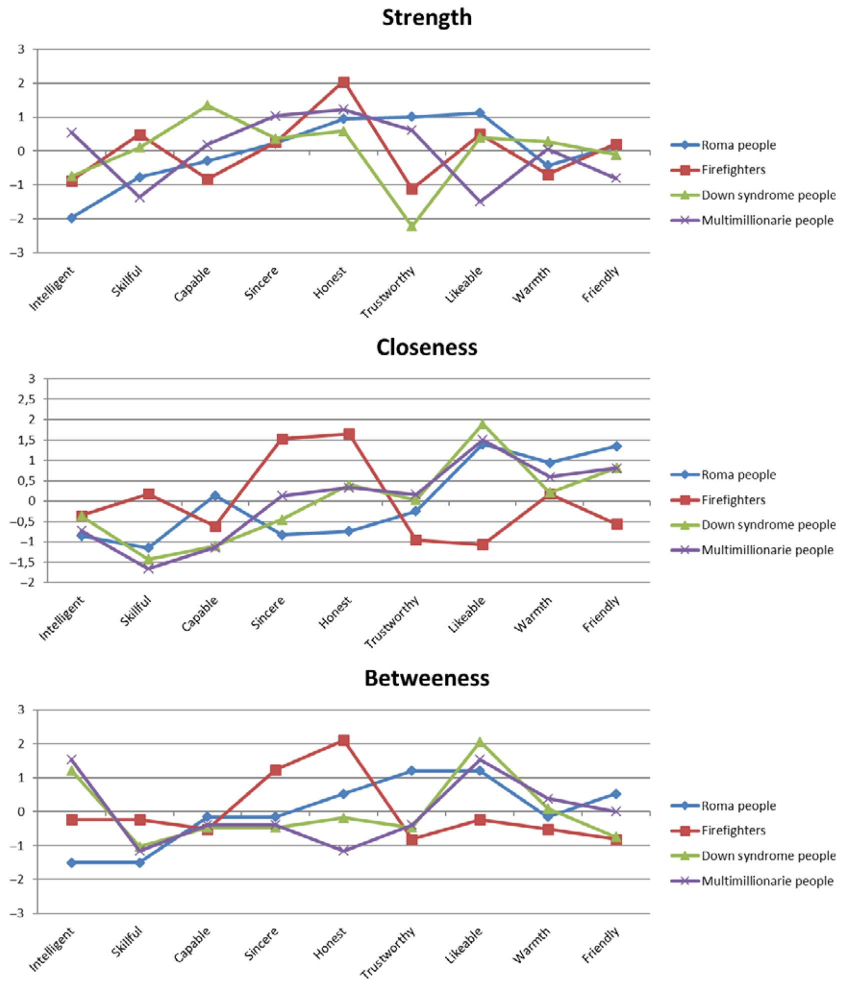

Fig. 2: Standardized centrality indices for each group target in Study 1. [Colour figure can be viewed at wileyonlinelibrary.com]

the other hand, in the rest of the networks the *likeable* feature has the highest closeness in each respective plot, although the other two sociability-related features also show high levels of direct and indirect influence. Finally, the betweenness indices show a similar pattern to those referred to the closeness. The ability to disrupt information flow in the network is high for honest and sincere in the case of the firefighters group whereas the same happens to likeable in the case of the other three groups. Additionally, the *intelligent* feature shows high betweenness in the networks of Down syndrome and multimillionaire groups.

Centrality and stability estimations can be seen in Figure 3 and CS-coefficients in Table 3. These results indicate that under subsetting cases closeness and betweenness estimations showed low stability whereas strength estimations showed moderate stability (see Epskamp et al., 2017).[3]

[3]We believe that comparing network models with all the possible factorial alternatives is beyond this article's scope. Nevertheless, we would like to show the fit of differences among the network models presented in this article and the three-factor structure proposed in the original manuscript on which our items are based. As it can be seen, in our study network models always shows better fit than CFA models.

Discussion

This study applied empirical network models to a set of group features representing three different kinds of content: competence, morality, and sociability. The results allow a more detailed analysis of the relationships among group features. Features related to different contents can be connected and clustered in different ways depending on the specific group that is evaluated. Since the application of empirical network models is focused in the structure conformed by the group features and not in scaling people along two or three specific stereotype contents, these results should not be taken to contradict previous results obtained within the SCM framework. In fact, they could explain, partially, why defining the number of stereotype contents (i.e., dimensions) using factor analysis can lead to different results in different studies. The premise of the existence of two/three dimensions in which group features can be scaled (i.e., stimulus scaling, not person scaling) has remained unchanged since Rosenberg et al. (1968). However, as it has been shown, the co-occurrence of group features is due not only to their shared content but also to the specific characteristics of each group.

