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Cogn Ther Res (2018) 42:103–113
DOI 10.1007/s10608-017-9876-3

ORIGINAL ARTICLE

Social Anxiety Disorder as a Densely Interconnected Network of Fear and Avoidance for Social Situations

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Published online: 17 October 2017
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Abstract The hallmark symptoms of social anxiety disorder (SAD) are fear and avoidance of social evaluative situations. Yet, even people without SAD sometimes fear and avoid certain social situations without ever developing the disorder. Apart from differences in number and severity, uncertainty abounds about how fear and avoidance of distinct interpersonal and social evaluative situations organize differently in people with and without SAD. Inspired by novel network approaches to psychopathology, we sought to characterize the network structure of fear and avoidance of distinct social evaluative situations among individuals with ($n = 238$) and without SAD ($n = 232$). Although the network structure and node centrality metrics did not differ between the groups, the network for those with SAD was more strongly interconnected than that of people free of the diagnosis. This study is the first to provide evidence that SAD can be conceptualized as a densely interconnected network of fear and avoidance of social situations. Our results are consistent with the network theory of mental disorders that regards networks with strong between-symptom connections as more pathogenic than similar networks with weaker connections. As prior studies indicated that overall network connectivity can predict the course of mental disorders, our findings set the scene for novel indicators of SAD prognosis.

Electronic supplementary material The online version of this article (doi:10.1007/s10608-017-9876-3) contains supplementary material, which is available to authorized users.

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Keywords Social anxiety disorder · Network analysis · Network comparison test · Anxiety disorders · Fear · Avoidance · Social rank · Computational social science

Introduction

Social anxiety disorder (SAD) is characterized by intense fear and avoidance of a wide range of interpersonal and social evaluative situations, leading to considerable distress and impaired functioning (American Psychiatric Association [APA] 2013). Until recently, ontological discourse on SAD was mainly confined to the question of whether this syndrome constitutes a discrete, categorical entity (APA 2013) or a continuum in which an increasing number of feared and avoided situations results in increasing functional impairment (e.g., Acarturk et al. 2008; Ruscio et al. 2008). Yet both perspectives interpret the emergence and covariance of symptoms as reflecting an underlying, latent common cause, whether construed categorically or dimensionally.

The network approach to psychopathology (Borsboom 2008, 2017; Borsboom and Cramer 2013) offers a radically new way of understanding SAD. According to this approach, a mental disorder is not the underlying cause of symptoms. Rather, it is an emergent phenomenon that arises from causal interactions among symptoms. Cutting-edge computational methods enable one to visualize disorders as complex networks comprising symptoms ("nodes") and the associations ("edges") connecting them. In this perspective, the stronger the association between two nodes, the thicker the line (edge) connecting them in the network. Hence, edge thickness signifies the likelihood that activation of one node will activate the other one. For example, for people with SAD, a node representing "fear of meeting strangers" may be strongly connected to a node representing "avoidance of

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meeting strangers" as well as to nodes representing "fear of going to a party" and "fear of calling someone you don't know well." Yet this node may be weakly connected to nodes representing "avoidance of taking a test" and "fear of returning goods to a store."

Accordingly, highly interconnected networks, characterized by many strong connections among symptoms, are more likely pathogenic than similar networks characterized by weaker connections (Borsboom 2017; Borsboom and Cramer 2013; Fried and Cramer 2017)—a prediction confirmed in several studies (Pe et al. 2015; van Borkulo et al. 2015; Wigman et al. 2013). For instance, one study showed that symptom networks are more densely connected for individuals with major depressive disorder than in healthy subjects (Pe et al. 2015). Another study revealed that greater overall network connectivity predicts difficulty recovering from major depressive disorder (e.g., van Borkulo et al. 2015).

