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

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A R T I C L E I N F O

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A B S T R A C T

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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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 other items which share a connection with it in the network. Centrality estimates are standardized with a mean of 0 and a standard deviation of 1, and strength centrality is the main metric used in this paper since it is the most robustly estimated centrality metric described in the literature (Epskamp et al., 2017). However, centrality measures are relative metrics, since the centrality of each node is estimated in comparison with other nodes (there is always a highly central node, no matter how weak the edges in the network are). We therefore also estimated node predictability as described by Haslbeck and Fried (2017). Node predictability represents the shared variance of each node with all its neighbors, which constitutes an absolute measure of its interconnectedness (Fried et al., 2018).

The spinglass algorithm was used to identify communities of items in the GGM. It is based on the principle that edges should connect nodes of the same community, whereas nodes belonging to different communities should not be connected (Yang et al., 2016). It is important to note that an item can only be part of one community using this procedure. Since the spinglass algorithm can give different results in the same sample, we assessed the stability of the solution by running the algorithm 100 times and extracted the number of communities with the highest frequency. To complement the results, we also used the walktrap algorithm, which is based on the principle that adjacent nodes tend to belong to the same community (Yang et al., 2016). The walktrap algorithm is shown to have high accuracy in simulation studies (Golino and Epskamp, 2017; Demetriou et al., 2017).

2.2.3. Accuracy and stability

We tested the accuracy of edge weights and the stability of the order of centrality estimation through bootstrapping (Epskamp et al., 2017; we used 2000 bootstraps). We bootstrapped 95% confidence intervals of all edge weights, followed by the edge-weights comparison test and an edge weight difference test to see which edges differ from each other in size significantly (to answer the question is edge A significantly larger than edge B). We used the subsetting bootstrap procedure that re-estimates the network with a dropping percentage of participants to determine the stability of centrality estimation, and results in a centrality-stability coefficient (CS-coefficient) that should not be lower than 0.25 and preferably above 0.5. Finally, we performed a centrality difference test to see which centrality estimates differ statistically from each other (to answer the question is node A significantly more central than node B).

3. Results

3.1. Empathy network

Fig. 1 illustrates the estimated network of the 28-item IRI.

Overall, most items are positively connected within the network. Item 16 ("After seeing a play or movie, I have felt as though I were one of the characters") is strongly connected to item 23 ("When I watch a good movie, I can very easily put myself in the place of a leading character") (weight 0.38). Item 4 ("Sometimes I don't feel very sorry for other people when they are having problems") has a wide edge to item 14 ("Other people's misfortunes do not usually disturb me a great deal") (weight 0.29). Other strong edges include item 10 ("I sometimes feel helpless when I am in the middle of a very emotional situation") and item 17 ("Being in a tense emotional situation scares me"), item 24 ("I tend to lose control during emergencies") and item 27 ("When I see someone who badly needs help in an emergency, I go to pieces"), item 25 ("When I'm upset at someone, I usually try to "put myself in his shoes" for a while") and item 28 ("Before criticizing somebody, I try to imagine how I would feel if I were in their place").

The spinglass algorithm identifies a mean of four communities of items corresponding to the four factors of the IRI as proposed originally and confirmed by Braun et al. (2015). Cluster A is composed of items 1, 16, 23, 26, 5, 12, 7, forming the *fantasy* component (FS). Cluster B is formed by items 25, 28, 21, 8, 11, 15, 3, all of which constitute the *perspective-taking* component (PT). Cluster C is formed by items 22, 20, 2, 14, 18, 4, 9 and reflects the *empathic concern* component (EC). Cluster D is formed by items 10, 17, 6, 24, 27, 13, 19 and represents the *personal distress* component (PD).

The walktrap algorithm identifies 5 communities of items. Most items belong to the same communities in the spinglass solution above, whereas items 6 ("In emergency situations, I feel apprehensive and ill-at-ease"), 10 ("I sometimes feel helpless when I am in the middle of a very emotional situation") and 17 ("Being in a tense emotional situation scares me") form a new community of items (community 5).

