Research paper

Mapping network connectivity among symptoms of social anxiety and comorbid depression in people with social anxiety disorder

Alexandre Heeren[a,b,c,d,*], Payton J. Jones[a], Richard J. McNally[a]

[a] Department of Psychology, Harvard University, Cambridge, MA, USA
[b] Psychological Science Research Institute, Université Catholique de Louvain, Louvain-la-Neuve, Belgium
[c] Clinical Neuroscience Division, Institute of Neuroscience, Université Catholique de Louvain, Louvain-la-Neuve, Belgium
[d] National Foundation for Scientific Research, Brussels, Belgium

ARTICLE INFO

ABSTRACT

Background: Social anxiety disorder (SAD) and depressive symptoms often covary. Yet, uncertainty still abounds vis-à-vis the individual symptom-to-symptom associations between these two disorders. Inspired by the network approach to psychopathology that conceptualizes comorbidity as a natural consequence arising from bridge symptoms that can transmit activation from one disorder to the other, we applied network analytic methods to characterize the associations among core symptoms of SAD—i.e. fear and avoidance of social situations—and comorbid depressive symptoms among 174 individuals with DSM-IV-TR criteria for SAD.
Methods: We first explored the general structure of these symptoms by estimating a regularized partial correlation network using the graphical LASSO algorithm. Then, we specifically focused on the symptoms' importance and influence. Of critical interest was the estimation of the unique influence of each symptom from one disorder to all symptoms of the other disorder using a new metric called bridge expected influence.
Results: The graphical LASSO revealed several cross-associations between SAD and comorbid depression. For each disorder, symptoms exhibiting the strongest cross-association with the other disorder were identified.
Limitations: Given our cross-sectional data, our findings can only suggest hypotheses about cause-effect relationships.
Conclusions: This study adds to a small but growing empirical literature revealing that the co-occurrence between two disorders is best portrayed as sets of symptom-to-symptom connections. As some individual symptoms show differential association in the co-occurrence between SAD and depression, those symptoms may be valuable targets for future research and treatment.

Social anxiety disorder (SAD) and depressive symptoms often covary; the lifetime comorbidity rates of major depression in patients with SAD range between 44% and 74.5% (Brown et al., 2001; Perugi et al., 2001; Schneier et al., 1992; Van Ameringen et al., 1991). Moreover, SAD often emerges before depressive symptoms. Indeed, SAD diagnosis predated any episode of mood disorders in 81.7% of patients with SAD (Van Ameringen et al., 1991). Likewise, in the general population, individuals with SAD had the highest likelihood of developing a major depression in the two years following the onset of SAD (Regier et al., 1998), especially in adolescents and young adults (Bittner et al., 2004; Stein et al., 2001). Moreover, longitudinal studies show that individuals with SAD are about three times more likely than those without SAD to develop depression (Beesdo et al., 2007; Stein et al., 2001).

The presence of comorbid depressive symptoms in people with SAD

has clinical implications. First, comorbid depressive symptoms predict SAD persistence (Alpert et al., 1997; Stein et al., 2001) and recurrence (Bruce et al., 2005; Scholten et al., 2013). Second, depressive symptoms were associated with severity and generalization of the social fears and alcohol abuse among patients with SAD (Perugi et al., 2001). Third, patients with SAD and comorbid depressive symptoms are at elevated risk for attempting suicide (Cox et al., 1994; Sareen et al., 2005). Fourth, SAD patients with comorbid depressive symptoms are less likely to benefit from treatment for SAD in the short term (Ledley et al., 2005) or to maintain their gains over time (Marom et al., 2009). Especially, certain symptoms of depression such as insomnia and fatigue may interfere with CBT for SAD (e.g., Kushnir et al., 2014).

Although the presence of depressive symptoms in SAD is well documented, uncertainty remains regarding how core symptoms of SAD—i.e. fear and avoidance of social situations—are associated with

---

* Correspondence to: Department of Psychology, Harvard University, 1232 William James Hall 33 Kirkland Street, Cambridge, MA 02138, USA.
E-mail addresses: alexandre.heeren@uclouvain.be, alexandreheeren@fas.harvard.edu (A. Heeren).

depressive symptoms, and *vice versa*. Of clinical importance, distinct types of social fear may vary in terms of their debilitating nature. Theorists of SAD have argued that social fears involving interactions with strangers (e.g., Carron et al., 1999; Kagan, 2014; Kashdan and Wenzel, 2005) or authority figures (e.g., Gilbert, 2000; Swallow and Kuiper, 1988) may predict an especially inauspicious course, including risk for comorbid disorders. As a result, one cannot rule out the possibility that fear and avoidance vis-à-vis a given social situation may relate to different symptoms of depression. For instance, fear of talking to unfamiliar people may promote avoidance of going to a party, which, in turn, may influence depressive symptoms such as pessimism and self-dislike, worsening, in turn, the fear of talking to unfamiliar people.

In recent years, the theoretical (Borsboom, 2017; Borsboom and Cramer, 2013) and computational (e.g., Epskamp et al., 2012) advances in network analysis have opened up new vistas for understanding mental disorders as systems of interacting symptoms (Borsboom, 2017; Fried et al., 2016; McNally, 2016). Psychopathology networks comprise nodes (symptoms) and the edges (associations) connecting them. The network approach conceptualizes an episode of disorder as emerging from the pairwise interactions among symptoms. According to this perspective, symptoms possess independent causal powers that influence other symptoms (e.g., fear motivates avoidance; insomnia causes fatigue); they are not merely passive indicators of an underlying disease. Hence, symptoms are constitutive, not reflective, of disorder (Borsboom and Cramer, 2013).

Of critical importance, the network approach enables one to identify nodes that are central to the network based on the amount and direction of influence that flows from one node to other ones (Borgatti, 2005; Valente, 2012). Therefore, activation issuing from a node having strong connections to many other nodes can spread to other nodes, thereby producing a cascade of activation in the entire network (Borsboom and Cramer, 2013; Valente, 2012). Such highly influential nodes are thus especially important for the development, persistence, and remission of mental disorders (Borsboom and Cramer, 2013). By turning off such a node, one can affect other nodes both directly and indirectly (e.g., via paths through other nodes), thereby producing recovery from disorder (Hofmann et al., 2016; McNally, 2016; Valente, 2012).

If one accepts that symptoms and associations between them are what constitute a mental disorder, then the associations between symptoms of different disorders constitute pathways that can bridge those disorders (Borsboom and Cramer, 2013; Cramer et al., 2010). Traditionally, comorbid mental disorders have been understood as different underlying entities. Conversely, the network approach holds that the two disorders co-occur because of the mutual interactions among their symptoms (Cramer et al., 2010). Hence, comorbidity arises as a natural consequence of bridge symptoms—that is, a symptom that can transmit activation from one disorder to the other (Cramer et al., 2010; Fried and Cramer, 2017). Accordingly, bridge symptoms are key to disentangling co-occurrence between disorders (Bekhuis et al., 2016; Borsboom and Cramer, 2013; Fried and Cramer, 2017). Yet, uncertainty still abounds vis-à-vis the individual symptom-to-symptom association between SAD and depressive symptoms.