However, not all nodes are equally important (Borgatti 2005; Valente 2012). Highly central nodes—ones having strong connections to many other nodes—are especially important for the development, persistence, and remission of mental disorders (Borsboom and Cramer 2013). Accordingly, when a highly central node is activated (i.e., the symptom is present), it is likely to activate other symptoms, thereby producing an episode of disorder (Borsboom and Cramer 2013). By turning off a highly central node, one can thus 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).

The network approach has ignited an explosion of research on a wide range of mental disorders (for reviews, see Fried and Cramer 2017; Fried et al. 2017; McNally 2016). However, only one study concerned SAD (Heeren and McNally 2016b). We found that fear and avoidance were highly central nodes in people with the disorder. In the present study, we expanded our network research on SAD in three principal ways. First, we conducted a fine-grained analysis of SAD symptoms such that each node represented fear (or avoidance) of a specific social-evaluative situation (e.g., speaking to authority figures; going to a party; eating in public; taking a test). Indeed, psychologists have argued that some social fears may vary in terms of their debilitating impact on functioning. For instance, situations involving interactions with strangers (e.g., Kagan 2014) or authority figures (e.g., Weisman et al. 2011) may be more pathogenic than others (e.g., giving a speech). The computational methods of network analysis enable one to identify the most important (central) social fears and avoidance behaviors in a social anxiety system. Because turning off a highly central node can produce a beneficial cascade of downstream benefits that fosters recovery from disorder (McNally 2016; Valente 2012), this knowledge also yields strong clinical implications—i.e., pointing to key situations for exposure therapy.

Second, many people are shy, socially anxious, and avoidant of some social-evaluative situations (e.g., speaking in public) without meeting the diagnostic criteria for SAD (e.g., Wakefield et al. 2005). Accordingly, how does the network comprising fears and avoidance of these situations differ between people with and without the disorder? As Borsboom's (2017) work implies, overall network connectivity should be greater in people with SAD than in people without the disorder. Indeed, in a highly connected network, the activation of any node can easily trigger other nodes and spread to the entire network, activating and self-reinforcing the entire network system (Valente 2012). Yet, to date, no study has examined whether individuals with SAD have a more densely interconnected network than do people free of the diagnosis.

Third, an important property of complex network system is community structure. A community is a group of nodes which are highly interconnected, but only sparsely connected to other groups of nodes (Fortunato 2010; Newman 2006). Most real-world networks, such as those involving routers and computers connected by physical links or neural networks within the brain, contain communities (Han et al. 2016). Detecting communities has practical implications. For example, it can be more important to identify central nodes within communities to understand network function than to identify central nodes within an entire network [e.g., as in genome-scale protein domain identification or in the clarification of intricate relationships among characters from different tribes in international hit series such as *Game of Thrones* (Beveridge and Shan 2016; Fan et al. 2012)]. Accordingly, one may wonder whether fear and avoidance of social situations cohere as a single large network system or constitute distinct communities of nodes serving different functions (e.g., fear of interacting with another person versus performing or speaking to a group). Moreover, one may wonder whether the network for people with SAD has the same community structure as that for people without the disorder.

To accomplish these aims, we applied computational analyses to characterize networks comprising fears and avoidance of diverse social-evaluative situations in people with and without SAD (Epskamp et al. 2017a).

Method

Participants

Both people with and without SAD constituted a convenience sample for our study. Participants in both groups were

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recruited from the population of Wallonia and Brussels-Capital regions in Belgium via media and listserv advertisements inviting people to participate in research on social anxiety (for full protocols, see Heeren et al. 2011, 2012a, b, 2015a, b, 2016, 2017a, b).

The SAD group comprised 238 individuals (178 female) with DSM-IV-TR diagnosis of SAD, generalized type.[1] Eligible individuals had to be free of neurological problems, current substance abuse or dependence, and current psychological or psychopharmacological treatment. In each study, these criteria were checked through a medical interview and by using the Mini-International Neuropsychiatric Interview (MINI; Sheehan et al. 1998). A clinical psychologist completed all the interviews. Their ages ranged from 18 to 66 years ($M = 29.72$, $SD = 13.39$) and their education completed after primary school from 6 to 17 years ($M = 14.16$, $SD = 2.86$).