Furthermore, in some cases, two items from different communities (as identified by the spinglass algorithm) have a positive connection: for example, this is the case of item 1 ("I daydream and fantasize, with some regularity, about things that might happen to me") and item 10 ("I sometimes feel helpless when I am in the middle of a very emotional situation"), item 23 ("When I watch a good movie, I can very easily put myself in the place of a leading character") and item 22 ("I would describe myself as a pretty soft-hearted person"), item 8 ("I try to look at everybody's side of a disagreement before I make a decision") and item 9 ("When I see someone being taken advantage of, I feel kind of protective towards them").

Mean node predictability is 0.27, which means that on average, 27% of the variance of each node is explained by its neighbors: assuming that all edges go to the node under investigation from its neighbors, we can see how well the given node can be predicted by the other nodes surrounding it (Haslbeck and Fried, 2017).

3.2. Centrality analysis

In Fig. 2, we illustrate the strength centrality estimates for the 28 questionnaire items.

Item 14 ("Other people's misfortunes do not usually disturb me a great deal") has the highest standardized strength centrality in the network. Other central items include node 10 ("I sometimes feel helpless when I am in the middle of a very emotional situation "), and node 26 ("When I am reading an interesting story or novel, I imagine how I would feel if the events in the story were happening to me"). Items 1 ("I daydream and fantasize, with some regularity, about things that might happen to me") and 15 ("If I'm sure I'm right about something, I don't waste much time listening to other people's arguments") show the lowest strength centrality values.

3.3. Network accuracy and stability

The edge weight bootstrap revealed relatively small CIs, which indicates a more precise estimation. The edge weight difference test reveals that the empathy network is accurately estimated and that the strongest edges are significantly stronger than other edges.

The subset bootstrap shows that the order of item strength centrality is more stable than the other kinds of centrality values, which is consistent with numerous prior papers (e.g. Armour et al., 2017; Epskamp et al., 2017). CS-values obtained are 0.44 for node betweenness, 0.67 for node closeness and 0.75 for node strength. CS-values should preferably be above 0.5 and should not in any case be lower than 0.25: our results are above 0.5 and are therefore very stable. The centrality difference test shows that highest centrality estimates are statistically different from lowest centrality estimates, even though a statistical difference is not shown among nodes with the highest strength centrality estimates. Figures for all results are available in the supplementary materials.

4. Discussion

The network analysis we presented is, to our knowledge, the first one applied to empathy research. This study highlights connections