The purpose of our study was to apply network analytic methods to characterize the associations among core symptoms of SAD—i.e. fear and avoidance of social situations—and comorbid depressive symptoms in a convenience sample of individuals with a primary SAD. To accomplish this aim, we first explored the general structure of the network. Then, we specifically focused on the nodes' importance and influence. Of critical interest was the examination and identification of bridge symptoms—i.e. SAD symptoms that have strong associations with depressive symptoms, and *vice versa*.

1. Method

1.1. Participants

The sample consisted of 174 individuals (72% female) with a primary DSM-IV-TR diagnosis of SAD. In addition, 47 had a comorbid diagnosis of major depressive disorder, 26 had a diagnosis of depression (not otherwise specified), and 5 had a diagnosis of dysthymia. The participants constitute a convenience sample of individuals who were recruited for five other studies who had, as a result of participating in those studies, completed questionnaires measuring symptoms of social anxiety and depression used in the present network study (for full protocols, see Heeren et al., 2015a, 2015b, 2016, 2017a, 2017b). Each study included a nonprobability sampling approach and the different databases have been carefully checked to avoid potential multiple entries of the same participants.

To be eligible, individuals had to meet (a) DSM-IV-TR criteria for SAD, (b) have no current substance abuse or dependence, (c) no current neurological problems or use of psychotropic medications, and (d) no current psychological or psychiatric treatment. Participants were first screened via the self-report version of the Liebowitz Social Anxiety Scale (LSAS; Liebowitz, 1987). Eligible participants had to score above 56 on the LSAS (i.e., the cut-off score for probable diagnosis of SAD in the French version of the scale; Bouvard and Cottraux, 2010). Participants were then assessed by a clinical psychologist who used the screening version of the Mini-International Neuropsychiatric Interview (M.I.N.I; Sheehan et al., 1998). Each participant was tested individually in a quiet room. Each study was approved by the Ethical Committee of the Université Catholique de Louvain (UCL, Belgium) and conducted according to the Declaration of Helsinki. Participants' characteristics appear in Table 1.

1.2. Materials and measures

1.2.1. Measures of social anxiety symptoms

The LSAS is a 24-item scale that measures fear and avoidance of a range of social and performance situations (see Table 2). Participants rate each of the 24 social situations on a 4-point Likert-type scale, once for the intensity of fear (0, *None*; 1, *Mild*; 2 *Moderate*; 3 *Severe*) and once for frequency of avoidance of the situation (0, *Never*; 1, *Occasionally*; 2 *Often*; 3 *Usually)*. We used the validated French versions of this scale (Heeren et al., 2012). The internal reliability of LSAS was high in the current sample, with a Cronbach's alpha of .81 for the global scale score (.82 for the fear scale score and .80 for the avoidance scale score).

1.2.2. Measure of depressive symptoms

The Beck Depression Inventory (BDI-II; Beck et al., 1996) is a 21-item instrument designed to measure both the presence and severity of depressive symptoms. Each item consists of a group of four statements measuring the symptoms of depression (e.g., loss of interest) that range in intensity, each item being scored on a scale value of 0–3. We used the validated French versions of this scale (BDI-II; Beck et al., 1998). The

Table 1
Demographic and clinical measures for individuals with social anxiety disorder.

	Mean (*SD*)	Min-Max
Demographic measures		
Age	28.40 (11.26)	18–67
Educational level (in years)	10.78 (2.33)	0–15
Clinical measures		
BDI-II	12.86 (8.15)	1–37
LSAS	71.67 (13.69)	57–112

Note. Education level was assessed according to the numbers of years of education completed after finishing primary school. BDI-II = Beck Depression Inventory; LSAS = Liebowitz Social Anxiety Scale.

Table 2
Social situations indexed in the Liebowitz Social Anxiety Scale and depressive symptoms as denoted in the Beck Depression Inventory-II.

Construct	Items
Social situations	1. Telephoning in public; 2. Participating in small groups; 3. Eating in public places; 4. Drinking with others in public places; 5. Talking to people in authority; 6. Acting, performing or giving a talk in front of an audience; 7. Going to a party; 8. Working while being observed; 9. Writing while being observed; 10. Calling someone you don't know very well; 11. Talking with people you don't know very well; 12. Meeting strangers; 13. Urinating in a public bathroom; 14. Entering a room when others are already seated; 15. Being the center of attention; 16. Speaking up at a meeting; 17. Taking a test; 18. Expressing a disagreement or disapproval to people you don't know very well; 19. Looking at people you don't know very well in the eyes; 20. Giving a report to a group; 21. Trying to pick up someone; 22. Returning goods to a store; 23. Giving a party; 24. Resisting a high-pressure salesperson.
Depressive symptoms	1. Sadness; 2. Pessimism; 3. Past failure; 4. Loss of pleasure; 5. Guilty feelings; 6. Punishment feelings; 7. Self-dislike; 8. Self-criticalness; 9. Suicidal thoughts or wishes; 10. Crying; 11. Agitation; 12. Loss of interest; 13. Indecisiveness; 14. Worthlessness; 15. Loss of energy; 16. Changes in sleeping pattern; 17. Irritability; 18. Changes in appetite; 19. Concentration difficulty; 20. Tiredness or Fatigue; 21. Loss of interest in sex.

internal reliability of BDI was high in the current sample, with a Cronbach's alpha of .86 for the global scale score.

1.3. General procedure

For the analyses reported here, we used the data from the initial assessment of the aforementioned studies. For each study, participants first completed demographic and LSAS questionnaires prior to completing the BDI.

2. Data analytic plan

2.1. Network estimation

We used a Graphical Gaussian Model (GGM) to estimate networks whose edges represent conditional independence relationships between nodes when controlling for the effects of all other nodes (Epskamp et al., 2017a). We regularized our model by running the graphical LASSO (Least Absolute Shrinkage and Selection Operator; Friedman et al., 2008). The aims of this procedure are two-fold. First, it computes (regularized) partial correlations between pairs of symptoms, thereby eliminating spurious associations (edges) attributable to the influence of other symptoms in the network. Second, it shrinks trivially small associations to zero, removing them from the graph as potentially "false positive" edges, and thereby returning a sparse graph comprising only the strongest edges. We used the R package *qgraph* (Epskamp et al., 2012) that automatically implements the graphical LASSO regularization in combination with extended Bayesian Information Criterion (EBIC) model selection (Foygel and Drton, 2010). First, 100 different network models with different degree of sparsity are estimated. Second, the model with the lowest EBIC is selected, given a certain value on the hyperparameter gamma (γ), which controls the trade-off between including false-positive edges (i.e., high specificity) and removing true edges (i.e., high sensitivity). The hyperparameter γ is usually set between zero and .5 (Epskamp et al., 2017a). The closer one chooses a value of γ near .5, the more the EBIC will favor a simpler model containing fewer edges, whereas the closer one chooses a value of γ near zero, the more the EBIC will favor a model with more edges. Following previous studies (e.g., Beard et al., 2016; Bernstein et al., 2017), we opted to set γ to .5 to be confident that our edges are genuine. Finally, because the LSAS and BDI-II items are ordinal, we followed recent studies (e.g., McNally et al., 2017a) and calculated the polychoric correlations among variables before conducting the regularization.

