Psychiatry Research 272 (2019) 252–257

Contents lists available at ScienceDirect

Psychiatry Research

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

Network analysis of Contingencies of Self-Worth Scale in 680 university students

Giovanni Briganti[a,b,*], Eiko I. Fried[c], Paul Linkowski[a]

[a] Department of Clinical Epidemiology and Biostatistics, School of Public Health, Université libre de Bruxelles, Route de Lennik 808, 1070 Brussels, Belgium
[b] Department of Pathophysiology, École Supérieure de la Santé, Place du Chateau 3, 1014 Lausanne, Switzerland
[c] Department of Clinical Psychology, University of Leiden, Wassenaarseweg 52, 2333 AK Leiden, The Netherlands

ARTICLE INFO

Keywords:
Personality
Behavior

ABSTRACT

This study investigates the Contingencies of Self-Worth Scale (CSWS) in a sample of 680 university students from a network perspective. We estimated regularized partial correlations among seven CSWS domains: *family support, competition, appearance, God's love, academic competence, virtue* and *other's approval. Competition – academic competence* and *competition – appearance* represent the strongest connections in the network. Mean node predictability (shared variance with surrounding nodes) is 0.25. *Appearance and academic competence* were the most central (i.e., interconnected) domains in the network. Future studies should explore the network structure of self-worth in other healthy adult samples, and also in people with psychopathology. We provide the anonymized dataset as well as the full code in the supplementary materials to ensure complete reproducibility of the results.

1. Introduction

The human desire to feel worthy is an important constituent of human behavior (Pyszczynski et al., 2004). A troubled self-esteem has been shown to contribute to several psychiatric disorders such as eating disorders (Pearl et al., 2014), substance abuse (James, 2011), and schizophrenia (Xu et al., 2013).

The Contingencies of Self-Worth Scale (CSWS) is a psychometric tool proposed by Crocker et al. (2003) to assess seven domains of self-esteem: *(1) family support* measures the influence of perceived approval, support and love from family members on the feeling of self-worth (e.g., item 7 "Knowing that my family members love me makes me feel good about myself"); *(2) competition* evaluates how self-worth is influenced by feeling better than others (e.g., item 12 "Knowing that I am better than others on a task raises my self-esteem"); *(3) appearance* quantifies how physical traits influence the way people evaluate themselves (e.g., item 1 "When I think I look attractive, I feel good about myself"); *(4) God's love* measures the association between religiosity and self-esteem (e.g., item 2 "My self-worth is based on God's love"); *(5) academic competence* evaluates the impact of grades on self-esteem (e.g., item 20 "Doing well in school gives me a sense of self-respect"); *(6) virtue* measures the connection between self-worth and the adherence to a moral code (e.g., item 5 "Doing something I know is wrong makes me lose my self-respect"); *(7) other's approval* measures the influence of perceived approval from others on self-esteem (e.g., item 9 "I can't respect myself if others don't respect me"). This model of self-esteem has already undergone structural validation (Crocker et al., 2003) which makes it an interesting tool for exploring the construct of self-esteem (Geng and Jiang, 2013).

A common understanding of self-esteem is that the seven domains are all observable indicators of self-esteem, that is, the domains of the questionnaire do not actively contribute to the construct – they are effects of the construct. In the last decade, a new way of conceptualizing psychological constructs has been proposed: network theory, which hypothesizes psychological constructs as interacting systems. Network models are related statistical models that can be used to try to uncover such structures in data: a network is formed by pairwise interactions of its components (Borsboom and Cramer, 2013) usually calculated as regularized partial correlations (Epskamp and Fried, 2018). Components of a network mutually influence each other to actively participate in the emergence of a construct. Mental disorders such as depression (Beard et al., 2016; Boschloo et al., 2016; Fried et al., 2017; Mullarkey et al., 2018), schizophrenia (Galderisi et al., 2018), post-traumatic stress disorder (Fried et al., 2018), autism, and obsessive-compulsive disorder (Ruzzano et al., 2015) have been conceptualized and analyzed statistically from a network perspective. Network structures of psychological constructs such as empathy (Briganti et al., 2018), personality (Costantini et al., 2015), health-related quality of life

* Corresponding author at: Department of Clinical Epidemiology and Biostatistics, School of Public Health, Université libre de Bruxelles, Route de Lennik 808, 1070 Brussels, Belgium.
E-mail address: giovanni.briganti@hotmail.com (G. Briganti).

https://doi.org/10.1016/j.psychres.2018.12.080
Received 30 August 2018; Received in revised form 16 December 2018; Accepted 16 December 2018
Available online 19 December 2018

(Kossakowski et al., 2016), intelligence (Van Der Maas et al., 2006), and attitudes (Dalege et al., 2017) have also been studied.

