Psychiatry Research 265 (2018) 87–92

Contents lists available at ScienceDirect

Psychiatry Research

journal homepage: www.elsevier.com/locate/psychres

Network analysis of empathy items from the interpersonal reactivity index in 1973 young adults

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ARTICLE INFO

Keywords:
IRI
Empathy
Network analysis

ABSTRACT

The aim of this work is to perform a network analysis on the French adaptation of the interpersonal reactivity index (IRI) scale from a large Belgian database and provide additional information for the construct of empathy. We analyze a database of 1973 healthy young adults who were queried on the IRI scale. A regularized partial correlation network is estimated. In the visualization of the model, items are displayed as nodes, edges represent regularized partial correlations between the nodes. Centrality denotes a node's connectedness with other nodes in the network. The spinglass algorithm and the walktrap algorithm are used to identify communities of items, and state-of-the-art stability analyses are carried out. The spinglass algorithm identifies four communities, the walktrap algorithm five communities. Positive edges are found among nodes belonging to the same community as well as among nodes belonging to different communities. Item 14 ("Other people's misfortunes do not usually disturb me a great deal") shows the highest strength centrality score. The network edges and node centrality order are accurately estimated. Network analysis highlights interesting connections between indicators of empathy; how these results impact empathy models must be assessed in further studies.

1. Introduction

Empathy is a main component of short-term as well as long-term human interactions. Despite its importance and because of its complexity, a unified definition is yet to be found. For some authors, empathy incarnates the ability to perceive and be sensitive to others' emotions and the desire for their well-being (Decety et al., 2016). It is not to be confused with sympathy, which is considered to be a part of empathy and defined as the consciousness of another's emotions and feelings without sharing them, together with a feeling of pity (Wispé, 1986). Empathy is a key item to mental health professionals because it belongs to a collection of indicators of good outcomes in psychotherapy (Elliott et al., 2011). In 1980, Mark H. Davis presented a self-report empathy questionnaire, the interpersonal reactivity index (IRI), where he identified the construct as built upon two dimensions (Davis, 1980). The first one represents the cognitive dimension, or the tendency to adopt others' perspectives and feelings; the second one represents an affective dimension reflecting one's feeling of another's emotional state (Decety and Jackson, 2004). Out of these two dimensions Davis identified four components in his model of empathy: (1) *fantasy* (belonging to the cognitive dimension), or the tendency to get involved in the actions and feelings of one or more fictional characters in movies, books or plays (e.g., item 23—"When I watch a good movie, I can very easily put myself in the place of a leading character"); (2) *perspective taking* (also belonging to the cognitive dimension), or the tendency to comprehend others' point of view (e.g., item 25—"When I am upset at someone, I try to put myself in his shoes for a while"); (3) *empathic concern* (belonging to the affective dimension), the feeling of concern and sympathy for people in distress (e.g., item 9—"When I see someone being taken advantage of, I feel kind of protective toward them"); (4) *personal distress* (also belonging to the affective dimension), or the feeling of unease in difficult, tense or emotional situations (e.g., item 10—"I sometimes feel helpless when I am in the middle of a very emotional situation"). Even though the two-dimension model is frequently accepted (Bohart and Greenberg, 1997; Davis, 1980; Decety and Jackson, 2004; Reniers et al., 2011), further models were proposed, such as Blair's (2005), which distinguished three components (motor, cognitive empathy and emotional). Cliffordson (2002) proposed a hierarchical model putting the empathic concern factor at the top of the pyramid. Empathy is an important issue for psychiatrists. Its dysfunctioning is part of major psychiatric diseases such as psychopathy and autism (Blair, 2005) and is perceived by patients as a key element to

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https://doi.org/10.1016/j.psychres.2018.03.082
Received 13 September 2017; Received in revised form 27 March 2018; Accepted 29 March 2018
Available online 19 April 2018
0165-1781/

treatment (Ross and Watling, 2017)

In the last few years, a new way of analyzing data in psychology and psychiatry has arisen: network analysis. In this conceptual model (Borsboom and Cramer, 2013), pairwise interactions among symptoms represent a network of mutually influencing elements. This model has affirmed itself as a way of analyzing mental disorders such as depression (Beard et al., 2016; Boschloo et al., 2016; Fried et al., 2017), posttraumatic stress disorder (Bryant et al., 2017), as well as autism and obsessive–compulsive disorder (Ruzzano et al., 2015) by focusing on the interaction between symptoms, attributes, emotions, and behaviors (for a review, see Fried et al., 2017).

Network analysis provides a new opportunity to conceive psychological constructs not as the consequence of an underlying disease as in the latent variable model, but instead as constituted by the mutual interaction of its items. While largely applied to research on mental illness, network models have been used in other psychological sciences such as personality (Costantini et al., 2015), health-related quality of life (Kossakowski et al., 2016), intelligence (Van Der Maas et al., 2006), and attitudes (Dalege et al., 2017). Network models have also been used to specifically investigate the structure of multivariate data in psychology, for instance to identify the number of item clusters: this is the case of recent papers concerning PTSD (Glück et al., 2017) and development (Demetriou et al., 2017).