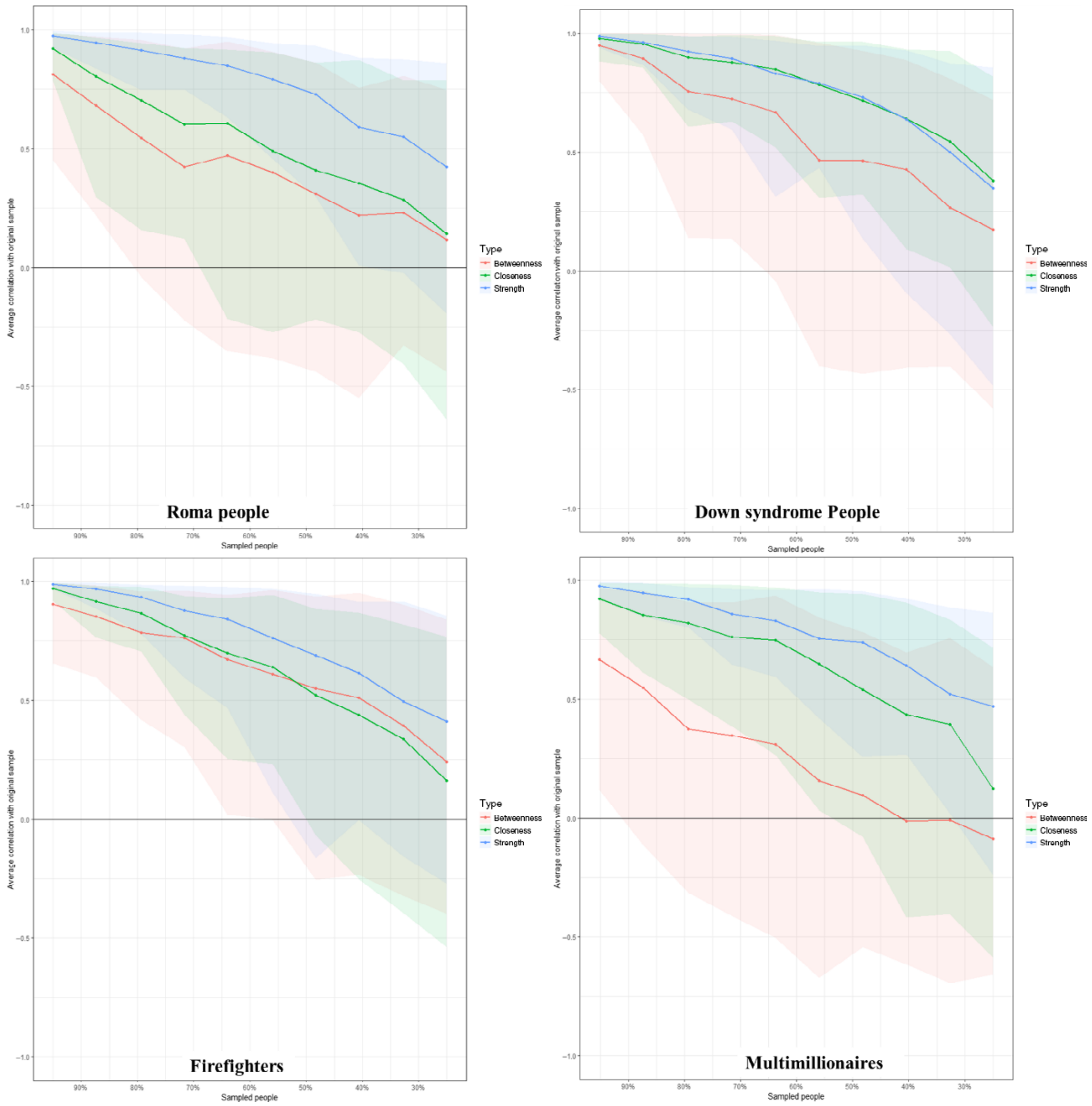

Fig. 3: Mean correlations between centrality indices of the original sub-samples and samples with persons dropped in Study 1. Lines represent the average centrality estimations and areas depict the range from the 2.5th quantile to the 97.5th quantile. [Colour figure can be viewed at wileyonlinelibrary.com]

Table 3. Correlation stability coefficients for each sub-sample

	$CS_{strength}$	$CS_{closeness}$	$CS_{betweeness}$
Sub-sample 1 (Roma People)	.28	.05	0
Sub-sample 2 (Professional firefighters)	.28	.12	0
Sub-sample 3 (People with Down syndrome)	.29	.21	.13
Sub-sample 4 (Multimillionaire people)	.29	.05	0

In this study, different clusters of features have been found for different groups. It could be the case that distinctive features of a group determine the way in which features are clustered and that this goes beyond the traditional distinction in two or three dimensions. As such, sometimes the expected clusters according to stereotype content cannot be distinguished. For example, can firefighters perform their job in a competent but non-moral way? Or in a moral but incompetent way? On the basis of the obtained networks in this study one would say not: people expect firefighters to be competent and moral (and that people with Down syndrome are moral and sociable). On the other hand, in the case of the Roma group, the bigger distances among dense substructures could imply that there is a larger chance for people to expect that features of this group vary more freely according to their competence, morality, or sociability.

Regarding these results, it is important to highlight that, although the application of exploratory graph analysis for studying the structures conformed by group features has shown promise in this study, this procedure is still in its initial stages. It has been only tested in simulated datasets with dichotomous variables and further information is needed to know how these models deal with non-normal distributions (i.e., Golino & Epskamp, 2017). Therefore, it would be advisable to test its performance in more assorted scenarios.

Centrality indicators allow performing a more accurate analysis on the relative influence of each group feature in their respective networks. Probably the most informative insight into how each node is connected to the rest of elements in the network is provided by closeness indices. The different closeness pattern for the firefighter group, in contrast to the other groups, could perhaps be explained by the fact that different kinds of groups (in this case social categories vs. task groups) would conform to different cognitive structures that will affect the stereotyping process (see Hamilton, Sherman, Crump, & Spencer-Rodgers, 2009).

Our results highlight the centrality of the likeability features for Roma People, multimillionaires, and people with Down syndrome. For practical purposes, it could be said that if any member of these groups is perceived as (un)likeable it will affect the other group features. Changing perceived likeableness would demand more effort than to change any other feature in the network, because further changes in the connected nodes will be needed. These inferences could to a lesser extent also be applied to the other two features representing sociability related content. In this vein, although the importance of morality has been highlighted in the impression formation processes (Brambilla et al., 2012; Goodwin, 2015; Goodwin et al., 2014), these results provide empirical evidence for the influence of sociability-related content features. Similar conclusions can be drawn on the firefighters group but related to their perceived honesty and sincerity. In other words, if somebody would perceive a firefighter as dishonest or insincere, the most probable reaction would be to associate this firefighter with most negative appreciations in the other features.

Study 2

Study 1 shows how network models can capture the complexity and the dynamics within the belief system conformed by the perceived associations between group features. The objective of Study 2 is to show how the value of empirical network models can be extended beyond the structure of stereotypes. Specifically, the current study aims to test if one of the stereotype structures found in Study 1 replicates in a different sample and framed with additional variables, and the way in which a network can represent stereotypes in the broader framework of prejudice or intergroup attitudes by including global evaluations and IERs in the network model.

The second aim of the present research is derived from the notion that social categories activate intergroup attitudes and that these attitudes are based on global automatic evaluations, stereotypes, and IER (e.g., Stangor, 2016). Empirical network models can help to represent intergroup attitudes as networks where all evaluative reactions toward the group target show their mutual connections and the way in which these evaluative reactions cluster. Specifically, although features with morality-related content have been shown to be related to global evaluations (e.g., Brambilla et al., 2011; Sayans-Jiménez et al., 2017), it is expected that any positive feature would be positively related to the global evaluation of the social object, as has been shown in a previous study (Sayans-Jiménez, Cuadrado, et al., 2017).

Stereotypes are also known to be related to different IERs toward the social object (e.g., Cuddy et al., 2007). In the framework of intergroup relations, anger and fear have, for example, been shown to predict offensive and evasive action tendencies toward other groups (Mackie et al., 2000). In this vein, it is expected that stereotypes are related to these basic IERs. Morality-related features might show higher connections with those IERs than those related to competence because of the benefit or harm that morality goals could cause people surrounding the target, including the observer. In this study empirical networks are estimated on a set of group features, IERs, and global evaluation referred to the group of Roma People.

Method

Participants. Five hundred and fifty people, 280 women and 270 men, participated in this study. Incidental quota sampling was performed in provinces of southeast Spain (*a priori* fixed quota). The gender quota was 50% for women and 50% for men. The sex quota was 50.09% for women and the rest men. The age intervals of the quota were 35% for ages 18–35, 36% for 36–55, and 29% for 56 and over. The mean age of men was 45.97 years ($SD = 17.53$) and of women 46.57 years ($SD = 17.97$). None of the participants themselves belonged to the Roma group.

In this study the number of observations according to the suggestions of Bühlmann and van de Geer (2011) should be 765. However, more recently, Epskamp (2016) has shown that the estimation of psychological networks with the GeLasso-procedure produces accurate estimations if the network is composed of 25 variables (more than in Study 2) and 500 observations. This is one of the advantages of the Lasso-regularization, that it is possible to achieve a high specificity even in small samples.

Measures. Four sets of items were administered to provide insight into stereotype structure and the broader evaluative context in which the stereotype is embedded (i.e., intergroup attitudes). Specifically, we investigate stereotypes, IERs, and global evaluations toward the Roma People group. Stereotypes are again assessed with a questionnaire including items referred to competence, morality, and sociability stereotype contents. Moreover, because stereotypes are closely related to IERs (e.g., Cuddy et al., 2007) we now assess two kinds of IERs items previously used by Mackie et al. (2000) in the context of intergroup emotion theory: anger and fear. We also included a semantic differential scale of evaluation which relationships with stereotype content measures has been shown in Kervyn, Fiske, and Yzerbyt (2013). Finally, we assess socio-demographic data (i.e., gender, age).

Competence, morality, and sociability scales. In this study the same set of features as in Study 1 were used to assess stereotypes.