Researchers usually analyze constructs as network composed of *items* – answers of the observed group to a given questionnaire such as the Interpersonal Reactivity Index (Briganti et al., 2018). However, scales in psychology are usually constructed to assess one underlying dimension; this means that they often feature several highly similar items that might measure the same thing, which has been discussed as a challenge for network models (Fonseca-Pedrero et al., 2018). In that case, the meaning of the connection between items changes: an association between X and Y simply reflects the shared variance of the two items, and not a genuine mutual relation (Fried and Cramer, 2017). This limitation also holds for the Contingencies of Self-Worth Scale where a common cause is plausible: items in a given domain might measure the same construct, and can therefore also be explored with factor models.

Our work thus aims to apply network modeling to the construct of contingent self-worth as described by Crocker et al. (2003) while addressing the challenge of items measuring the same variable, using both structural equation models and network models. The primary goal is to explore connections between domains of the CSWS; it is plausible to conceptualize the construct of self-worth as a network and consider that its various domains interact and influence each other instead of being separate consequences with the same origin. Second, we want to estimate the expected influence (EI) of domains in the network, which can be thought of as the importance of a domain in the network. EI is calculated as the sum of all connections of a domain (Robinaugh et al., 2016). Finally, we want to estimate domain predictability (Haslbeck and Fried, 2017), which reflects the percentage of shared variance of a domain with surrounding domains in the network. Although we expected EI and predictability to be related (i.e., domains high on either are likely high on the other), EI provides a measure of the *relative* importance of a construct, whereas predictability provides insights into *absolute* value (Haslbeck and Fried, 2017).

2. Methods

2.1. Participants

This study is based on a dataset composed of 680 French-speaking university students: 59% of them were women and 41% men. The subjects were 17–25 years old (M = 19 years, SD = 1.5 years).

2.2. Measurement

The CSWS is composed of 35 items (Table 1) meant to assess self-worth contingency in the following seven domains: *family support, competition, appearance, God's love, academic competence, virtue and other's approval*. The items are shuffled in the questionnaire. Item score ranges from 1 (strongly disagree) to 7 (strongly agree); some reverse-scored items are included (items 4, 6, 10, 13, 15, 23 and 30).

The dataset was anonymized, and its analysis was approved by the Ethical Committee of the Erasme university hospital. The anonymized dataset used for the final analysis is included in the supplementary materials, as well as the full R-code, to ensure complete reproducibility of the results.

Table 1
35-item Contingencies of Self-Worth Scale.