This paper extends this conceptual framework to the psychological construct of empathy. Network analysis facilitates the identification of interactions between psychological variables such as items on self-report questionnaires; allows for the estimation of item communities (i.e. clusters of items that are closely related with each other); and can give insights into the connectedness or importance of items within the network, often referred to as 'centrality' (Boccaletti et al., 2006).

According to Davis' model (1980), we might expect significant positive relations between items from the Empathic concern scale and items from the Perspective taking and the Fantasy scales.

Inspired by network analysis in other fields of psychological science, we apply network models for the first time to the domain of empathy research, specifically, to the 28-item French version of the IRI (Braun et al., 2015). This paper highlights potential insights that network analysis can offer—as a complementary tool to factor modeling that is more established in the field—to empathy research. The primary aim of the paper is to explore empathy items and their relationships in an empathy network, and the secondary aim is to build up on prior factor modeling work in this dataset. Braun and colleagues (2015) used confirmatory or exploratory factor analysis (CFA and EFA) to investigate the factor structure in the present data, and we want to use community detection algorithms to see whether the results align with prior work, and to discuss why the identified communities have a radically different interpretation (Demetriou et al., 2017; Golino and Epskamp, 2017).

We provide the full code and data in the supplementary materials to make this paper fully reproducible.

2. Methods

2.1. Database

The database for this study (Briganti et al., 2018; the same for the Braun study analysis) was composed of 1973 French-speaking students in several universities or schools for higher education in the following fields: engineering (31%), medicine (18%), nursing school (16%), economic sciences (15%), physiotherapy, (4%), psychology (11%), law school (4%) and dietetics (1%). The subjects were 17–25 years old (M = 19.6 years, SD = 1.6 years), 57% were females and 43% were males. Even though the full dataset was composed of 1973 participants, only 1270 answered the full questionnaire: we dealt with missing data by using pairwise complete observations in estimating a Gaussian graphical model (see section 2.2.1), meaning that we used all available information from every subject.

The IRI is composed of 28 items meant to assess the four following components: fantasy, perspective taking, empathic concern and personal distress. In the questionnaire, the items are mixed; reversed items (items 3, 4, 7, 12, 13, 14, 15, 18, 19) are present. Items are scored from 0 to 4, where "0″ means "Doesn't describe me very well" and "4″ means "Describes me very well"; reverse-scoring is calculated afterwards. The IRI questionnaires were anonymized. The reanalysis of the database in this retrospective study was approved by the ethical committee of the Erasmus Hospital.

(Insert 28 item IR from Table_IRI)

2.2. Network analysis

The software used for the analysis is R (version 3.4.0, open source, available at https://www.r-project.org/). We used the packages qgraph, version 1.4.4 (Epskamp et al., 2012) and glasso (Friedman et al., 2014) for network estimation and visualization, mgm, version 1.2–2 for node predictability (Haslbeck and Waldorp, 2016), igraph, version 1.1.2 (Csardi and Nepusz, 2006) for the spinglass algorithm, walktrap algorithm and bootnet, version 1.0.1 (Epskamp et al., 2017) for stability. We provide further information about the packages used to carry out the analysis in the supplementary materials.

2.2.1. Network estimation

We estimated Spearman correlations for the 28 ordinal items, which was the input to estimate a Gaussian graphical model (GGM), a regularized partial correlation network (Epskamp and Fried, 2018). We used Spearman correlations instead of polychoric correlations because of low variability between items that can lead to zeroes in the marginal crosstables (discussed in detail in Epskamp and Fried, 2018). The graphical lasso (least absolute shrinkage and selection operator) was used to regularize the edge weight parameters resulting from the GGM, which ensures avoiding the estimation of spurious edges.

Nodes represent items from the French adaptation of IRI. Edges are connections between two nodes: they are regularized partial correlations between two items of the questionnaire. An edge between two items therefore means that there is an association after controlling for all other nodes in the network. Statistically speaking, an edge between items in the IRI network can be interpreted as following: when two nodes A and B are strongly connected and the observed group scores high on A, the observed group is more likely to also score high on B, controlling for all other nodes in the network.

Nodes are placed in the network using the Fruchterman–Reingold algorithm, which determines the position of the node based on the sum of connections it has with other nodes (Fruchterman and Reingold, 1991). Each edge has a sign: blue edges represent positive regularized partial correlations whereas red edges represent negative regularized partial correlations. The corresponding thickness and saturation of an edge denote its weight (i.e. the strength of association).

2.2.2. Network inference

The centrality plot illustrates the centrality of a node in connection with other nodes. Boccaletti et al. (2006) described three types of centrality: strength, betweenness, and closeness. One can understand strength centrality as the sum of direct connections a given node has in the network; betweenness is understood as the shortest paths that go through the node under investigation; closeness measures the sum of shortest paths from the node under investigation to all other nodes in the network (Opsahl et al., 2010). Since centrality represents the relative importance of a node in a network, three possible interpretations to a central item were conceptualized (Freeman, 1978): control, independence or activity. Statistically speaking, a central item shares the most variance with all other items. Conceptually, and in case of IRI, which is a self-administered scale, we suggest that the answer of a subject to a central item might predict the way the subject answers to