Intergroup emotional reaction scales. Two scales were designed based on items used by Mackie et al. (2000) with the answer categories being: *none* (1), *almost none* (2), *few* (3), *half* (4), *many* (5), *almost all* (6), and *all* (7). The instructions for these items are similar to those for stereotypes:

> What we are asking you to do is indicate how many people in this group (none, almost none, a few, half, many, almost all, all) you think would cause the following emotions in you. Take your time and answer the following questions imagining how many people in this Roma ethnic group, whom you do not know, you think would cause the following emotions in you.

The items of both scales were mixed and randomized. The *anger* scale measures how much people of the Roma group are associated with an angry IER. It is comprised of the following items: rage, fury, anger, irritation, and frustration. The *fear* scale is intended to measure how much people of the Roma group are associated with the IER of fear. It is comprised of the following items: fear, panic, and vulnerability.

Semantic differential of evaluation. A seven-item semantic differential (see Osgood, Suci, & Tannenbaum, 1957) with a seven-point response scale on which items have been validated in Spanish (Díaz-Guerrero & Salas, 1975) was used. All items referred to valence and its intensity associated with the object. The objective of this composite measure was to capture the global evaluation toward an object using a set of pairs of adjectives of which semantic meaning is not directly related to the attitudinal target (i.e., answers are based on the relationship of the target with the connotative evaluative meaning of the adjectives). The pairs of adjectives used were: Sweet-Bitter, Transparent-Opaque, Light-Dark, Perfect-Imperfect, Whole-Broken, Tasty-Unpleasant, and Innocuous-Poisonous (the item scores were ranged from 1 to 7). The order and the direction of the items were randomized to control method effects (acquiescence and item wording effects—positive/negative). After the application, the items were recoded so that they could be interpreted more easily. Cronbach alpha for this scale was .80. Higher scores entail more positive global evaluations.

Procedure. The survey was administered by trained staff in different places and times. There was no time limit. Respondents' anonymity and confidentiality were guaranteed. All subjects gave their written informed consent. The trained staff confirmed that all the participants were over 18, that they were participating voluntarily, that they knew their answers would be handled with scientific purposes, that they were aware they could stop their collaboration at any time, and that they were participating freely. The variables were always presented in the same order: stereotypes of the target group, IERs, semantic differential, and socio-demographic variables. This procedure was approved by the Human Research Bioethical Committee of University of Almería, Spain.

Data analysis. The network was estimated and the community analysis was performed in the same way as in Study 1. Casewise deletion was used for handling missing data.

Results

Descriptive statistics were calculated for all items (see Table 4).

Empirical scores of competence and sociability items were distributed around the midpoint of the scale whereas morality items scores were slightly lower. There was not extreme skewness or kurtosis in any item (see Appendix). Seventy-five incomplete cases were removed. The obtained empirical network and its partial correlations and their 95% bootstrapped confidence intervals can be seen in Figure 4 and Table 5 respectively. These results can be analyzed together with the centrality indices shown in Figure 5; this way it is possible to obtain greater insight into the relative influence of each node on the whole network. As can be seen, network models reflect the broader evaluative context in which the stereotype is embedded.

First of all, although five kinds of variables were included, community analysis detects four dense substructures within the network. These analyses indicate that morality-related features and the global evaluation were clustered in only one substructure. It can be also seen how group features are essentially clustered according to their content, as in the sample with Roma People as group target in Study 1. Moreover, a global analysis of the network allows appreciating the separation between the IER variables and the rest of them. IERs conform to two different substructures clearly distinguishable from group features, but still negatively connected to the global evaluation. High centrality indicators of the anger variables reflect the strong connectivity existing within this substructure.

Table 4. Descriptive statistics for all the items in the Study 2

	M (*SD*)
Competence	
Skillful [Habilidosas]	4.50 (1.19)
Intelligent [Inteligentes]	4.18 (1.24)
Capable [Capacitadas]	3.94 (1.25)
Morality	
Sincere [Sinceras]	3.26 (1.33)
Honest [Honestas]	3.47 (1.19)
Trustworthy [De Confianza]	3.04 (1.24)
Sociability	
Likeable [Simpáticas]	4.39 (1.17)
Warmth [Cariñosas]	4.34 (1.20)
Friendly [Amistosas]	4.36 (1.03)
Anger ER	
Rage [Ira]	3.16 (1.67)
Fury [Rabia]	3.26 (1.74)
Anger [Enfado]	3.41 (1.65)
Irritation [Irritación]	3.73 (1.69)
Frustration [Frustración]	3.24 (1.64)
Fear ER	
Fear [Temor]	3.53 (1.58)
Panic [Pánico]	3.29 (1.58)
Vulnerability [Vulnerabilidad]	3.55 (1.48)
Semantic differential	
Sweet-Bitter [Dulces-amargas]	3.74 (1.33)
Transparent-Opaque [Transparentes-opacas]	3.48 (1.30)
Light-Dark [Claras-Oscuras]	3.13 (1.35)
Perfect-Imperfect [Perfectas-Imperfectas]	3.11 (1.10)
Whole-Broken [Enteras-Rotas]	4.11 (1.16)
Tastey-Unpleasant [Sabrosas-Desagradables]	3.48 (1.15)
Innocuous –Poisonous [Inocuas-Venenosas]	3.46 (1.25)

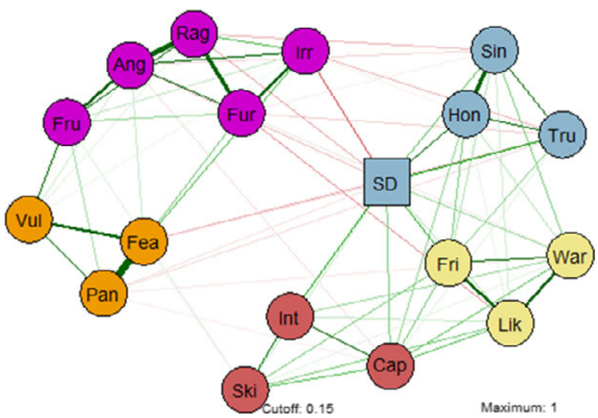

Fig. 4: Empirical network model for stereotypes, emotional reactions, and global evaluation toward Roma People in Study 2. Each node represents an item referred to the social target with the exception of *SD*, which represents the total score of the Semantic Differential scale. The edges represent the relationship among attributes. The thicker the edge is, the greater is the relationship between attributes. Attributes of each substructure are colored the same. Positive relationships are represented in green while negative are red. Ski: skillful; Int: intelligent; Cap: capable; Sin: sincere; Hon: honest; Tru: trustworthy; Lik: likeable; War: warmth; Fri: friendly; Fur: fury; Rag: rage; Ang: anger; Irr: irritation; Fru: frustration; Fea: fear; Pan: panic; Vul: vulnerability; SD: Semantic differential of evaluation. [Colour figure can be viewed at wileyonlinelibrary.com]

At the same time, it can be seen how the global evaluation stands out due to the high number of connections with the rest of the variables within the network. These connections are particularly strong with the morality-related content features honest and trustworthy. The importance of the global evaluation can be also appreciated observing its centrality indices.

A more specific analysis of the relationships within the network shows how sociability features connect to both competence and morality features, whereas these last two sets of features are hardly connected. Regarding the relationships between stereotypes and IERs, the network shows how the morality-related features are the most related (negatively) to anger variables. However, most of the relations between stereotypes and IERs cross-cut the global evaluation. Finally, the importance of the morality-related features in this network, where additional variables to stereotypes have been included, can also be observed in the centrality indices.