Item	Domain color	Item meaning from Contingencies of Self-Worth Scale by Crocker	Domain
1	Dark yellow	When I think I look attractive, I feel good about myself.	Appearance
2	Light yellow	My self-worth is based on God's love.	God's love
3	Orange	I feel worthwhile when I perform better than others on a task or skill.	Competition
4	Dark yellow	My self-esteem is unrelated to how I feel about the way my body looks. (Reversed)	Appearance
5	Blue	Doing something I know is wrong makes me lose my self-respect.	Virtue
6	Dark blue	I don't care if other people have a negative opinion about me. (Reversed)	Other's approval
7	Red	Knowing that my family members love me makes me feel good about myself.	Family support
8	Light yellow	I feel worthwhile when I have God's love.	God's love
9	Dark blue	I can't respect myself if others don't respect me.	Other's approval
10	Red	My self-worth is not influenced by the quality of my relationships with my family members. (Reversed)	Family support
11	Blue	Whenever I follow my moral principles, my sense of self-respect gets a boost.	Virtue
12	Orange	Knowing that I am better than others on a task raises my self-esteem.	Competition
13	Light blue	My opinion about myself isn't tied to how well I do in school. (Reversed)	Academic competence
14	Blue	I couldn't respect myself if I didn't live up to a moral code.	Virtue
15	Dark blue	I don't care what other people think of me. (Reversed)	Other's approval
16	Red	When my family members are proud of me, my sense of self-worth increases.	Family support
17	Dark yellow	My self-esteem is influenced by how attractive I think my face or facial features are.	Appearance
18	Light yellow	My self-esteem would suffer if I didn't have God's love.	God's love
19	Light blue	Doing well in school gives me a sense of self- respect.	Academic competence
20	Orange	Doing better than others gives me a sense of self- respect.	Competition
21	Dark yellow	My sense of self-worth suffers whenever I think I don't look good.	Appearance
22	Light blue	I feel better about myself when I know I'm doing well academically.	Academic competence
23	Dark blue	What others think of me has no effect on what I think about myself. (Reversed)	Other's approval
24	Red	When I don't feel loved by my family, my self- esteem goes down.	Family support
25	Orange	My self-worth is affected by how well I do when I am competing with others.	Competition
26	Light yellow	My self-esteem goes up when I feel that God loves me.	God's love
27	Light blue	My self-esteem is influenced by my academic performance.	Academic competence
28	Blue	My self-esteem would suffer if I did something unethical.	Virtue
29	Red	It is important to my self-respect that I have a family that cares about me.	Family support
30	Dark yellow	My self-esteem does not depend on whether or not I feel attractive. (Reversed)	Appearance
31	Light yellow	When I think that I'm disobeying God, I feel bad about myself.	God's love
32	Orange	My self-worth is influenced by how well I do on competitive tasks.	Competition
33	Light blue	I feel bad about myself whenever my academic performance is lacking.	Academic competence
34	Blue	My self-esteem depends on whether or not I follow my moral/ethical principles.	Virtue
35	Dark blue	My self-esteem depends on the opinions others hold of me.	Other's approval

2.3. Network analysis

Data were analyzed with R software (version 3.4.3, open source, available at https://www.r-project.org/). Packages used to carry out the analysis include qgraph, (Epskamp et al., 2012) and glasso (Friedman et al., 2014) for network estimation and visualization, mgm for node predictability (Haslbeck and Waldorp, 2016), igraph (Csardi and Nepusz, 2006) and bootnet (Epskamp et al., 2017a) for stability. Further information about all packages used (e.g., specific version numbers) is included in the supplementary materials (Briganti, 2018).

2.3.1. Sum score vs. factor analysis

Items from CSWS subdomains tend to measure the same construct, which is a situation which a network of all individual items can be problematic because different nodes measure the same underlying psychological construct (Fried and Cramer, 2017). Therefore, we chose to estimate a network of 7 *domains* instead of a network of 35 *items*. The preferred way for doing so is using generalized network psychometrics framework (Epskamp et al., 2017b) via the R-package lvnet. Unfortunately, the method does not currently scale well, and was not applicable to the current datasets due to the large number of items.

Instead, we studied the network structure of self-worth domains with nodes reflecting sum scores of the 7 CSWS domains, and used these factor scores as variables in the Gaussian Graphical Model (GGM), a regularized partial correlation network as described by Epskamp and Fried (2018). As an additional sensitivity analysis, we also estimated a factor model using confirmatory factor analysis for each of the 7 CSWS domains, and then used these factor scores in a GGM. We expected somewhat stronger relations, because factor scores are disattenuated for measurement unreliability and therefore likely increase the relations among variables (Spearman, 1904). Results are reported in the supplementary materials.

2.3.2. Network estimation

A network structure is composed of nodes and edges: nodes represent, in this case, domains from the CSWS, and edges are connections between two domains. A regularized partial correlation network was estimated on the correlation matrix of the 7 domains; as described above, sumscores for each participant were used. Edge weight parameters that resulted from the GGM were regularized by using the graphical lasso (least absolute shrinkage and selection operator): this procedure avoids the estimation of spurious edges (Tibshirani, 1996). The estimation procedure selected the network (out of 100 networks) with the lowest lambda value (lambda being the tuning parameter for this procedure); in these situations, it is recommended to lower the tuning parameter to 0.001, and we followed this recommendation. For the GGM, an edge represents the regularized partial correlation (or conditional dependence relation) between two domains, controlling for all other domains. If two nodes are connected, this means they are conditionally dependent, given all other nodes in the network. When visualizing the model output as graph, blue edges indicate positive relations, and red edges negative relations. The corresponding thickness of an edge represents its weight (i.e., the strength of association between nodes, ranging from -1 to 1). The Fruchterman–Reingold algorithm (Fruchterman and Reingold, 1991) was used to place nodes in a network.