The healthy comparison group consisted of 232 individuals (179 female) who had no history of psychiatric disorder. Their ages ranged from 18 to 67 years ($M = 30.89$, $SD = 12.19$) and their education completed after primary school from 6 to 17 years ($M = 14.23$, $SD = 2.50$). The groups did not differ in terms of age [$t(468) = 0.98$, $p = .32$], years of education [$t(468) = 0.30$, $p = .77$], or gender ratio [$\chi^2(1, N = 470) = 0.36$, $p = .55$].

Measures

The Liebowitz Social Anxiety Scale (LSAS; Liebowitz 1987) is a widely-used, 24-item scale that measures fear and avoidance of social and performance situations (e.g., returning goods to a store, talking with people you do not know very well; see Table 1). 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 self-report version of this scale (Heeren et al. 2012c). The internal reliability of LSAS was high in the current sample, with a Cronbach's alpha of .85 for the global scale score among individuals with SAD (.81 for the fear scale score and .79 for the avoidance scale score) and .86 among the healthy comparison participants (.80 for the fear scale score and .78 for the avoidance scale score). LSAS total score was significantly higher for the SAD group ($M = 77.75$, $SD = 15.43$) than for the healthy one [$M = 25.83$, $SD = 11.45$, $t(468) = 41.35$, $p < .00001$]. Moreover, each LSAS-item value was significantly higher for the SAD group than for the healthy comparison group. The means and standard deviations for each item as well as the effect sizes of the group difference are in the Supplementary Materials (Table S1).

Table 1 Items from the Liebowitz Social Anxiety Scale (LSAS) designating situations that are the focus of fear (nodes f1–f24) and avoidance (nodes a1–a24)

Numbers	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

Data Analytic Procedure

Network Estimation

We used a Graphical Gaussian Model (GGM) to estimate two networks, one for the SAD group and one for the healthy comparison group. For both networks, edges represent conditional independence relationships between nodes when controlling for the effects of all other nodes (Epskamp et al. 2017a). It is common to regularize GGMs via the graphical LASSO (Least Absolute Shrinkage and Selection Operator), which serves two primary functions (Friedman et al. 2008). First, it computes regularized partial correlations between pairs of nodes, thereby eliminating spurious associations (edges) attributable to the influence of other nodes in the network. Second, it shrinks trivially small associations to zero, thereby removing potentially "false positive" edges from the graph and producing a sparse graph comprising

[1] Given that the initial dataset only included 26 patients with a non-generalized form of SAD, the SAD group only included individuals with a generalized form.

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only the strongest edges. We used the R package *qgraph* (Epskamp et al. 2012) that automatically implements the graphical LASSO regularization in combination with an extended Bayesian Information Criterion (EBIC) model selection (Foygel and Drton 2011). In this approach, 100 different network models are estimated with different degrees of sparsity. Then, the model with the lowest EBIC value is selected, given a certain value of the hyperparameter gamma (γ); this procedure strikes a balance between including false-positive edges and removing true edges. The hyperparameter γ is usually set between zero and 0.5 (Epskamp et al. 2017a). As the value of γ nears 0.5, the EBIC will favor a simpler model that contains fewer edges. As the value of γ nears zero, the EBIC will favor a model with a greater number of edges. Following previous studies (e.g., Beard et al. 2016; Bernstein et al. 2017; McNally et al. 2017), we set γ to 0.5 to increase the likelihood that all edges are authentic.

Node Centrality

To quantify the importance of each node in the graphical LASSO network, we computed centrality indices (Opsahl et al. 2010). The *betweenness* centrality of a node equals the number of times that it lies on the shortest path length between any pair of other nodes. *Closeness* centrality indicates the average distance of a node from all other nodes in the network, and is computed as the inverse of the weighted sum of shortest path lengths to a given node from all other nodes in the network. Node *strength* is the sum of the weights of the edges attached to that node. Each index was calculated with the R package *qgraph* (Epskamp et al. 2012). Higher values reflect greater centrality in the network. We created centrality plots that depict these values as *z*-scores for ease of interpretation.