Centrality stability estimations can be seen in Figure 6. CS-coefficients were: $CS_{strength}$ (cor = .7) = .52, $CS_{closeness}$ = (cor = .7 = .21, $CS_{betweeness}$ (cor = .7) = .13. These results indicate that under subsetting cases closeness and betweenness estimations showed low stability; however, these estimations are better than in the four sub-samples of Study 1. On the other hand, the stability of strength estimation is confirmed because its CS-coefficient is higher than .5 (see Epskamp et al., 2017).

Discussion

This study illustrates the ability of an empirical network to offer an integrated picture of an intergroup attitudinal system containing stereotypes (i.e., using group features and the substructures they conform), IERs, and global evaluations. The employed models permit us to look at the individual connections among each group feature with each specific IER, and the global evaluation. Information like this offers insight into the conformed structure among the different kinds of variables. In this vein, it can be observed how IER variables show higher connectivity within each kind of emotional reaction than group features in their respective substructures. Additionally, it can be seen how almost each node is connected to the global evaluation of the social object. These results support the hypothesis of the high connotative evaluations linked to social categories (Van Bavel & Cunningham, 2009).

Although related, the variables employed in this study are clustered in different substructures according to their contents with the exception of the semantic differential, similar to what was found in Study 1 for Roma People. However, the clustering of the semantic differential together with the morality-related features is not surprising. Not only because these global evaluations and morality had shown high correlations in previous studies (e.g., Brambilla et al., 2011, Sayans-Jiménez, Cuadrado, et al., 2017) but also because the "morality construct" (here represented as a dense substructure of morality-related content features) and global evaluations have very similar operational

Table 5. Partial correlations [95% bootstrapped confidence intervals] of the network representing stereotypes, emotional reactions, and global evaluation toward Roma People

Variables	Correlations	Variables	Correlations	Variables	Correlations	Variables	Correlations	Variables	Correlations	Variables	Correlations
Ang–Fea	.02 [.00: .09]	Fri–Fur	.00 [−.02: .00]	Hon–SD	.22 [.11: .30][a]	Lik–Fea	.03 [.00: .08]	Sin–Pan	.00 [−.05: .00]	Tru–Irr	−.05 [−.11: .00]
Ang–Fru	.28 [.19: .37][a]	Fri–Irr	.00 [−.02: .02]	Hon–Tru	.26 [.16: .36][a]	Lik–Fri	.27 [.15: .37][a]	Sin–Rag	−.04 [−.09: .00]	Tru–Lik	.00 [.00: .04]
Ang–Irr	.20 [.10: .29][a]	Fri–Pan	.00 [.00: .05]	Hon–Vul	.00 [−.02: .03]	Lik–Fru	.00 [.00: .06]	Sin–SD	.09 [.01: .17][a]	Tru–Pan	−.01 [−.08: .00]
Ang–Pan	.00 [.00: .03]	Fri–Rag	.00 [.00: .04]	Hon–War	.03 [.00: .13]	Lik–Fur	−.08 [−.13: .00]	Sin–Tru	.20 [.10: .30][a]	Tru–Rag	.00 [−.03: .00]
Ang–SD	−.03 [−.09: .00]	Fri–SD	.12 [.03: .20][a]	Int–Ang	.00 [.00: .05]	Lik–Irr	.01 [.00: .06]	Sin–Vul	.00 [.00: .03]	Tru–SD	.14 [.05: .22][a]
Ang–Vul	.01 [.00: .08]	Fri–Vul	.00 [−.04: .02]	Int–Cap	.22 [.12: .30][a]	Lik–Pan	.00 [.00: .04]	Sin–War	.08 [.00: .16]	Tru–Vul	.00 [−.04: .02]
Cap–Ang	−.03 [−.07: .00]	Fru–Fea	.00 [.00: .05]	Int–Fea	.02 [.00: .08]	Lik–Rag	.00 [−.02: .00]	Ski–Ang	.00 [−.04: .00]	Tru–War	.00 [−.05: .02]
Cap–Fea	.00 [−.03: .00]	Fru–Pan	.04 [.00: .11]	Int–Fri	.00 [−.04: .03]	Lik–SD	.03 [.00: .12]	Ski–Cap	.09 [.00: .19]	Vul–SD	.00 [−.05: .00]
Cap–Fri	.08 [.00: .19]	Fru–SD	.00 [−.07: .00]	Int–Fru	.01 [.00: .06]	Lik–Vul	.02 [.00: .09]	Ski–Fea	−.03 [−.09: .00]	War–Ang	−.01 [−.07: .00]
Cap–Fru	.00 [.00: .03]	Fru–Vul	.23 [.10: .31][a]	Int–Fur	.00 [−.04: .00]	Lik–War	.31 [.18: .41][a]	Ski–Fri	.09 [.00: .19]	War–Fea	.00 [−.02: .01]
Cap–Fur	.00 [−.04: .00]	Fur–Ang	.15 [.06: .26][a]	Int–Hon	.00 [.00: .07]	Pan–SD	.00 [−.05: .00]	Ski–Fru	.05 [.00: .12]	War–Fri	.18 [.06: .29][a]
Cap–Hon	.07 [.00: .15]	Fur–Fea	.00 [.00: .06]	Int–Irr	.00 [−.03: .01]	Pan–Vul	.18 [.06: .29][a]	Ski–Fur	.00 [.00: .01]	War–Fru	.00 [−.05: .00]
Cap–Irr	.00 [−.04: .00]	Fur–Fru	.03 [.00: .15]	Int–Lik	.04 [.00: .13]	Rag–Ang	.40 [.28: .49][a]	Ski–Hon	.00 [−.07: .00]	War–Fur	.00 [−.03: .00]
Cap–Lik	.10 [.00: .20]	Fur–Irr	.32 [.21: .40][a]	Int–Pan	.00 [−.07: .00]	Rag–Fea	.00 [.00: .00]	Ski–Irr	.02 [.00: .09]	War–Irr	.00 [.00: .06]
Cap–Pan	−.01 [−.08: .00]	Fur–Pan	.09 [.00: .14]	Int–Rag	.00 [−.03: .00]	Rag–Fru	.24 [.15: .33][a]	Ski–Lik	.08 [.00: .17]	War–Pan	−.03 [−.10: .00]
Cap–Rag	.00 [−.05: .00]	Fur–Rag	.34 [.22: .42][a]	Int–SD	.16 [.05: .23][a]	Rag–Irr	.07 [.00: .19]	Ski–Pan	−.02 [−.09: .00]	War–Rag	.00 [−.03: .00]
Cap–SD	.07 [.00: .15]	Fur–SD	.00 [−.05: .00]	Int–Sin	−.03 [−.09: .00]	Rag–Pan	.00 [.00: .07]	Ski–Rag	.00 [−.04: .00]	War–SD	.05 [.00: .12]
Cap–Sin	.00 [−.03: .04]	Fur–Vul	.00 [.00: .07]	Int–Ski	.25 [.14: .33][a]	Rag–SD	−.05 [−.1: .00]	Ski–SD	.03 [.00: .11]	War–Vul	.00 [−.05: .01]
Cap–Tru	.02 [.00: .11]	Hon–Ang	.00 [−.01: .00]	Int–Tru	.00 [−.02: .06]	Rag–Vul	.01 [.00: .08]	Ski–Sin	−.03 [−.09: .00]		
Cap–Vul	.00 [−.06: .01]	Hon–Fea	.00 [−.05: .00]	Int–Vul	.00 [−.01: .05]	Sin–Ang	−.02 [−.08: .00]	Ski–Tru	.00 [−.02: .05]		
Cap–War	.08 [.00: .19]	Hon–Fri	.07 [.00: .16]	Int–War	.06 [.00: .15]	Sin–Fea	.00 [.00: .06]	Ski–Vul	.00 [−.01: .07]		
Fea–Pan	.58 [.48: .64][a]	Hon–Fru	.00 [.00: .05]	Irr–Fea	.10 [.02: .17][a]	Sin–Fri	.05 [.00: .14]	Ski–War	.03 [.00: .13]		
Fea–SD	−.03 [−.08: .00]	Hon–Fur	.00 [.00: .03]	Irr–Fru	.02 [.00: .12]	Sin–Fru	.00 [.00: .04]	Tru–Ang	.00 [−.05: .00]		
Fea–Vul	.26 [.16: .34][a]	Hon–Irr	.00 [−.07: .00]	Irr–Pan	.00 [.00: .03]	Sin–Fur	.00 [−.06: .00]	Tru–Fea	−.06 [−.11: .00]		
Fri–Ang	.00 [−.05: .00]	Hon–Lik	.02 [.00: .11]	Irr–SD	−.11 [−.17: −.03]	Sin–Hon	.37 [.25: .45][a]	Tru–Fri	.07 [.00: .16]		
Fri–Fea	.00 [−.03: .03]	Hon–Pan	.00 [−.04: .00]	Irr–Vul	.00 [.00: .07]	Sin–Irr	−.01 [−.07: .00]	Tru–Fru	.00 [.00: .05]		
Fri–Fru	.01 [.00: .07]	Hon–Rag	.00 [.00: .00]	Lik–Ang	.00 [−.05: .00]	Sin–Lik	.02 [.00: .10]	Tru–Fur	−.02 [−.07: .00]		