2.3.3. Network stability

Stability tests are necessary to safely interpret network inference results from a network analysis. To answer the question "is edge *X* significantly stronger than edge *Y*?", 95% confidence intervals of the edge weights were estimated through bootstrapping (Epskamp et al., 2017a; 2000 bootstraps were used), and the edge weight difference test was performed. Note that the edge weight difference tests do presently not account for multiple testing and should be interpreted conservatively. To answer the question "is the EI of node *X* stronger than the EI of node *Y*", we performed the centrality difference test.

2.3.4. Network inference

To investigate the network structure of self-worth, we computed two different local inference measures: node predictability and EI.

Expected influence is the sum of a node's connections and represents the relative importance of a node in a network (Robinaugh et al., 2016) – relative because even in weakly connected networks (with overall low edge weights), there will always be a node with a high expected influence in case of standardized results.

Node predictability is an absolute measure of the interconnectedness of a given node in the network and represents its shared variance with surrounding nodes (Fried et al., 2018). Node predictability can be interpreted as the upper bound of controllability: if one assumes that all edges for node *X* are directed towards that node, predictability provides an estimate of how much influence we can have on *X* via all other nodes.

3. Results

3.1. Descriptive statistics

Plots illustrating mean and standard deviation values for the seven domains in the network are reported in the supplementary materials. Means range from 12.4 (*God's love)* to 26.6 (*academic competence*). Standard deviations range from 5.2 (*appearance*) to 9 (*God's love*). *God's love* has the lowest mean as well as the highest standard deviation in the network.

3.2. Network of self-worth

Fig. 1 illustrates the estimated the seven-domain network of self-worth. The network is composed of domains that connect with each other. Each domain is represented with a different color. *Competition* and *academic competence* share the strongest connection in the network; *other's approval* also shares a strong edge with *appearance. Competition* and *appearance* as well as *academic competence* and *family support* are also positively connected. *Family support* is positively connected with most domains. *God's love* is only connected to *virtue. Appearance* and *virtue* share a negative connection.

The factor score network (reported in the supplementary materials) resulted in considerably stronger associations, which can be expected due to disattenuation. The adjacency matrices were correlated 0.95 between both methods (sum score and factor score).

3.3. Network stability

Edge weight bootstrap reports relatively small CIs, as is expected from a network with several hundred participants and only 7 nodes; this means that edge weight estimation is precise. The edge weight difference test reveals that stronger edges in the network are significantly stronger than the other edges. In other words, stronger edges in Fig. 1 can be interpreted as being considerably stronger than weaker edges. For instance, the edges between *competition* and *academic competence* and *competition* and *appearance* represent the statistically strongest edge coefficients in the network, significantly stronger than all other edges but not statistically different from one another. EI difference tests show that EI estimates in nodes with high EI are statistically different from EI estimates in nodes with low EI. Description and figures of the stability analysis are available in the supplementary materials.