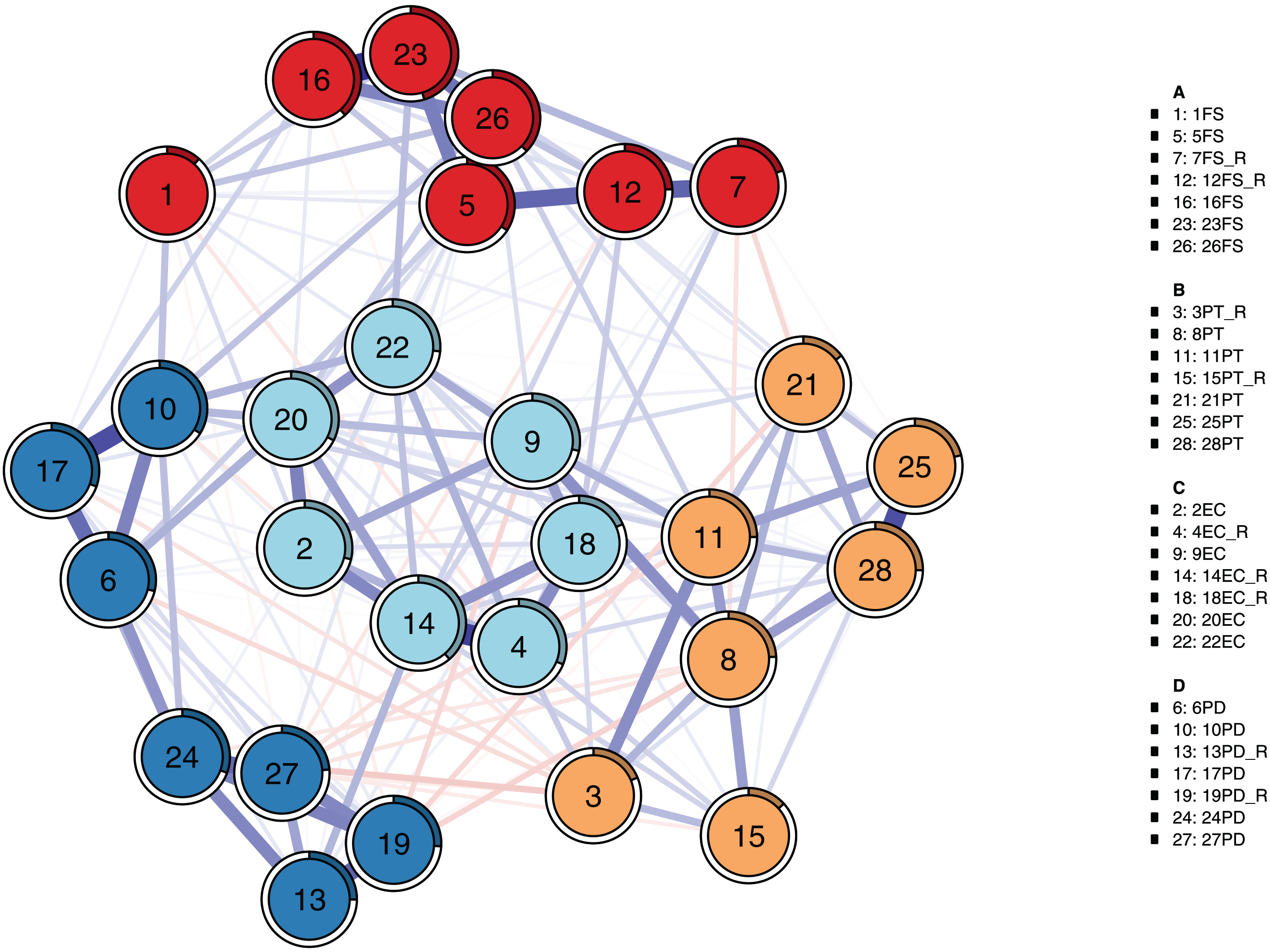

Fig. 1. Network composed of the 28-item IRI. Each item is represented by a node (1 to 28) and belongs to a different community of empathy, indicated by a code in the column on the right: Fantasy Scale (FS), Perspective Taking (PT), Empathic Concern (EC) and Personal Distress (PD). Reversed items are marked with an R (e.g. 7FS_R indicates a reversed item). Blue lines are positive connections, red lines are negative connections. The thickness of the line represents the connection strength. Colored areas in the rings surrounding the nodes represent the node predictability (percentage of variance of a given node explained by surrounding nodes).

between empathy components and provides new insights on how they might interact: some items are more interconnected than others, items differ in centrality, and interactions exist between items from different empathy components.

Positive connections are found throughout the network, confirming that, in our sample, most items from the IRI share some variance and are connected. However, some items present weak with others; this means that some nodes are conditionally independent of all other items in the network. The spinglass algorithm identifies on average four communities of items in the network, corresponding to the four a priori components of Davis' construct: *fantasy* (cluster A), *perspective taking* (cluster B), *empathic concern* (cluster C) and *personal distress* (cluster D).

The identification of these four node communities supports, using a different method, the results of Braun et al.'s confirmatory factor analysis study (Braun et al., 2015). This is not necessarily surprising, given that network and factor models are, under certain conditions, mathematically interchangeable (Kruis and Maris, 2016). Even though communities might be mathematically close to factors, from a network perspective they mean something entirely different: they are clusters of interrelated items that stem from mutual dynamics; they actively contribute to the construct of empathy itself.

However, the walktrap algorithm identified five communities, describing a fifth community formed by items 6, 10 and 17. This is a consequence of the strong connection and clustering of these three items, which nonetheless share two important connections with the rest of the *personal distress* cluster (6–24 and 10–24).