Community Detection

To examine whether the nodes cohere as a single system or as linked communities ("subnetworks"), we implemented the spin glass algorithm (Reichardt and Bornholdt 2006). This algorithm tests for communities—clusters of nodes—whereby the number and weighted strength of edges within a cluster exceeds the number and weighted strength of edges between clusters. To implement the algorithm, we used the *spinglass.community* function ($\gamma = 1$, start temperature = 1, stop temperature = .01, cooling factor = .99, spins = 48) of the R package *igraph* (Csardi and Nepusz 2006).

Network Comparison Test: SAD Group versus Healthy Group

Given that networks with strong between-symptom connections should be more pathogenic than similar networks with weaker connections (Borsboom 2017), our main focus was to compare the networks of the SAD and healthy groups in terms of *global network strength*, defined as the weighted sum of the absolute connections within a network (Barrat et al. 2004). Higher values reflect greater interconnectivity among nodes. We focused on the *global network strength* because previous network research in psychopathology has indicated that strength is the most stable and reliable centrality metric (e.g., Beard et al. 2016; Bernstein et al. 2017; McNally et al. 2017)—a prediction confirmed in the present study (see below). To test for differences in *global network strength* between the SAD and healthy comparison groups, we used the Network Comparison Test (NCT). The NCT is a two-tailed permutation test in which the difference between two groups is calculated repeatedly (10,000 times) for randomly regrouped individuals (van Borkulo et al. 2015). This produces a distribution of values under the null hypothesis (i.e., assuming equality between the groups) that enables one to test whether the observed difference in global network strength differs significantly ($p < .05$) between the SAD and the healthy comparison groups. To accomplish this, we used the R package *NCT* (van Borkulo et al. 2015).

Robustness of the Networks Estimates

We evaluated the robustness of our findings by using the R package *bootnet* (Epskamp et al. 2017a). We first estimated the accuracy of the edge weights by using 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 edge weights (i.e., regularized partial correlation coefficients between symptom pairs). This displays the sampling variation.

We then evaluated the stability of the centrality metrics by implementing a subset bootstrap procedure (Costenbader and Valente 2003). To do so, we repeatedly correlated centrality metrics of the original dataset with centrality metrics calculated from a subsample of participants missing via person-dropping bootstraps as implemented in *R* package *bootnet* (Epskamp et al. 2017a). If correlation values decline substantially as participants are removed, then this centrality index would be considered as less stable. We set the bootstraps to 1000. We calculated the centrality stability correlation coefficient (CS-coefficient) to quantify the effects of this person-dropping procedure. The CS-coefficient represents the maximum proportion of participants that can be dropped while maintaining 95% probability that the correlation between centrality metrics from the full data set and the subset data are at least .70. A minimum CS-coefficient of .25 is recommended for interpreting centrality indices (Epskamp et al. 2017a).