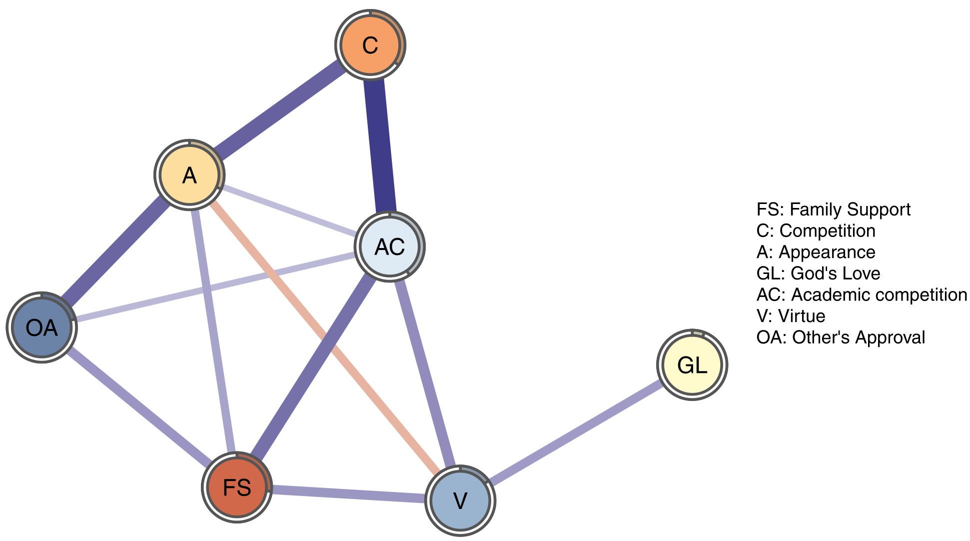

Fig. 1. 7-domain CSWS network. Each node represents a domain: FS is – *Family support*‖, C is – *Competition*‖, A is – *Appearance*‖, GL is – *God's love*‖, AC is – *Academic competence*‖, V is – *Virtue*‖ and OA is – *Other's approval*‖. Blue edges represent positive connections and red edges represent negative connections; the thicker the connection the stronger it is. The pie chart surrounding the node represents node predictability (percentage of shared variance with all connected nodes).

3.4. Network inference

3.4.1. Expected influence

Fig. 2 illustrates the EI estimates for the self-worth network.

Academic competence and *family support* domains have the highest EI values. This means from a statistical point of view that these are the most connected domains in the network. On the other hand, *God's love* has the lowest EI value. This means that it is the domain that least influences the rest of domains in the network.

Correlation between EI and predictability is 0.96.

3.4.2. Node predictability

Mean node predictability ranges from 0.06 to 0.40, with an average of 0.25. This means that on average, 25% of the variance of the node in the network can be explained by its neighbors. *God's love* is the domain with the lowest node predictability: it shares 6% of variance with its surrounding nodes. *Academic competence* has the highest node predictability: it shares 40% of its variance with its surrounding nodes. Competition has the second highest node predictability (0.35).

4. Discussion

To our knowledge, we have conducted the first network analysis of the psychological construct self-worth contingencies. Overall, the seven domains of self-worth form a heterogeneous system in which domains are not uniformly positively connected with each other. This is interesting, because a homogeneous network with uniformly positive connections would be expected if all domains are passive and interchangeable measures of one latent variable: self-worth. Below, we discuss the findings in more detail.

Academic competence and *competition* share the strongest connection in the network: it is reasonable to consider that the impact on self-esteem of competing with others and obtaining good grades are connected while following a university curriculum. The same kind of connection is found between *appearance* and *other's approval*; this means that, while considering self-worth, if physical appearance is important to an individual, so is the approval of others, and vice versa. *Competition* also shares a strong connection with *appearance*, which means that physical appearance might be important for individuals competing with others (and vice-versa). *Family support* and *other's approval* share

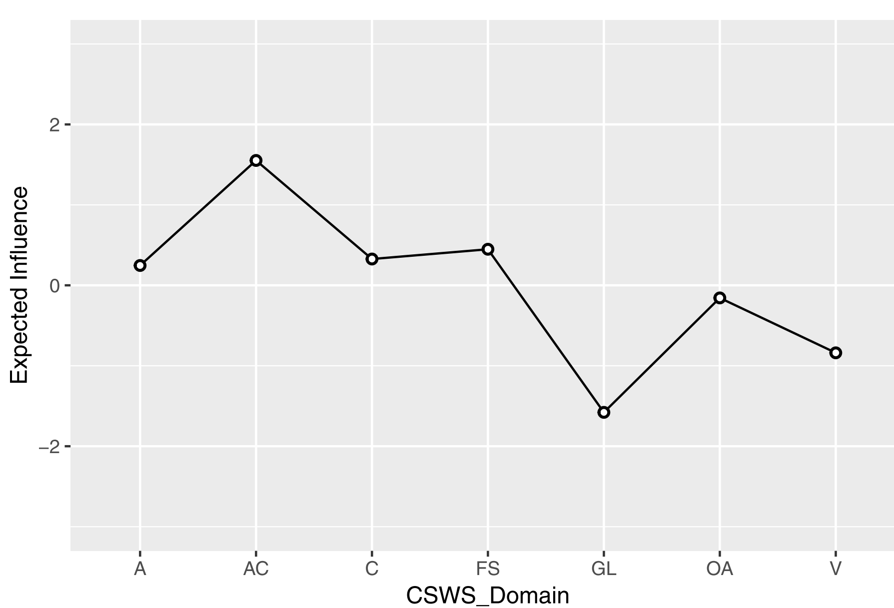

Fig. 2. Expected influence centrality estimates for the 7-domain CSWS network. *X*-axis represents the 7 domains: *family support* (FS), *competition* (C), *appearance* (A), *God's love* (GL), *academic competence* (AC), *virtue* (V) and *other's approval* (OA). *Y*-axis represents standardized *z*-scores.

connections with most domains in the network. *Appearance* showed a negative connection to *virtue*: that means that people that base their self-worth upon acting and living by a moral code might not draw self-worth from physical appearance (and vice-versa), controlling for all other associations in the network. While there is no prior work on partial correlations, previous work on zero-order correlations found a positive association between the two domains (Crocker et al., 2003).