2.2. Node centrality

Commonly used centrality indices do not distinguish between positive and negative edges. For instance, a node's strength centrality is computed by adding the absolute values of the edges incident on the node, irrespective of the sign of an edge. Hence, edge weights of −.20 and .20 sum to .40, not zero. This seldom presents a problem for most psychopathology networks as symptoms usually positively correlate with one another. However, associations between symptoms of distinct disorders could be either positive or negative, generating negative and positive edges (Robinaugh et al., 2016). Thus, the commonly used centrality indices may insufficiently gauge the genuine nature of a node's influence within instances where negative edges do occur (e.g., depression and complicated grief; Robinaugh et al., 2016). Moreover, standard measures of node centrality will provide a progressively inaccurate gauge of a node's influence to the extent that the network has edges depicting negative correlations (Everett and Borgatti, 2014). To overcome this limitation, Robinaugh and colleagues (2016) have devised the one-step (EI1) and two-step (EI2) expected influence metrics, two novel measures of node importance that can accommodate signed edges.

EI1 aims to assess a node's influence with its immediate neighbors (i.e. the nodes with which it shares an edge). EI1 of a node equals to the summed weight, including positive and negative values, of its edges shared with the remaining nodes in the network. However, EI1 does not incorporate information about the expected influence of a node's neighbors. This is unfortunate as such information is highly relevant to assess the ultimate influence of a node within the entire network. For instance, if a node X is connected only to a node Y, and node Y has low EI1, then change in node X will have little influence on the remainder of the network. In contrast, if node Y has many strong edges, the change in node X may have a large effect on the network by virtue of its influence on the highly influential node Y (Robinaugh et al., 2016).

To take into account the secondary influence of a node via the influences of its immediate neighbors (i.e. the nodes with which it shares an edge), Robinaugh and his colleagues (2016) also devised the EI2 index. EI2 of a node equals its EI1 plus the sum of the EI1 values of the remaining nodes in the network multiplied by the weighted edge between the neighboring nodes. The added expected influence of the neighboring nodes is weighted because the secondary influence of a given node through its neighbor will vary as a function of the strength of the edge between the two nodes (for a precise mathematical formulation, see Robinaugh et al., 2016). In contrast to measures of EI1, EI2 aim to assess the nature and the strength of a node's cumulative influence within the network, and thus the role it may be expected to play in the activation, persistence, and remission of the network (Robinaugh et al., 2016).

Each index was calculated with the R package *networktools* (Jones, 2017). For each index, higher values reflect greater influence in the network. We created plots that depict these values. For ease of comparison and interpretation, we reported z-scores rather than raw values.

Recent commentators have argued that differential variability ("restricted range") in symptom severity ratings can distort conclusions about node importance (e.g., Terluin et al., 2016). Following recent publications (McNally et al., 2017a), we thus tested whether differential variability in nodes impact on nodes' importance by computing the correlation between the nodes expected influence and variance in symptom severity rating.

2.3. Node bridge influence

To clarify the associations among core symptoms of SAD and co-morbid depressive symptoms, we analyzed the unique association of each core symptom of SAD with depressive symptoms, and *vice versa,* by calculating what we called the "bridge expected influence". Bridge expected influence can be separated into "bridge EI1" and "bridge EI2": bridge EI1 measures the sum of edge weights from a given node to all nodes of the opposite disorder; bridge EI2 additionally takes into account the secondary influence of a node via the influences of its immediate neighbors. For both bridge EI1 and bridge EI2, higher values reflect greater influence on nodes of the other disorder. Values were calculated using the *bridge* function of the R package *networktools* (Jones, 2017). We created plots that depict these values. For ease of comparison and interpretation, we reported *z*-scores rather than raw values.

3. Results

In the figures depicting the networks and the centrality plots, we used the following abbreviations to designate the fear and avoidance of social situations as well as depressive symptoms. Each social situation from the LSAS is designated by a number ranging from 1 to 24 accompanied either by the letter "f" or "a", representing fear and avoidance, respectively. Depressive symptoms are identified by the letter "d" and a number ranging from 1 to 21, referring to the 21 symptoms of the BDI-II. Social situations and depressive symptoms are listed in Table 2.

3.1. Graphical LASSO network

Fig. 1 depicts the graphical LASSO network, which denotes regularized partial correlations. Node placement was determined by Fruchterman and Reingold's (1991) algorithm whereby nodes nearer to the center of the graph tend to have the strongest connections with other nodes. A thicker edge denotes a larger association. Blue edges represent positive regularized partial correlations, whereas red ones represent negative regularized partial correlations. Several features were immediately apparent. First, with respect to nodes denoting SAD symptoms, strong edges were present between nodes denoting fear and avoidance of similar social situations and a few of them emerge as strongly connected to the entire network (e.g., fear and avoidance of expressing a disagreement to unfamiliar people, fear and avoidance of looking at unfamiliar people eye-to-eyes, fear and avoidance of talking to people in authority, and fear and avoidance of participating in small groups). Second, with respect to nodes denoting depressive symptoms, loss of pleasure (d4), self-criticism (d8), self-dislike (d7), loss of interest (d12), worthlessness (d14), and loss of energy (d15) emerge as nodes strongly connected to entire network.