Some items belonging to a given community are connected to those from different communities, suggesting—from a network perspective—that empathy communities interact with each other in the network through specific items. For example, there is a connection between items 8 and 9, respectively belonging to the *perspective taking* and *empathic concern* subscales.

Items belonging to the *empathic concern* community (9, 14 and 20) have high centrality values; this finding supports Cliffordson's theory that puts *empathic concern* at the basis (in this case, at the center) of empathy. Items from the *empathic concern* cluster are connected to all the other communities in the network. Item 14 shows the highest centrality value: to interpret this finding, one must associate the statistical meanings of centrality and network connections (edges). First, strength centrality (the main subtype used) means that the sum of all edges of item 14 to all other nodes is the highest in the IRI network; second, a connection between item 14 and another item means for instance that a high-score answer to item 14 (which is reversed) lets us guess a high-score answer to all the items item 14 is connected to, controlling all other nodes. We can then interpret the high centrality of item 14 as the one that might influence and/or might be influenced by

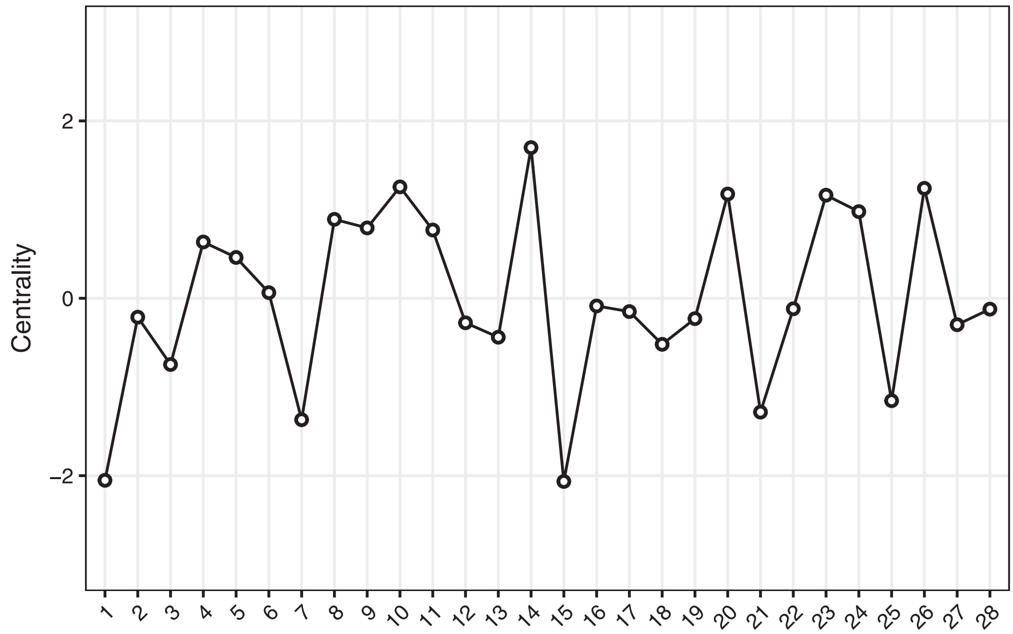

Fig. 2. Strength centrality estimates for the 28-item IRI. The *Y*-axis represents the centrality indices as standardized *z*-scores (the greater the estimate the more central the item is), and the *X*-axis represents the 28 IRI items.

Table 1
28-item interpersonal reactivity index.