Negative edges have not been observed commonly in the psychopathology network literature, which calls for an explanation. In this case, the negative association between appearance and virtue might be plausible from a theoretical perspective. Since both subscales are positively associated with academic competence and family support, the finding implies that in individuals whose self-worth is simultaneously contingent on academic competence and family support, knowing that self-esteem is more contingent on virtue allows predicting that their self-esteem is less likely to be also contingent on physical appearance (and vice versa). Two other possibilities also come to mind. First, negative connections in Gaussian Graphical Models can arise when dealing with small samples and/or when estimating polychoric correlations (Epskamp and Fried, 2018), which we can rule out as explanation here. Second, collider structures in conditional dependence networks can induce spurious negative relations between two nodes in case they both cause a third node (Greenland et al., 1999).

God's love is a relatively disconnected node: it shares only one positive connections with *virtue*: this is not surprising, since in the original work (Crocker et al., 2003) *God's love* showed its strongest correlation with *virtue*. From a network perspective, this means that *God's love* is largely conditionally independent from other domains in the network. From a network perspective, one plausible interpretation of the conditional independence of *God's Love* in the self-esteem network is that people may derive a sense of self-worth from their religious belief (in this case, feeling that they have the love of God) regardless of the other contingencies; this may highlight religious belief as an independent source of self-esteem in people. Another possible interpretation of this finding is statistical, i.e., a floor effect or a ceiling effect: because of a low or high parameter, the domain might share few connections with other domains. This may be applicable to our findings, since *God's love* has the highest standard deviation among all domains in the network, as well as the lowest mean.

We identified strong differences in predictability, ranging from 6% *(God's love)* to 40% (*academic competence*). Average node predictability is 0.25, which means that on average, 25% of the variance of the nodes is explained by other nodes in the network. From a network perspective, we can infer that some domains such *as academic competence* are well explained by its surrounding domains. *Academic competence* and *God's* love are respectively the most and least predictable nodes in the network.

The analysis of EI shows that *academic competence*, and *family support* have the highest values in the network: this means that these two domains share the strongest connections in the network and therefore may influence or be influenced by other domains of contingent self-worth the most. Node predictability is therefore simpler to interpret than EI and gives us a clear information about how a node is influenced by surrounding nodes, assuming all edges are directed towards this node.

This study should be interpreted in the light of some limitations. First, our network is estimated from a sample of university students. While the CSWS was originally developed based on a similar sample (Crocker et al., 2003), it is worth noting that results of our study may not generalize to other samples. Second, the current cross-sectional dataset does not allow for causal or even granger-causal inference. For instance, we cannot interpret whether a given domain causes or is caused by domains sharing a connection with it. This requires temporal follow-up studies, which would be most interesting across important developmental periods such as adolescents and early adulthood. Third, the network model we estimated is a between-subjects models. This also means that inferences from the study should only be drawn for a group of people, and it is unclear if and how well the present between-subjects network structure describes individuals' networks of self-worth contingency.

Future research may endeavor to apply self-worth contingency networks in other kinds of samples, both healthy and with different kinds of psychopathology, as to analyze possible differences in network structure, node predictability and centrality.

Acknowledgments

The present study was supported by the Belgian National Fund for Scientific Research (grants 1.5.123.04, 1.5.175.06 and 3.4.553.01.F). Eiko I. Fried was in part supported by the European Research Council Consolidator Grant no. 647209.

The authors would like to thank Chantal Kempenaers, M.S., and Jennifer Crocker, Ph.D, for their help in the early conception of the manuscript.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.psychres.2018.12.080.

References

Beard, C., Millner, A.J., Forgeard, M.J.C., Fried, E.I., Hsu, K.J., Treadway, M.T., et al., 2016. Network analysis of depression and anxiety symptom relationships in a psychiatric sample. Psychol. Med. 46, 3359–3369. https://doi.org/10.1017/S0033291716002300.