Notably, there were also several features of cross-associations between SAD and comorbid depressive symptoms. On the one hand, several nodes denoting SAD symptoms were strongly connected to depressive symptoms. For instance, avoidance of participating in small groups (a2) was connected to loss of interest (d12), worthlessness (d14), loss of pleasure (d4), and suicidal ideation (d9). On the other hand, a few nodes denoting depressive symptoms were highly connected to SAD symptoms. For example, suicidal ideation (d9) and loss
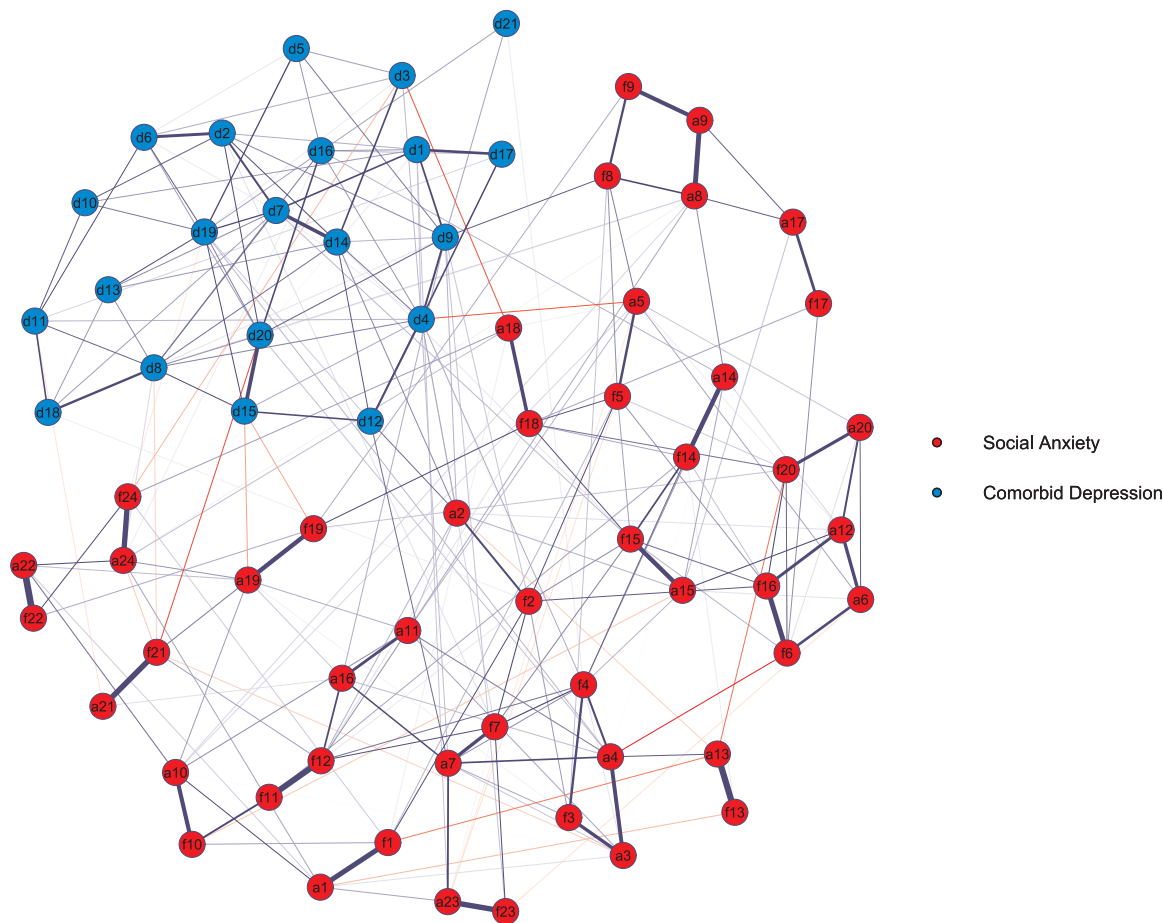

Fig. 1. Network constructed depicting the regularized partial correlations among symptoms of SAD and comorbid depression in people with SAD. Note. The thickness of an edge reflects the magnitude of the association (the thickest edge representing a value of .52). Blue lines represent positive correlations, whereas red lines represent negative correlations. Items are detailed in Table 2. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article).
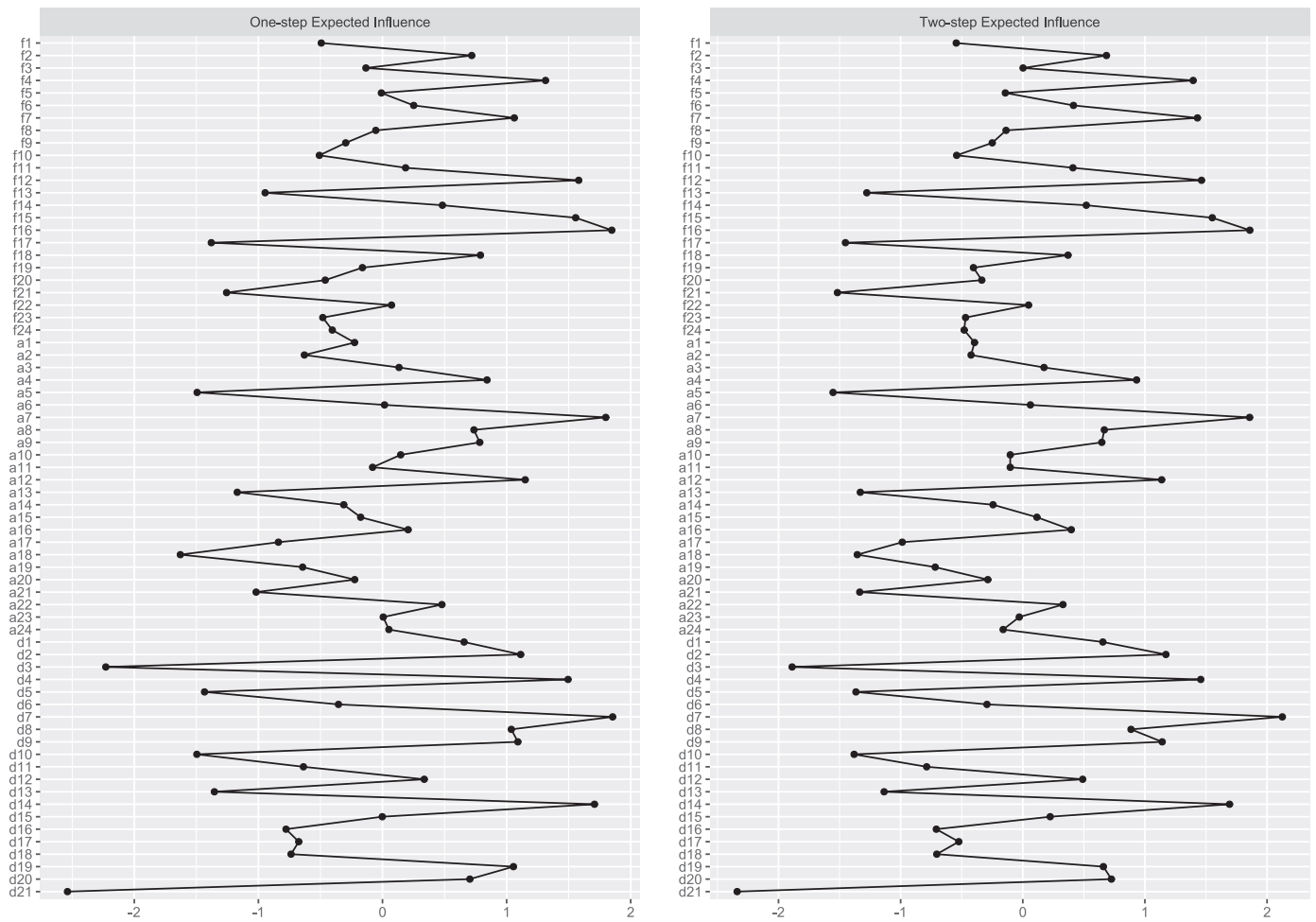
Fig. 2. Plot denoting the one-step and two-step expected influence metrics for the graphical LASSO network. Note. Items are detailed in Table 2.

of interest (d12) both appeared highly connected to SAD nodes. It is worth noting that there were also a couple negative edges between SAD and depressive symptoms [e.g., avoidance of expressing a disagreement or disapproval to unfamiliar people (a18) and past failure (d3)].