Note: Ski, skillful; Int, intelligent; Cap, capable; Sin, sincere; Hon, honest; Tru, trustworthy; Lik, likeable; War, warmth; Fri, friendly; Fur, fury; Rag, rage; Ang, anger; Irr, irritation; Fru, frustration; Fea, fear; Pan, panic; Vul, vulnerability; SD, semantic differential of evaluation.

[a]Reliable correlations.

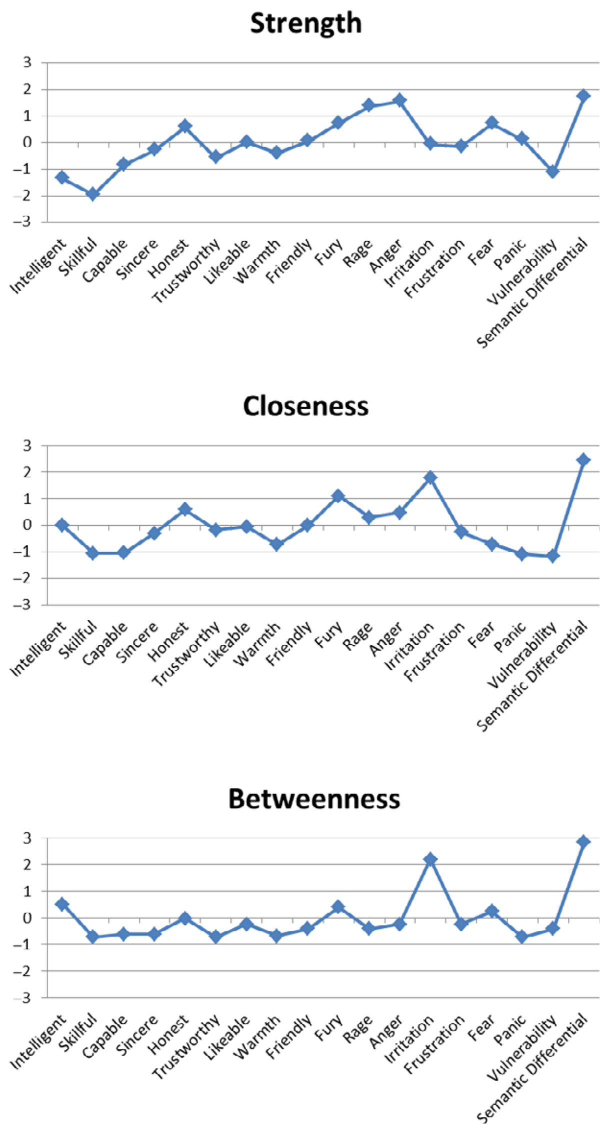

Fig. 5: Centrality indices for stereotypes, emotional reactions, and global evaluation toward Roma ethnic people in Study 2. [Colour figure can be viewed at wileyonlinelibrary.com]

definitions (i.e., perceived morality reflects moral goals, and the benefit or harm that such goals could cause).

The analysis of the centrality indices provides information about the influence exerted by the global evaluation throughout the network. The relationship of the global evaluation with almost all the individual features highlights how important global evaluations are in the context of intergroup relations, even when items and scales framed in the SCM are used. These connections show an inverse relationship between levels of IERs (as used in this study) and global evaluations. Conversely, the group features used in this study are positively related to the global evaluation. As a result of these relations, it appears that a change in the global evaluation of the target could exert an influence on the whole network. Furthermore, its high betweenness provides information about the potential ability of global evaluations to connect stereotypes with IERs. Therefore, based on these results, it could be assumed that changes in stereotypes would be transmitted to IERs mostly through the global evaluation.

General Discussion

In two studies we have aimed to show the value of empirical network models for research on stereotypes. We found that network models can provide more insight into the structure of stereotypes than the traditionally employed factor analysis. Apart from providing information about how group features can be clustered based on their common relationships (like the traditional approaches), networks additionally show the individual relationship between features. This facilitates the representation of stereotypes as cognitive knowledge structures (as suggested in Cox & Devine, 2015), and the study of the most probable paths by which stereotype change/influence would be transmitted. Employing network models could help to resolve the discussion about the number of dimensions that most adequately represents stereotypes. In addition, knowing the relative importance of each node within the network could help, for instance, to identify which group features should be made salient, or changed, in order to improve group representations in contexts of intergroup conflict.

Together with the utility of empirical network models for studying stereotypes, their structure, and their dynamics, this research has also shown that these models can be used to represent structural models within a broader context of psychosocial variables. Specifically, we intended to provide network models as a tool not only to make predictions based on group features, but also to allow the integration of information of different relevant bases of information that affect intergroup attitudes.

The results offered in this research show that it is possible to adopt the most recent attitudinal models to the study of intergroup attitudes using group features (to measure stereotypes) and additional variables. In accordance with Dalege et al. (2016), we posit that intergroup attitudes can be conceptualized as networks composed of evaluative reactions toward the social target. In these networks different bases of information will form a *small-world structure* where highly connected components will be clustered in different substructures. This enables social researchers to address research on intergroup attitudes by integrating the study of its different bases of information in a dynamic, bidirectional, and interactive way.

Finally, we would like to provide some conclusions specifically related to the study of stereotype content. In the first place, our results show how group features can be empirically clustered independently of their content, as in the case of the professional firefighter group. Second, in accordance with Landy et al. (2016) relationships between sociability and competence related content features were found. In most of the networks these substructures were closer to each other than to morality-related features. These connections could be due to the fact that these two kinds of content could be taken as a group's ability to achieve its goals, as highlighted by Landy et al. (2016).