Borsboom, D., Cramer, A.O.J., 2013. Network analysis: an integrative approach to the structure of psychopathology. Annu. Rev. Clin. Psychol. 9, 91–121. https://doi.org/10.1146/annurev-clinpsy-050212-185608.

Boschloo, L., Borkulo, C.D.van, Borsboom, D., Schoevers, R.A., 2016. A prospective study on how symptoms in a network predict the onset of depression. PPS 85, 183–184. https://doi.org/10.1159/000442001.

Briganti, G., 2018. Data for: "Network Analysis of Contingencies of Self-Worth Scale in 680 University Students". Mendeley Data, v2. doi:10.17632/rtyrnscyrh.3.

Briganti, G., Kempenaers, C., Braun, S., Fried, E.I., Linkowski, P., 2018. Network analysis of empathy items from the interpersonal reactivity index in 1973 young adults. Psychiatry Res. 265, 87–92. https://doi.org/10.1016/j.psychres.2018.03.082.

Costantini, G., Richetin, J., Borsboom, D., Fried, E.I., Rhemtulla, M., Perugini, M., 2015. Development of indirect measures of conscientiousness: combining a facets approach and network analysis. Eur. J. Personal. 29, 548–567. https://doi.org/10.1002/per.2014.

Crocker, J., Luhtanen, R.K., Cooper, M.L., Bouvrette, A., 2003. Contingencies of self-worth in college students: theory and measurement. J. Personal. Soc. Psychol. 85, 894–908. https://doi.org/10.1037/0022-3514.85.5.894.

Csardi, G., Nepusz, T., 2006. The igraph software package for complex network research. Inter J. Complex Syst 1695. https://cran.r-project.org/web/packages/igraph/citation.html.

Dalege, J., Borsboom, D., van Harreveld, F., van der Maas, H.L.J., 2017. Network analysis on attitudes. Soc. Psychol. Personal. Sci. 8, 528–537. https://doi.org/10.1177/1948550617709827.

Epskamp, S., Borsboom, D., Fried, E.I., 2017. Estimating psychological networks and their accuracy: a tutorial paper. Behav. Res. 1–18. 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 visualizations of relationships in psychometric data. J. Stat. Softw. 48. https://doi.org/10.18637/jss.v048.i04.

Epskamp, S., Fried, E.I., 2018. A tutorial on regularized partial correlation networks. Psychol. Methods. https://doi.org/10.1037/met0000167.

Epskamp, S., Rhemtulla, M., Borsboom, D., 2017. Generalized network psychometrics: combining network and latent variable models. Psychometrika 82, 904–927. https://doi.org/10.1007/s11336-017-9557-x.

Fonseca-Pedrero, E., Ortuño, J., Debbané, M., Chan, R.C.K., Cicero, D., Zhang, L.C., et al., 2018. The network structure of schizotypal personality traits. Schizophr. Bull. 44 (Suppl2), S468–S479. https://doi.org/10.1093/schbul/sby044.

Fried, E.I., Borkulo, C.D.van, Cramer, A.O.J., Boschloo, L., Schoevers, R.A., Borsboom, D., 2017. Mental disorders as networks of problems: a review of recent insights. Soc. Psychiatry Psychiatr. Epidemiol. 52, 1–10. https://doi.org/10.1007/s00127-016-1319-z.

Fried, E.I., Cramer, A.O.J., 2017. Moving forward: challenges and directions for psychopathological network theory and methodology. Perspect. Psychol. Sci. 12, 999–1020. https://doi.org/10.1177/1745691617705892.