To estimate the accuracy of the edge weights, we used a non-parametric bootstrap approach to calculate 95% confidence intervals (CIs) for the edges by sampling the data with 1000 replacements, calculating edges to create a distribution of the edges weights (i.e., regularized partial correlation coefficients between symptom pairs) values by using the *R* package *bootnet* (Epskamp et al., 2017a). This displays the sampling variation. The bootstrapped CIs for the edges indicate that the edges are fairly stable and a number of edges exhibit values significantly different from zero (Fig. S1).

3.2. Expected influence

Analyses of expected influence confirmed the aforementioned observations (Fig. 2). First, nodes denoting avoidance of going to a party (a7), fear and avoidance of meeting strangers (f12 and a12), fear of speaking up at a meeting (f16), and fear of being the center of attention (f15) were among the SAD symptoms exhibiting the highest levels of both EI1 and EI2. Second, self-dislike (d7), tiredness (d20), worthlessness (d14), self-criticism (d8), pessimism (d2), and loss of pleasure (d4) were among the depressive symptoms exhibiting the highest levels of EI1 and EI2.

Because the two-tailed Pearson correlation between the node variance and EI1 was nonsignificant, $r(67) = -.13$, $p = .28$, differential variability across symptoms does not pose a problem for interpreting a

node's EI1 (see Terluin et al., 2016). The two-tailed Pearson correlation between the node variance and EI2 was likewise nonsignificant, $r(67) = -.18$, $p = .15$. Finally, EI1 and EI2 were highly correlated, $r(67) = .98$, $p < .001$, consistent with previous studies (e.g., Robinaugh et al., 2016).

3.3. Bridge expected influence

Fig. 3 depicts the "bridge EI1" and "bridge EI2" values. Nodes denoting avoidance of participating in small groups (a2), avoidance of going to a party (a7), and fear of working while being observed (f8) were the SAD symptoms exhibiting the highest levels of both bridge EI1 and EI2 on all depressive symptoms. Suicidal ideation (d9) and loss of interest (d12) were the depressive symptoms exhibiting the highest levels of bridge EI1 on SAD symptoms. Bridge EI2 also disclosed loss of pleasure (d4) as a depressive symptom exerting a strong bridging influence on SAD symptoms. Consistent with expected influence metrics, "bridge EI1" and "bridge EI2" were highly correlated, $r(67) = .97$, $p < .001$.

4. Discussion

Many people with SAD also suffer from depression. To our knowledge, this is the first study to examine the empirical network structure of fear and avoidance of distinct situations among individuals with SAD and their relation with comorbid depression symptoms. Perhaps the most striking result was the observation, in line with previous network studies (e.g., Bekhuis et al., 2016; McNally et al., 2017b; Robinaugh
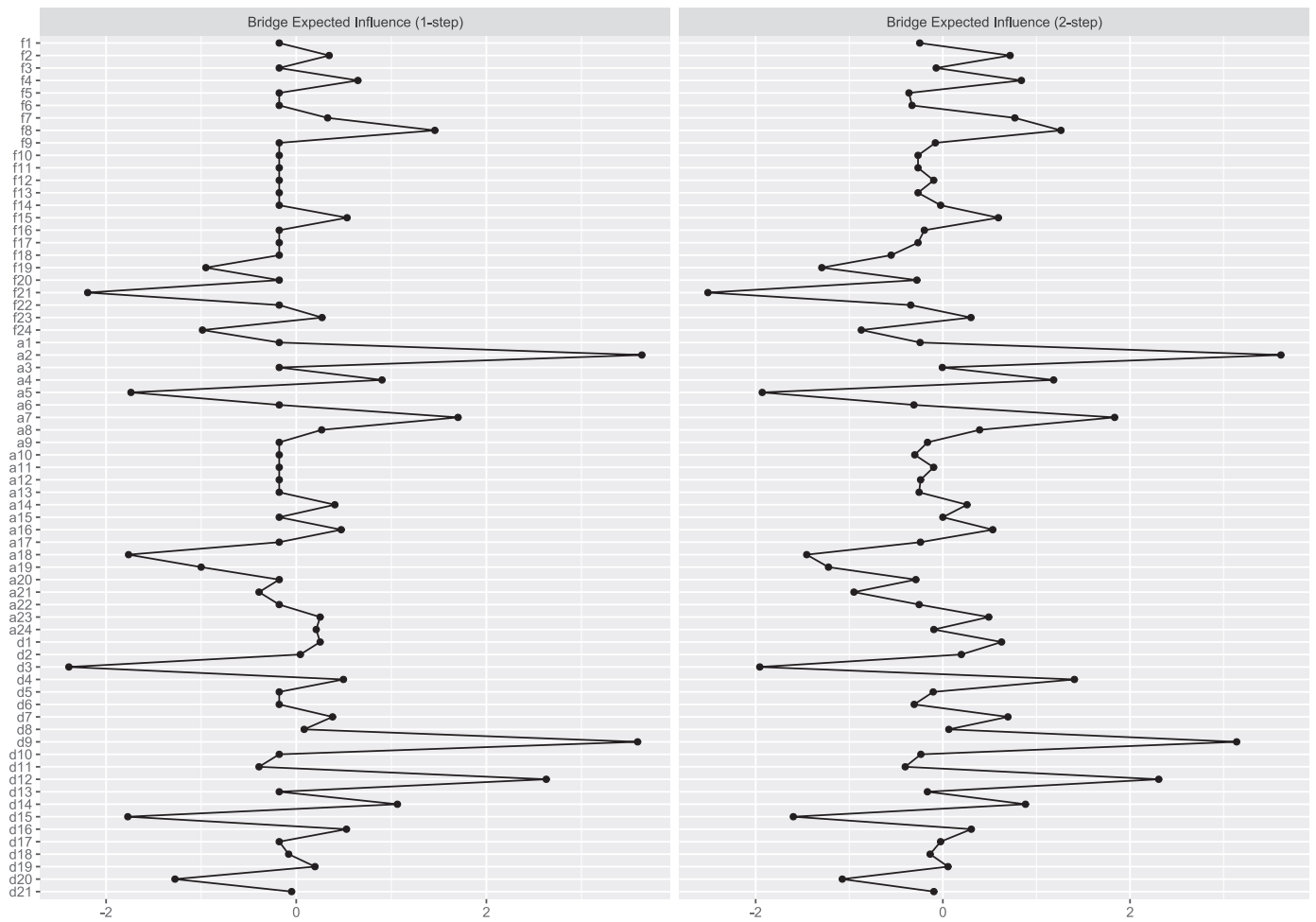
Fig. 3. Plot denoting the bridge one-step and the bridge two-step expected influence metrics for the graphical LASSO network. Note. Items are detailed in Table 2.

et al., 2014), that not all nodes were equally important in determining the co-occurrence between fear and avoidance of distinct situations with comorbid depression among individuals with SAD.