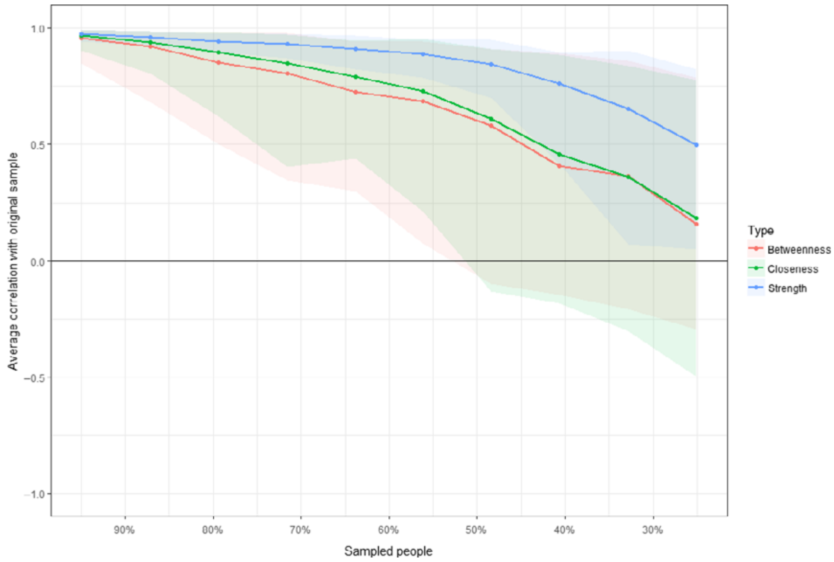

Fig. 6: Mean correlations between centrality indices of the original sample and samples with persons dropped in Study 2. Lines represent the average centrality estimations and areas depict the range from the 2.5th quantile to the 97.5th quantile. [Colour figure can be viewed at wileyonlinelibrary.com]

In conclusion, empirical network models have proven to be an analytical technique suitable for the study of stereotypes and intergroup attitudes. These kinds of tools allow us to represent the inherent complexity of the structure of intergroup attitudes. Moreover, using empirical network models it is not necessary to choose between two or three dimensions to represent these stereotypes. As such, representing stereotypes as cognitive knowledge structures, and intergroup attitudes as networks composed of evaluative reactions toward the social target, is not only a way to avoid constraints that are associated with commonly used analytic techniques, but also an approach that can help researchers to adequately reflect the inherent complexities of social perceptions.

Conflict of Interest

The authors confirm they have no conflict of interest to declare. Authors also confirm that this article adheres to ethical guidelines specified in the APA Code of Conduct as well as the authors' national ethics guidelines.

References

Abele, A. E., & Wojciszke, B. (2014). Communal and agentic content in social cognition: A dual perspective model. *Advances in Experimental Social Psychology*, *50*, 195–255. https://doi.org/10.1016/b978-0-12-800284-1.00004-7

Amodio, D. M. (2014). The neuroscience of prejudice and stereotyping. *Nature Reviews Neuroscience*, *15*, 670–682. https://doi.org/10.1038/nrn3800

Ashmore, R. D., & Tumia, M. L. (1980). Sex stereotypes and implicit personality theory. I. A personality description approach to the assessment of sex stereotypes. *Sex Roles*, *6*, 501–518. https://doi.org/10.1007/bf00287882

Brambilla, M., & Leach, C. W. (2014). On the importance of being moral: The distinctive role of morality in social judgment. *Social Cognition*, *32*, 397–408. https://doi.org/101521soco2014324397

Brambilla, M., & Riva, P. (2016). Predicting pleasure at others' misfortune: Morality trumps sociability and competence in driving deservingness and schadenfreude. *Motivation and Emotion*, *41*, 243–253. https://doi.org/10.1007/s11031-016-9594-2

Brambilla, M., Rusconi, P., Sacchi, S., & Cherubini, P. (2011). Looking for honesty: The primary role of morality (vs. sociability and competence) in information gathering. *European Journal of Social Psychology*, *41*, 135–143. https://doi.org/10.1002/ejsp.744

Brambilla, M., Sacchi, S., Pagliaro, S., & Ellemers, N. (2013). Morality and intergroup relations: Threats to safety and group image predict the desire to interact with outgroup and ingroup members. *Journal of Experimental Social Psychology*, *49*, 811–821. https://doi.org/10.1016/j.jesp.2013.04.005

Brambilla, M., Sacchi, S., Rusconi, P., Cherubini, P., & Yzerbyt, V. Y. (2012). You want to give a good impression? Be honest! Moral traits dominate group impression formation. *British Journal of Social Psychology*, *51*, 149–166. https://doi.org/10.1111/j.2044-8309.2010.02011.x

Brown, T. A. (2006). *Confirmatory factor analysis for applied research*. New York, NY: Guilford Press.

Bruckmüller, S., & Abele, A. E. (2013). The density of the Big Two: How are agency and communion structurally represented? *Social Psychology*, *44*, 63–74. https://doi.org/10.1027/1864-9335/a000145

Bühlmann, P., & van de Geer, S. (2011). *Statistics for high-dimensional data: Methods, theory and applications*. New York, NY: Springer-Verlag. https://doi.org/10.1007/978-3-642-20192-9

Cameron, J. A., & Trope, Y. (2004). Stereotype-biased search and processing of information about group members. *Social Cognition*, *22*, 650–672. https://doi.org/10.1521/soco.22.6.650.54818

Clauset, A., Newman, M. E. J., & Moore, C. (2004). Finding community structure in very large networks. *Physical Review. E, Statistical, Nonlinear, and Soft Matter Physics*, *70*, 066111. https://doi.org/10.1103/physreve.70.066111

Cox, W. T. L., & Devine, P. G. (2015). Stereotypes possess heterogeneous directionality: A theoretical and empirical exploration of stereotype structure and content. *PLoS One*, *10*, 1–27. https://doi.org/10.1371/journal.pone.0122292

Cramer, A. O. J., Waldorp, L. J., van der Maas, H. L. J., & Borsboom, D. (2010). Comorbidity: A network perspective. *Behavioral and Brain Sciences*, *33*, 137–150. https://doi.org/10.1017/s0140525x09991567

Cuddy, A. J. C., Fiske, S. T., & Glick, P. (2007). The BIAS map: Behaviors from intergroup affect and stereotypes. *Journal of Personality and Social Psychology*, *92*, 631–648. https://doi.org/10.1037/0022-3514.92.4.631

Cuddy, A. J. C., Fiske, S. T., Kwan, V. S. Y., Glick, P., Demoulin, S., Leyens, J.-P., … Ziegler, R. (2009). Stereotype content model across cultures: Towards universal similarities and some differences. *British Journal of Social Psychology*, *48*, 1–33. https://doi.org/10.1348/014466608x314935

Dalege, J., Borsboom, D., van Harreveld, F., van den Berg, H., Conner, M., & van der Maas, H. L. J. (2016). Toward a formalized account of attitudes: The Causal Attitude Network (CAN) model. *Psychological Review*, *123*, 2–22. https://doi.org/10.1037/a0039802

Dalege, J., Borsboom, D., van Harreveld, F., & van der Maas, H. L. J. (2017). Network analysis on attitudes: A brief tutorial. *Social Psychological and Personality Science*, *8*, 529–537. https://doi.org/10.1177/1948550617709827

Dalege, J., Borsboom, D., van Harreveld, F., Waldorp, L. J., & van der Maas, H. L. J. (2017). Network structure explains the impact of attitudes on voting decisions. *Scientific Reports*, *7*, 1–11. https://doi.org/10.1038/s41598-017-05048-y

Díaz-Guerrero, R., & Salas, M. (1975). *El diferencial semántico del idioma español [The semantic differential of Spanish]*. Ciudad de México, México: Trillas.