Fried, E.I., Eidhof, M.B., Palic, S., Costantini, G., Huisman-van Dijk, H.M., Bockting, C.L.H., et al., 2018. Replicability and generalizability of posttraumatic stress disorder (PTSD) networks: a cross-cultural multisite study of PTSD symptoms in four trauma

patient samples. Clin. Psychol. Sci. https://doi.org/10.1177/2167702617745092.
Friedman, J.H., Hastie, T., Tibshirani, R., 2014. Glasso: graphical lasso-estimation of Gaussian graphical models. R package version 1.8. Retrieved from. https://CRAN.Rproject.org/package=glasso.
Fruchterman, T.M.J., Reingold, E.M., 1991. Graph drawing by force-directed placement. Softw: Pract. Exper. 21, 1129–1164. https://doi.org/10.1002/spe.4380211102.
Galderisi, S., Rucci, P., Kirkpatrick, B., Mucci, A., Gibertoni, D., Rocca, P., et al., 2018. Interplay among psychopathologic variables, personal resources, context-related factors, and real-life functioning in individuals with schizophrenia: a network analysis. JAMA Psychiatry 75, 396–404. https://doi.org/10.1001/jamapsychiatry.2017.4607.
Geng, L., Jiang, T., 2013. Contingencies of self-worth moderate the effect of specific self-esteem on self-liking or self-competence. Soc. Behav. Personal. 41, 95–107. https://doi.org/10.2224/sbp.2013.41.1.95.
Greenland, S., Pearl, J., Robins, J.M., 1999. Causal diagrams for epidemiologic research. Epidemiology 10, 37.
Haslbeck, J.M.B., Fried, E.I., 2017. How predictable are symptoms in psychopathological networks? A reanalysis of 18 published datasets. Psychol. Med. 47, 2767–2776. https://doi.org/10.1017/S0033291717001258.
Haslbeck, J.M.B., Waldorp, L.J., 2016. MGM: Structure Estimation for Time-Varying Mixed Graphical Models in High-Dimensional Data. arXiv preprint:1510.06871v2.
James, R., 2011. Correlates of sexual self-esteem in a sample of substance-abusing women. J. Psychoact. Drugs 43, 220–228. https://doi.org/10.1080/02791072.2011.605700.
Kossakowski, J.J., Epskamp, S., Kieffer, J.M., Borkulo, C.D.van, Rhemtulla, M., Borsboom, D., 2016. The application of a network approach to health-related quality of life (HRQoL): introducing a new method for assessing HRQoL in healthy adults and cancer patients. Qual. Life Res. 25, 781–792. https://doi.org/10.1007/s11136-015-1127-z.
Mullarkey, M.C., Marchetti, I., Beevers, C.G., 2018. Using network analysis to identify central symptoms of adolescent depression. J. Clin. Child Adolesc. Psychol. 0, 1–13. https://doi.org/10.1080/15374416.2018.1437735.
Pearl, R.L., White, M.A., Grilo, C.M., 2014. Overvaluation of shape and weight as a mediator between self-esteem and weight bias internalization among patients with binge eating disorder. Eat. Behav. 15, 259–261. https://doi.org/10.1016/j.eatbeh.2014.03.005.
Pyszczynski, T., Greenberg, J., Solomon, S., Arndt, J., Schimel, J., 2004. Why do people need self-esteem? A theoretical and empirical review. Psychol. Bull. 130, 435–468. https://doi.org/10.1037/0033-2909.130.3.435.
Robinaugh, D.J., Millner, A.J., McNally, R.J., 2016. Identifying highly influential nodes in the complicated grief network. J. Abnorm. Psychol. 125, 747–757. https://doi.org/10.1037/abn0000181.
Ruzzano, L., Borsboom, D., Geurts, H.M., 2015. Repetitive behaviors in autism and obsessive-compulsive disorder: new perspectives from a network analysis. J. Autism Dev. Disord. 45, 192–202. https://doi.org/10.1007/s10803-014-2204-9.
Spearman, C., 1904. The proof and measurement of association between two things. Am. J. Psychol. 15 (1), 72–101.
Tibshirani, R., 1996. Regression shrinkage and selection via the lasso. J. R. Stat. Soc. Ser. B (Methodological) 58, 267–288.
van der Maas, H.L.J., Dolan, C.V., Grasman, R.P.P.P., Wicherts, J.M., Huizenga, H.M., Raijmakers, M.E.J., 2006. A dynamical model of general intelligence: the positive manifold of intelligence by mutualism. Psychol. Rev. 113, 842–861. https://doi.org/10.1037/0033-295X.113.4.842.
Xu, Z.-Y., Zu, S., Xiang, Y.-T., Wang, N., Guo, Z.-H., Kilbourne, A.M., et al., 2013. Associations of self-esteem, dysfunctional beliefs and coping style with depression in patients with schizophrenia: a preliminary survey. Psychiatry Res. 209, 340–345. https://doi.org/10.1016/j.psychres.2013.02.012.