First, when considering the relationships between fear and avoidance of distinct situations among individuals with SAD, fear and avoidance of meeting strangers, avoidance of going to party, and fear of speaking up at a meeeting and of being the center of attention collectively appear as the most influential SAD nodes. Such observation does not come as a surprise; instead, they are in keeping with theories suggesting that social situations involving novel or unfamiliar individuals (e.g., Carron et al., 1999; Kagan, 2014; Kashdan and Wenzel, 2005) or to be at the center of attention (e.g., Cornwell et al., 2011) carry more weight than other types of social situations in the maintenance of SAD.

Second, although nodes denoting fear and avoidance of distinct situations do not cluster with those denoting comorbid depression symptoms, there were several bridge symptoms connecting the former to the latter and *vice versa.* Notably, we found that suicidal ideation, loss of interest, and loss of pleasure were the depression nodes exhibiting the strongest association with SAD symptoms. Conversely, avoidance of participating in small groups, avoidance of going to a party, and fear of working while being observed emerged as the SAD nodes exhibiting the strongest association with depressive symptoms. These results are thus suggestive of bridges through which activation issuing from one disorder potentially propagate to symptoms of the other disorder, activating the full picture of the co-occurrence between SAD and comorbid depressive symptoms among individuals with SAD.

Our study adds to a small but growing empirical literature revealing that the co-occurrence between two disorders is best portrayed as sets

of symptom-to-symptom connections (e.g., Bekhuis et al., 2016; McNally et al., 2015; Robinaugh et al., 2014). Our findings stress the relevance of approaching comorbidity by concentrating on individual symptoms and their connections (Cramer et al., 2010; Bekhuis et al., 2016; Fried, 2015).

Our findings have several therapeutic implications. Prior studies indicated that overall network connectivity can predict the prognosis of mental disorders (Boschloo et al., 2016; van Borkulo et al., 2015). Hence, turning off a highly connected node may foster a beneficial cascade of downstream benefits, deactivating other nodes, and reducing the overall network connectivity (McNally, 2016). Consequently, prevention and intervention strategies directly targeting bridge nodes are particularly important as they are likely to affect the co-occurrence between SAD and depression. Notably, as avoidance of participating in small groups was the SAD symptom exerting the strongest bridging influence on depressive symptoms, therapists may wish to target such avoidance prior to exposure therapy (Kim, 2005; Morgan and Raffle, 1999). Indeed, avoidance prevents recovery from SAD by thwarting opportunities for inhibitory learning by blocking access to information that is incompatible with threat-related beliefs (Aderka et al., 2013; Hofmann, 2007; Moscovitch, 2009). Likewise, as suicidal ideation and loss of interest appear as the two depressive symptoms exerting the strongest influence on SAD symptoms, our findings points to those symptoms as key targets for prevention and treatment. This point is particularly relevant as the presence of comorbid depressive symptoms has been associated with severity and generalization of the social fears and avoidance behaviors among patients with SAD (e.g., Perugi et al., 2001). Moreover, because patients with SAD and comorbid depressive

symptoms are particularly at elevated risk for attempting suicide (Cox et al., 1994; Sareen et al., 2005), suicidal ideation deserves a very careful audit during clinical assessment among patients with SAD.

The present study has several limitations. First, the edges were calculated with cross-sectional data, precluding strong inference vis-à-vis the cause-effect relationships among the variables (Maurage et al., 2013). Furthermore, cross-sectional edges represent both within- and between-subjects effects that cannot be disentangled. Although traditional longitudinal studies may allow tracking several variables over time, recently developed computational methods allow exploring the within- and between-person temporal dynamics of networks on intensive intraindividual time-series data (Epskamp et al., 2017b), enabling us to move closer to elucidating the causal dynamics regarding how social fears and avoidance trigger depressive symptoms over time and *vice versa*. Second, although a sample size of 174 participants is usually not regarded as a small sample for a clinical study, network models estimate a very large number of parameters, and cross-sample validations in larger samples are thus required to draw firm conclusions. Yet, on the other hand, results from the non-parametric bootstrap approach guarantee the generalizability of the present findings in similar samples. Third, although the present study focuses on the co-occurrence between symptoms of depression and SAD, each participant had a primary diagnosis of SAD. The critical next step is thus to explore the co-occurrence between these two disorders among a sample with a primary diagnosis of major depression. Fourth, the participants were relatively well-educated and predominantly female. Finally, theories of SAD posit that several cognitive mechanisms (e.g., attentional bias for threat, postevent processing) figure in the etiology and maintenance of the SAD, and perhaps its comorbidity (for a review, see Wong and Rapee, 2016). These variables are suitable for inclusion in network analyses (e.g., Heeren and McNally, 2016a; Heeren and McNally, 2016b; Jones et al., 2017). These limitations notwithstanding, this study is the first to examine the cross-associations between core symptoms of SAD and comorbid depressive symptoms among individuals with SAD, thus providing an important basis for hypothesizing how the two disorders covary.

Acknowledgments

Funding

Appendix A. Supplementary material

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.jad.2017.12.003.

References

Aderka, I., McLean, C.P., Huppert, J.D., Davidson, J.R.T., Foa, E.B., 2013. Fear, avoidance and physiological symptoms during cognitive-behavioral therapy for social anxiety disorder. Behav. Res. Ther. 51, 352–358.

Alpert, J.E., Uebelacker, L.A., McLean, N.E., Nierenberg, A.A., Pava, J.A., Worthington 3rd, J.J., Tedlow, J.R., Rosenbaum, J.F., Fava, M., 1997. Social phobia, avoidant personality disorder and atypical depression: co-occurrence and clinical implications. Psychol. Med. 27, 627–633.

Beard, C., Millner, A.J., Forgeard, M.J., Fried, E.I., Hsu, K.J., Treadway, M.T., Leonard, C.V., Kertz, S.J., Björgvinsson, T., 2016. Network analysis of depression and anxiety symptom relationships in a psychiatric sample. Psychol. Med. 14, 1–11.

Beck, A.T., Steer, R.A., Brown, G.K., 1996. Beck Depression Inventory Manual, 2nd ed. Psychological Corporation, San Antonio, TX, USA.

Beck, A.T., Steer, R.A., Brown, G.K., 1998. Beck depression inventory manual (2nd ed.) – French Adaptation, Editions du Centre de Psychologie Appliquée, Paris, France.

Bekhuis, E., Schoevers, R.A., van Borkulo, C.D., Rosmalen, J.G., Boschloo, L., 2016. The network structure of major depressive disorder, generalized anxiety disorder and somatic symptomatology. Psychol. Med. 46, 2989–2998.

Beesdo, K., Bittner, A., Pine, D.S., Stein, M.B., Höfler, M., Lieb, R., Wittchen, H.U., 2007. Incidence of social anxiety disorder and the consistent risk for secondary depression in the first three decades of life. Arch. Gen. Psychiatry 64, 903–912.