Durante, F., Fiske, S. T., Kervyn, N., Cuddy, A. J. C., Akande, A. D., Adetoun, B. E., & Storari, C. C. (2013). Nations' income inequality predicts ambivalence in stereotype content: How societies mind the gap. *British Journal of Social Psychology*, *52*, 726–746. https://doi.org/10.1111/bjso.12005

Epskamp, S. (2016). Regularized Gaussian psychological networks: Brief report on the performance of extended BIC model selection. *arXiv preprint*, page arXiv:1606.05771.

Epskamp, S., Borsboom, D., & Fried, E. I. (2017). Estimating psychological networks and their accuracy: A tutorial paper. *Behavior Research Methods*, *50*, 195–212. https://doi.org/10.3758/s13428-017-0862-1

Epskamp, S., Cramer, A. O. J., Waldorp, L. J., Schmittmann, V. D., & Borsboom, D. (2012). qgraph: Network visualization of relationships in psychometric data. *Journal of Statistical Software*, *48*, 1018. https://doi.org/10.18637/jss.v048.i04

Epskamp, S., Waldorp, L. J., Mõttus, R., & Borsboom, D. (2018). The Gaussian graphical model in cross-sectional and time-series data. *Multivariate Behavioral Research*, 1–28. https://doi.org/https//doi.org/10.1080/00273171.2018.1454823

Fiske, S. T., Cuddy, A. J. C., Glick, P., & Xu, J. (2002). A model of (often mixed) stereotype content: Competence and warmth respectively follow from perceived status and competition. *Journal of Personality and Social Psychology*, *82*, 878–902. https://doi.org/10.1037/0022-3514.82.6.878

Fiske, S. T., Xu, J., Cuddy, A. C., & Glick, P. (1999). (Dis)respecting versus (dis)liking: Status and interdependence predict ambivalent stereotypes of competence and warmth. *Journal of Social Issues*, *55*, 473–491. https://doi.org/10.1111/0022-4537.00128

Fortunato, S. (2010). Community detection in graphs. *Physics Reports*, *486*, 75–174. https://doi.org/10.1016/j.physrep.2009.11.002

Fried, E. I., Epskamp, S., Nesse, R. M., Tuerlinckx, F., & Borsboom, D. (2016). What are 'good' depression symptoms? Comparing the centrality of DSM and non-DSM symptoms of depression in a network analysis *Journal of Affective Disorders*, *189*, 314–320. https://doi.org/10.1016/j.jad.2015.09.005

Friedman, J., Hastie, T., & Tibshirani, R. (2008). Sparse inverse covariance estimation with the graphical lasso. *Biostatistics*, *9*, 432–441. https://doi.org/10.1093/biostatistics/kxm045

Fruchterman, T. M. J., & Reingold, E. M. (1991). Graph drawing by force-directed placement. *Software: Practice and Experience*, *21*, 1129–1164. https://doi.org/10.1002/spe.4380211102

Glick, P., & Fiske, S. T. (2001). Ambivalent stereotypes as legitimizing ideologies: Differentiating paternalistic and envious prejudice. In J. T. Jost & B. Major (Eds.), *The psychology of legitimacy: Ideology, justice, and intergroup relations* (pp. 278–306). New York, NY: Cambridge University Press.

Golino, H. F., & Epskamp, S. (2017). Exploratory graph analysis: A new approach for estimating the number of dimensions in psychological research. *PLoS One*, *12*, e0174035. https://doi.org/10.1371/journal.pone.0174035

Goodwin, G. P. (2015). Moral character in person perception. *Current Directions in Psychological Science*, *24*, 38–44. https://doi.org/10.1177/0963721414550709

Goodwin, G. P., Piazza, J., & Rozin, P. (2014). Moral character predominates in person perception and evaluation. *Journal of Personality and Social Psychology*, *106*, 148–168. https://doi.org/10.1037/a0034726

Hamilton, D. L., Sherman, S. J., Crump, S. A., & Spencer-Rodgers, J. (2009). The role of entitativity in stereotyping: Processes and parameters. In T. D. Nelson (Ed.), *Handbook of prejudice, stereotyping, and discrimination* (pp. 179–198). Mahwah, NJ: Erlbaum.

Jones, R. A., & Ashmore, R. D. (1973). The structure of intergroup perception: Categories and dimensions in views of ethnic groups and adjectives used in stereotype research. *Journal of Personality and Social Psychology*, *25*, 428–438. https://doi.org/10.1037/h0034162

Kervyn, N., Fiske, S. T., & Yzerbyt, V. Y. (2013). Integrating the stereotype content model (warmth and competence) and the Osgood semantic differential (valuation, potency, and activity). *European Journal of Social Psychology*, *43*, 673–681. https://doi.org/10.1002/ejsp.1978

Landy, J. F., Piazza, J., & Goodwin, G. P. (2016). When its bad to be friendly and smart: The desirability of sociability and competence depends on morality. *Personality and Social Psychology Bulletin*, *42*, 1272–1290. https://doi.org/10.1177/0146167216655984

Leach, C. W., Ellemers, N., & Barreto, M. (2007). Group virtue: The importance of morality (vs. competence and sociability) in the positive evaluation of in-groups. *Journal of Personality and Social Psychology*, *93*, 234–249. https://doi.org/10.1037/0022-3514.93.2.234

López-Rodríguez, L., Cuadrado, I., & Navas, M. (2013). Aplicación extendida del Modelo de Contenido de Estereotipos (MCE) hacia tres grupos de inmigrantes en España [Extended application of the Stereotype Content Model (SCM) towards three immigrant groups in Spain]. *Estudios de Psicología*, *34*, 197–208. https://doi.org/10.1174/021093913806751375

López-Rodríguez, L., & Zagefka, H. (2015). The effects of stereotype content on acculturation preferences and prosocial tendencies: The prominent role of morality. *International Journal of Intercultural Relations*, *45*, 36–46. https://doi.org/10.1016/j.ijintrel.2014.12.006

Mackie, D. M., Devos, T., & Smith, E. R. (2000). Intergroup emotions: Explaining offensive action tendencies in an intergroup context. *Journal of Personality and Social Psychology*, *79*, 602–616. https://doi.org/10.1037/0022-3514.79.4.602

Navas, M., & Cuadrado, I. (2003). Actitudes hacia inmigrantes africanos y gitanos: un estudio comparativo [Attitudes toward African immigrants and gypsies: A comparative study]. *Apuntes de Psicología*, *21*, 29–49. Retrieved from: https://www.apuntesdepsicologia.es/index.php/revista/article/viewFile/420/340

Newman, M. E. (2006). Modularity and community structure in networks. *Proceedings of the National Academy of Sciences of the United States of America*, *103*, 8577–8582. https://doi.org/10.1073/pnas.0601602103

Newman, M. E. J. (2004). Fast algorithm for detecting community structure in networks. *Physical Review. E, Statistical, Nonlinear, and Soft Matter Physics*, *69*, 1–5. 066133. https://doi.org/10.1103/physreve.69.066133

Osgood, C. E., Suci, G. J., & Tannenbaum, P. H. (1957). *The measurement of meaning*. Urbana, IL: University of Illinois Press.