Item	Item label	Domain color	Item meaning from interpersonal reactivity index by Davis (1980)
1	1FS	Green	I daydream and fantasize, with some regularity, about things that might happen to me.
2	2EC	Purple	I often have tender, concerned feelings for people less fortunate than me.
3	3PT_R	Yellow	I sometimes find it difficult to see things from the "other guy's" point of view. (Reversed)
4	4EC_R	Purple	Sometimes I don't feel very sorry for other people when they are having problems. (Reversed)
5	5FS	Green	I really get involved with the feelings of the characters in a novel.
6	6PD	Red	In emergency situations, I feel apprehensive and ill-at-ease.
7	7FS_R	Green	I am usually objective when I watch a movie or play, and I don't often get completely caught up in it. (Reversed)
8	8PT	Yellow	I try to look at everybody's side of a disagreement before I make a decision.
9	9EC	Purple	When I see someone being taken advantage of, I feel kind of protective towards them.
10	10PD	Red	I sometimes feel helpless when I am in the middle of a very emotional situation.
11	11PT	Yellow	I sometimes try to understand my friends better by imagining how things look from their perspective.
12	12FS_R	Green	Becoming extremely involved in a good book or movie is somewhat rare for me. (Reversed)
13	13PD_R	Red	When I see someone get hurt, I tend to remain calm. (Reversed)
14	14EC_R	Purple	Other people's misfortunes do not usually disturb me a great deal. (Reversed)
15	15PT_R	Yellow	If I'm sure I'm right about something, I don't waste much time listening to other people's arguments.(Reversed)
16	16FS	Green	After seeing a play or movie, I have felt as though I were one of the characters.
17	17PD	Red	Being in a tense emotional situation scares me.
18	18EC_R	Purple	When I see someone being treated unfairly, I sometimes don't feel very much pity for them. (Reversed)
19	19PD_R	Red	I am usually pretty effective in dealing with emergencies. (Reversed)
20	20FS	Green	I am often quite touched by things that I see happen.
21	21PT	Yellow	I believe that there are two sides to every question and try to look at them both.
22	22EC	Purple	I would describe myself as a pretty soft-hearted person.
23	23FS	Green	When I watch a good movie, I can very easily put myself in the place of a leading character.
24	24PD	Red	I tend to lose control during emergencies.
25	25PT	Yellow	When I'm upset at someone, I usually try to "put myself in his shoes" for a while.
26	26FS	Green	When I am reading an interesting story or novel, I imagine how I would feel if the events in the story were happening to me.
27	27PD	Red	When I see someone who badly needs help in an emergency, I go to pieces.
28	28PT	Yellow	Before criticizing somebody, I try to imagine how I would feel if I were in their place.

most answers of the IRI. However, when we look at the centrality difference test, we understand that the strength centrality of node 14 is not statistically different than strength centralities of nodes 10, 26, 20, 23 and 24, but is statistically different from that of all other nodes: this means that these nodes are roughly equivalent in their centrality. Node predictability, especially when focusing on the average, is somewhat more straightforward to interpret: on average, if we influence a group of nodes surrounding a given node, and assume that all edges go *towards this node*, we can influence 27% of its variance (Haslbeck and Waldorp, 2016).

Stability analysis shows that both centrality and edge weight estimates were reasonably stable.

Our results must be interpreted in the light of a number of limitations. First, our empathy network is estimated from a sample of young adults, which likely limits the generalizability of our results; further studies should investigate networks structures across different samples. Second, because we used cross-sectional data to carry out the analyses, we cannot determine the direction of edges. For instance, we cannot interpret whether the most central item activates other items, is activated by other items, or both. Third, similar to many other statistical models such as factor models, the network model used here estimates between-subjects effects on a group level. This means that network properties such as structure or centrality may not replicate in the same way in single individuals. Fourth, Marshall et al. (2013) provided evidence that the *order* in which items are presented in a questionnaire may influence their relationships. Again, this is a limitation for any statistical model based on the correlation matrix among items, such as factor models, and not a specific shortcoming over network models, but important enough to warrant mentioning. Fifth, network analysis, in which we interpret edges as putative causal connections, is based on the premise that nodes differ from each other meaningfully: if two nodes represent the same aspect of a construct, an edge is not a putative causal connection, but simply represents shared variance (Fried and Cramer, 2017). IRI might in some cases have this problem, for instance item 7 ("I am usually objective when I watch a movie or play, and I don't often get completely caught up in it") and item 12 ("Becoming extremely involved in a good book or movie is somewhat rare for me") seem to measure the same concept.

Future research may also endeavor to apply empathy networks in people with psychopathology.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.psychres.2018.03.082.

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