Bernstein, E.E., Heeren, A., McNally, R.J., 2017. Unpacking rumination and executive control: a network perspective. Clin. Psychol. Sci. 5, 816–826.

Bittner, A., Goodwin, R.D., Wittchen, H.U., Beesdo, K., Höfler, M., Lieb, R., 2004. What characteristics of primary anxiety disorders predict subsequent major depressive disorder? J. Clin. Psychiatry 65, 618–626.

Borgatti, S.P., 2005. Centrality and network flow. Soc. Netw. 27, 55–71.

Borsboom, D., 2017. A network theory of mental disorders. World Psychiatry 16, 5–13.

Borsboom, D., Cramer, A.O.J., 2013. Network analysis: an integrative approach to the structure of psychopathology. Annu. Rev. Clin. Psychol. 9, 91–121.

Boschloo, L., Schoevers, R.A., van Borkulo, C.D., Borsboom, D., Oldehinkel, A.J., 2016. The network structure of psychopathology in a community sample of preadolescents. J. Abnorm. Psychol. 125, 599–606.

Bouvard, M., Cottraux, J., 2010. Protocoles et échelles d'évaluation en psychiatrie et psychologie, 5th ed. Masson, Paris, France.

Brown, T.A., Campbell, L.A., Lehman, C.L., Grisham, J.R., Mancill, R.B., 2001. Current and lifetime comorbidity of the DSM-IV anxiety and mood disorders in a large clinical sample. J. Abnorm. Psychol. 110, 585–599.

Bruce, S.E., Yonkers, K.A., Otto, M.W., Eisen, J.L., Weisberg, R.B., Pagano, M., Shea, M.T., Keller, M.B., 2005. Influence of psychiatric comorbidity on recovery and recurrence in generalized anxiety disorder, social phobia, and panic disorder: a 12-year prospective study. Am. J. Psychiatry 162, 1179–1187.

Carron, A.V., Estabrooks, P.A., Horton, H., Prapavessis, H., Hausenblas, H.A., 1999. Reductions in the social anxiety of women associated with group membership distraction, anonymity, security, or diffusion of evaluation. Group Dyn. Theor. Res. 3, 152–160.

Cornwell, B.R., Heller, R., Biggs, A., Pine, D.S., Grillon, C., 2011. Becoming the center of attention in social anxiety disorder: startle reactivity to a virtual audience during speech anticipation. J. Clin. Psychiatry 72, 942–948.

Cox, B.J., Direnfeld, D.M., Swinson, R.P., Norton, G.R., 1994. Suicidal ideation and suicide attempts in panic disorder and social phobia. Am. J. Psychiatry 151, 882–887.

Cramer, A.O.J., Waldorp, L.J., van der Maas, H.L.J., Borsboom, D., 2010. Comorbidity: a network perspective. Behav. Brain Sci. 33, 137–193.

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, 1–18.

Epskamp, S., Borsboom, D., Fried, E.I., 2017a. Estimating psychological networks and their accuracy: a tutorial paper. Behav. Res Methods. http://dx.doi.org/10.3758/s13428-017-0862-1. (In press).

Epskamp, S., Waldorp, L.J., Mõttus, R., Borsboom, D., 2017b. Discovering Psychological Dynamics in Time-series Data. pp. 1–31, ArXiv Prepr. ID 1609.04156.

Everett, M.G., Borgatti, S.P., 2014. Networks containing negative ties. Soc. Netw. 38, 111–120.

Fried, E.I., 2015. Problematic assumptions have slowed down depression research: why symptoms, not syndromes are the way forward. Front. Psychol. 6, 309.

Fried, E.I., van Borkulo, C.D., Cramer, A.O.J., Boschloo, L., Schoevers, R.A., Borsboom, D., 2016. Mental disorders as networks of problems: a review of recent insights. Soc. Psychiatry Psychiatr. Epidemiol. 1, 1–10.

Fried, E.I., Cramer, A.O.J., 2017. Moving forward: challenges and directions for psychopathological network theory and methodology. Perspect. Psychol. Sci (In press).

Friedman, J.H., Hastie, T., Tibshirani, R., 2008. Sparse inverse covariance estimation with the graphical lasso. Biostatistics 9, 432–441.

Fruchterman, T.M.J., Reingold, E.M., 1991. Graph drawing by force-directed placement. Softw. Pract. Exp. 21, 1129–1164.

Foygel, R., Drton, M., 2010. Extended Bayesian information criteria for Gaussian graphical models. Adv. Neural Inf. 23, 2020–2028.

Gilbert, P., 2000. The relationship of shame, social anxiety and depression: the role of the evaluation of social rank. Clin. Psychol. Psychother. 7, 174–189.

Heeren, A., Billieux, J., Philippot, P., de Raedt, R., Baeken, C., de Timary, P., Maurage, P., Vanderhasselt, M.-A., 2017a. Impact of transcranial direct current stimulation on attentional bias for threat: a proof-of-concept study among individuals with social anxiety disorder. Soc. Cogn. Affect. Neurosci. 12, 251–260.

Heeren, A., Coussement, C., McNally, R.J., 2016. Untangling attention bias modification from emotion: a double-blind randomized experiment among individuals with social anxiety disorder. J. Behav. Ther. Exp. Psychiatry 50, 61–67.

Heeren, A., Dricot, L., Billieux, J., Philippot, P., Grynberg, D., de Timary, P., Maurage, P., 2017b. Correlates of social exclusion in social anxiety disorder: an fMRI study. Sci. Rep. 7, 260.

Heeren, A., Maurage, P., Philippot, P., 2015a. Revisiting attentional processing of non-emotional cues in social anxiety: a specific impairment for the orienting network of attention. Psychiatry Res. 228 (1), 136–142.

Heeren, A., Maurage, P., Rossignol, M., Vanhaelen, M., Peschard, V., Eeckhout, C., Philippot, P., 2012. The self-report version of the Liebowitz Social Anxiety Scale: psychometric properties of the French version. Can. J. Behav. Sci. 44, 99–107.

Heeren, A., Mogoaşe, C., McNally, R.J., Schmitz, A., Philippot, P., 2015b. Does attention bias modification improve attentional control? A double-blind randomized experiment with individuals with social anxiety disorder. J. Anxiety Disord. 29, 35–42.

Heeren, A., McNally, R.J., 2016a. An integrative network approach to social anxiety disorder: the complex dynamic interplay among attentional bias for threat, attentional control, and symptoms. J. Anxiety Disord. 42, 95–104.

Heeren, A., McNally, R.J., 2016b. A call for complexity in the study of social anxiety disorder: a commentary on Wong & Rapee. Front. Psychol. 7, 1963. http://dx.doi.org/10.3389/fpsyg.2016.01963.

Hofmann, S.G., 2007. Cognitive factors that maintain social anxiety disorder: a comprehensive model and its treatment implications. Cogn. Behav. Ther. 36, 195–209.