Pons, P., & Latapy, M. (2005). Computing communities in large networks using random walks. In P. Yolum, T. Güngör, F. Gürgen, & C. Özturan (Eds.), *Computer and Information Sciences—ISCIS 2005* (pp. 284–293). Berlin, Germany: Springer. https://doi.org/10.1007/11569596

Quadflieg, S., Flannigan, N., Waiter, G. D., Rossion, B., Wig, G. S., Turk, D. J., & Macrae, C. N. (2011). Stereotype-based modulation of person perception. *NeuroImage*, *57*, 549–557. https://doi.org/10.1016/j.neuroimage.2011.05.004

Raykov, T., & Marcoulides, G. A. (2001). Can there be infinitely many models equivalent to a given covariance structure model? *Structural Equation Modeling: A Multidisciplinary Journal*, *8*, 142–149. https://doi.org/10.1207/s15328007sem0801_8

Raykov, T., & Penev, S. (1999). On structural equation model equivalence. *Multivariate Behavioral Research*, *34*, 199–244. https://doi.org/10.1207/s15327906mb340204

Rosenberg, S., Nelson, C., & Vivekananthan, P. S. (1968). A multidimensional approach to the structure of personality impressions. *Journal of Personality and Social Psychology*, *9*, 283–294. https://doi.org/10.1037/h0026086

Sayans-Jiménez, P., Cuadrado, I., Rojas, A. J., & Barrada, J. R. (2017). Extracting the evaluations of stereotypes: bi-factor model of the stereotype content structure. *Frontiers in Psychology*, *8*, 1692. https://doi.org/10.3389/fpsyg.2017.01692

Sayans-Jiménez, P., Rojas, A. J., & Cuadrado, I. (2017). Is it advisable to include negative attributes to assess the stereotype content? Yes, but only in the morality dimension. *Scandinavian Journal of Psychology*, *58*, 170–178. https://doi.org/10.1111/sjop.12346

Schmittmann, V. D., Cramer, A. O. J., Waldorp, L. J., Epskamp, S., Kievit, R. A., & Borsboom, D. (2013). Deconstructing the construct: A network perspective on psychological phenomena. *New Ideas in Psychology*, *31*, 43–53. https://doi.org/10.1016/j.newideapsych.2011.02.007

Sloman, S. A. (1996). The empirical case for two systems of reasoning. *Psychological Bulletin*, *119*, 3–22. https://doi.org/10.1037/0033-2909.119.1.3

Srivastava, S., Guglielmo, S., & Beer, J. S. (2010). Perceiving others' personalities: Examining the dimensionality, assumed similarity to the self, and stability of perceiver effects. *Journal of Personality and Social Psychology*, *98*, 520–534. https://doi.org/10.1037/a0017057

Stangor, C. (2016). The study of stereotyping, prejudice, and discrimination within social psychology: A quick history of theory and research. In T. D. Nelson (Ed.), *Handbook of prejudice, stereotyping, and discrimination* (2nd ed., pp. 1–27). New York, NY, USA: Psychology Press.

Tibshirani, R. (1996). Regression selection and shrinkage via the Lasso. *Journal of the Royal Statistical Society B*, *58*, 267–288. https://doi.org/10.2307/2346178

Tyler, L., & Moss, H. (2001). Towards a distributed account of conceptual knowledge. *Trends in Cognitive Sciences*, *5*, 244–252. https://doi.org/10.1016/s1364-6613(00)01651-x

Urbiola, A., Willis, G. B., Ruíz-Romero, J., & Moya, M. (2014). La reducción del prejuicio hacia la población gitana en la vida real: Efectos de la visita a la exposición "Vidas Gitanas (Lungo Drom)" [Reduction of the prejudice toward gypsies in the real life: Effects of visiting "Gyspsy lifes (Lungo Drom)" exhibition]. *Psychosocial Intervention*, *23*, 11–16. https://doi.org/10.5093/in2014a1

Van Bavel, J. J., & Cunningham, W. A. (2009). Self-categorization with a novel mixed-race group moderates automatic social and racial biases. *Personality and Social Psychology Bulletin*, *35*, 321–335. https://doi.org/10.1177/0146167208327743

Van Bork, R., Epskamp, S., Rhemtulla, M., Borsboom, D., & van der Maas, H. L. J. (2017). What is the p-factor of psychopathology? Some risks of general factor modeling. *Theory & Psychology*, *27*, 759–773. https://doi.org/10.1177/0959354317737185

Appendix
Skewness and kurtosis in all samples

	Study 1								Study 2	
	Sub-sample 1 (Roma People)		Sub-sample 2 (firefighters)		Sub-sample 3					
					Down syndrome people		Multimillionaire people		Roma People	
	Sk	*K*	*Sk*	*K*	*Sk*	*K*	*Sk*	*K*	*Sk*	*K*
Competence									−0.41	0.21
Skillful [Habilidosas]	−1.07	1.16	–0.06	0.03	0.31	−0.01	−0.43	0.10	−0.08	−0.09
Intelligent [Inteligentes]	−1.60	2.85	0.10	0.17	0.11	−0.10	−0.59	1.00	0.20	−0.25
Capable [Capacitadas]	−1.56	4.08	−0.32	–0.90	0.18	−0.16	−0.60	0.62		
Morality									0.10	−0.51
Sincere [Sinceras]	−2.23	6.72	−0.30	−0.36	−0.50	−0.18	0.34	−0.26	−0.09	−0.24
Honest [Honestas]	−2.65	8.78	−0.15	−0.68	−0.24	−0.65	0.03	−0.23	0.25	0.13
Trustworthy [De Confianza]	−2.48	7.81	−0.49	−0.04	−0.39	−0.12	0.06	0.51		
Sociability									−0.45	0.24
Likeable [Simpáticas]	−0.75	−0.06	0.27	−0.33	−0.44	0.05	−0.14	0.00	−0.39	0.22
Warmth [Cariñosas]	−0.92	−0.03	0.16	−0.03	−0.91	1.22	0.09	−0.47	−0.25	−0.02
Friendly [Amistosas]	−0.98	0.65	0.08	−0.32	−0.29	0.01	0.30	0.16		
Anger ER									0.56	−0.41
Rage [Ira]									0.43	−0.71
Fury [Rabia]									0.24	−0.78
Anger [Enfado]									0.07	−0.77
Irritation [Irritación]									0.38	−0.64
Frustration [Frustración]										
Fear ER									0.24	−0.61
Fear [Temor]									0.53	−0.38
Panic [Pánico]									0.26	−0.46
Vulnerability [Vulnerabilidad]										
Semantic Differential									−0.04	−0.47
Sweet-Bitter [Dulces-amargas]									−0.13	−0.15
Transparent-Opaque [Transparentes-opacas]									−0.46	0.04
Light-Dark [Claras- Oscuras]									0.13	−0.34
Perfect-Imperfect [Perfectas-Imperfectas]									0.11	0.79
Whole-Broken [Enteras-Rotas]									0.03	−0.18
Tastey-Unpleasant [Sabrosas-Desagradables]									−0.01	−0.13
Innocuous –Poisonous [Inocuas-Venenosas]									−0.41	0.21

Note: *Sk*, Skewness; *K*, Kurtosis.