Hofmann, S.G., Curtiss, J., McNally, R.J., 2016. A complex network perspective on clinical science. Perspect. Psychol. Sci. 11, 597–605.

Jones, P.J., 2017. Networktools: Tools for Identifying Important Nodes in Networks. R Package Version 1.1.0. 〈https://CRAN.R-project.org/package=networktools〉.

Jones, P.J., Heeren, A., McNally, R.J., 2017. Commentary: a network theory of mental disorders. Front. Psychol. 8, 1305. http://dx.doi.org/10.3389/fpsyg.2017.01305.

Kagan, J., 2014. Temperamental contributions to the development of psychological profiles: II. Two candidates. In: Hofmann, S.G., DiBartolo, P.M. (Eds.), Social Anxiety: Clinical, Developmental, and Social Perspectives, 3rd ed. Elsevier, New York, NY, pp. 419–450.

Kashdan, T.B., Wenzel, A., 2005. A transactional approach to social anxiety and the genesis of interpersonal closeness: self, partner, and social context. Behav. Ther. 36, 335–346.

Kim, E.-J., 2005. The effect of the decreased safety behaviors on anxiety and negative thoughts in social phobics. J. Anxiety Disord. 19, 69–86.

Kushnir, J., Marom, S., Mazar, M., Sadeh, A., Hermesh, H., 2014. The link between social anxiety disorder, treatment outcome, and sleep difficulties among patients receiving cognitive behavioural group therapy. Sleep Med. 15, 515–521.

Ledley, D.R., Huppert, J.D., Foa, E.B., Davidson, J.R., Keefe, F.J., Potts, N.L., 2005. Impact of depressive symptoms on the treatment of generalized social anxiety disorder. Depress Anxiety 22, 161–167.

Liebowitz, M.R., 1987. Social phobia. Mod. Probl. Pharm. 22, 141–173.

Marom, S., Gilhoa-Schechtman, E., Aderka, I., Weizman, A., Hermesh, H., 2009. Impact of depression on treatment effectiveness and gains maintenance in social phobia: a naturalistic study of cognitive behavior group therapy. Depress Anxiety 26, 289–300.

Maurage, P., Heeren, A., Pesenti, M., 2013. Does chocolate consumption really boost Nobel award chances? The peril of over-interpreting correlations in nutrition and health studies. J. Nutr. 143, 931–933.

McNally, R.J., 2016. Can network analysis transform psychopathology? Behav. Res. Ther. 86, 95–104. http://dx.doi.org/10.1016/j.brat.2016.06.006.

McNally, R.J., Heeren, A., Robinaugh, D.J., 2017a. A Bayesian network analysis of posttraumatic stress disorder symptoms in adults reporting childhood sexual abuse. Eur. J. Psychotraumatol. 8 (Suppl 3), S1341276.

McNally, R.J., Mair, P., Mugno, B.L., Riemann, B.C., 2017b. Co-morbid obsessive-compulsive disorder and depression: a Bayesian network approach. Psychol. Med. 47, 1204–1214.

McNally, R.J., Robinaugh, D.J., Wu, G.W.Y., Wang, L., Deserno, M., Borsboom, D., 2015.

Mental disorders as causal systems: a network approach to posttraumatic stress disorder. Clin. Psychol. Sci. 3, 836–849.

Morgan, H., Raffle, C., 1999. Does reducing safety behaviors improve treatment response in patients with social phobia? Aust. N. Z. J. Psychiatry 33, 503–510.

Moscovitch, D.A., 2009. What is the core fear in social phobia? A new model to facilitate individualized case conceptualization and treatment. Cogn. Behav. Pract. 16, 123–134.

Perugi, G., Frare, F., Toni, C., Mata, B., Akiskal, H.S., 2001. Bipolar II and unipolar co-morbidity in 153 outpatients with social phobia. Compr. Psychiatry 42, 375–381.

Regier, D.A., Rae, D.S., Narrow, W.E., Kaelber, C.T., Schatzberg, A.F., 1998. Prevalence of anxiety disorders and their comorbidity with mood and addictive disorders. Br. J. Psychiatry 34, 24–28.

Robinaugh, D.J., LeBlanc, N.J., Vuletich, H.J., McNally, R.J., 2014. Network analysis of persistent complex bereavement disorder in conjugally bereaved adults. J. Abnorm. Psychol. 123, 510–522.

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.

Sareen, J., Cox, B.J., Afifi, T.O., de Graaf, R., Asmundson, G.J., ten Have, M., Stein, M.B., 2005. Anxiety disorders and risk for suicide ideation and suicide attempts: a population-based longitudinal study of adults. Arch. Gen. Psychiatry 62, 1249–1257.

Schneier, F.R., Johnson, J., Hornig, C.D., Liebowitz, M.R., Weissman, M.M., 1992. Social phobia: comorbidity and morbidity in an epidemiologic sample. Arch. Gen. Psychiatry 49, 282–288.

Scholten, W.D., Batelaan, N.M., van Balkom, A.J., W.J.H, Penninx, B., Smit, J.H., van Oppen, P., 2013. Recurrence of anxiety disorders and its predictors. J. Affect Disord. 147, 180–185.

Sheehan, D.V., Lecrubier, Y., Sheehan, K.H., Amorim, P., Janays, J., Weiller, E., Hergueta, T., Baker, G.C., Dunbar, G.C., 1998. The mini-international neuropsychiatric interview (M.I.N.I.): the development and validation of a structured diagnosis psychiatric interview for DSM-IV and ICD-10. J. Clin. Psychiatry 59 (Suppl 20), S22–S33.

Stein, M.B., Fuetsch, M., Muller, N., Hofler, M., Lieb, R., Wittchen, H.U., 2001. Social anxiety disorder and the risk of depression: a prospective community study of adolescents and young adults. Arch. Gen. Psychiatry 58, 251–256.

Swallow, S.R., Kuiper, N.A., 1988. Social comparison and negative self-evaluations: an application to depression. Clin. Psychol. Rev. 8, 55–76.

Terluin, B., de Boer, M.R., de Vet, H.C.W., 2016. Differences in connection strength between mental symptoms might be explained by differences in variance: reanalysis of network data did not confirm staging. PLoS One 11, e015520.

Valente, T.W., 2012. Network interventions. Science 337, 49–53.

Van Ameringen, M., Mancini, C., Styan, G., Donison, D., 1991. Relationship of social phobia with other psychiatric illness. J. Affect. Disord. 21, 93–99.

van Borkulo, C.D., Boschloo, L., Borsboom, D., Penninx, B.W.J.H., Waldorp, L.J., Schoevers, R.A., 2015. Association of symptom network structure with the course of depression. JAMA Psychiatry 72, 1219–1226.

Wong, Q.J.J., Rapee, R.M., 2016. The aetiology and maintenance of social anxiety disorder: A synthesis of complimentary theoretical models and formulation of a new integrated model. J. Affect. Disord. 203, 84–100.