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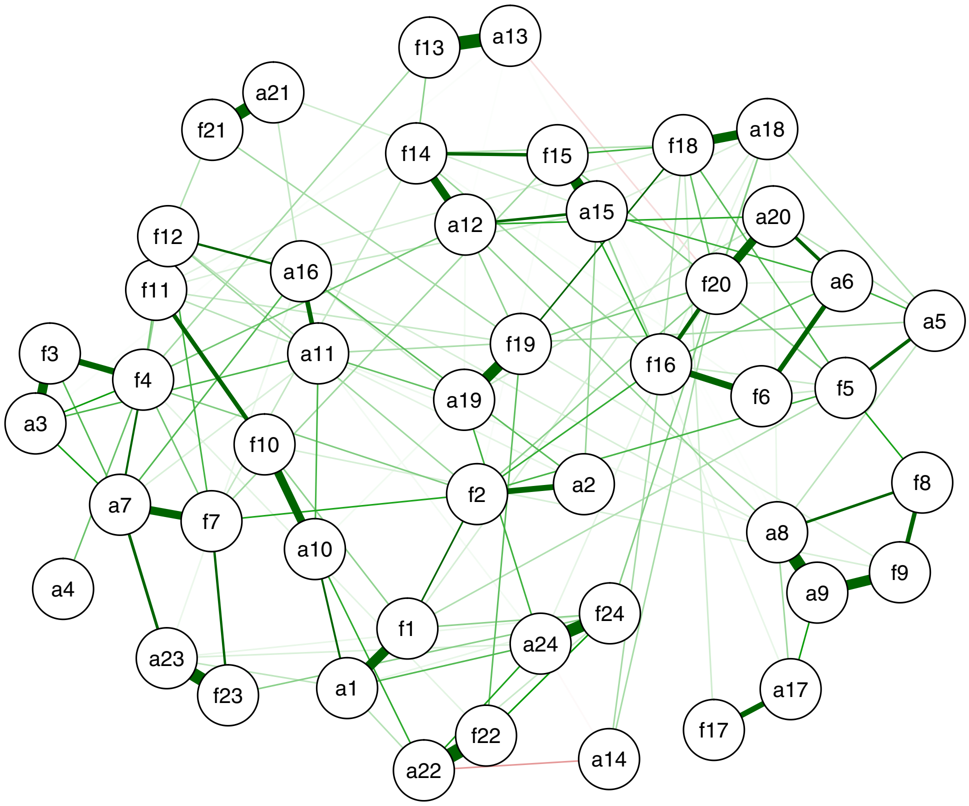

Fig. 1 Networks constructed via the graphical LASSO for people with social anxiety disorder. The thickness of an edge reflects the magnitude of the association (the thickest edge representing a value of .51). Green lines represent positive regularized partial correlations, whereas red lines represent negative regularized partial correlations. Each social situation from the LSAS is designated by a number ranging from 1 to 24 that is accompanied either by a letter "f" or "a", representing fear and avoidance, respectively. Social situations are listed in Table 1. (Color figure online)

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. Each social situation from the LSAS is designated by a number ranging from 1 to 24 that is accompanied either by a letter "f" or "a", representing fear and avoidance, respectively. Social situations are listed in Table 1.

Graphical LASSO Network

Figure 1 depicts the graphical LASSO network for individuals with SAD, which depicts 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. Green edges represent positive partial correlations, whereas red ones represent negative partial correlations.

Strong edges are apparent between nodes denoting fear and avoidance of similar social situations (a1 and f1, a2 and f2, etc.). Fear and avoidance of eye contact with strangers (f19 and a19) as well as fear of participating in small groups (f2) emerge as nodes strongly connected to the entire network.

Node Centrality

The *z*-scored centrality indices appear in Fig. 2. Fear of eye contact with strangers (f19), fear of speaking up at a meeting (f16), fear of participating in small groups (f2), avoidance of meeting strangers (a12), and avoidance of going to parties (a7) were among the most central nodes across the three indices. Fear of speaking up at a meeting (f16), fear of meeting strangers (f12), and avoidance of writing while being observed (a9) exhibited especially high levels of strength centrality. Avoidance of drinking with others in public places (a4), avoidance of entering a room when others are already seated (a14), and fear of taking a test (f17) exhibited consistently low centrality across indices.

Community Detection Analysis

The spin glass algorithm detected one community of nodes in the graphical LASSO network, indicating that it constitutes a single system without subnetworks.

Comparing the Networks of the SAD and Healthy Comparison Groups

The graphical LASSO network for the healthy comparison group appears in Fig. 3. As evident from Fig. 3, it has markedly fewer edges, and many of these are not especially

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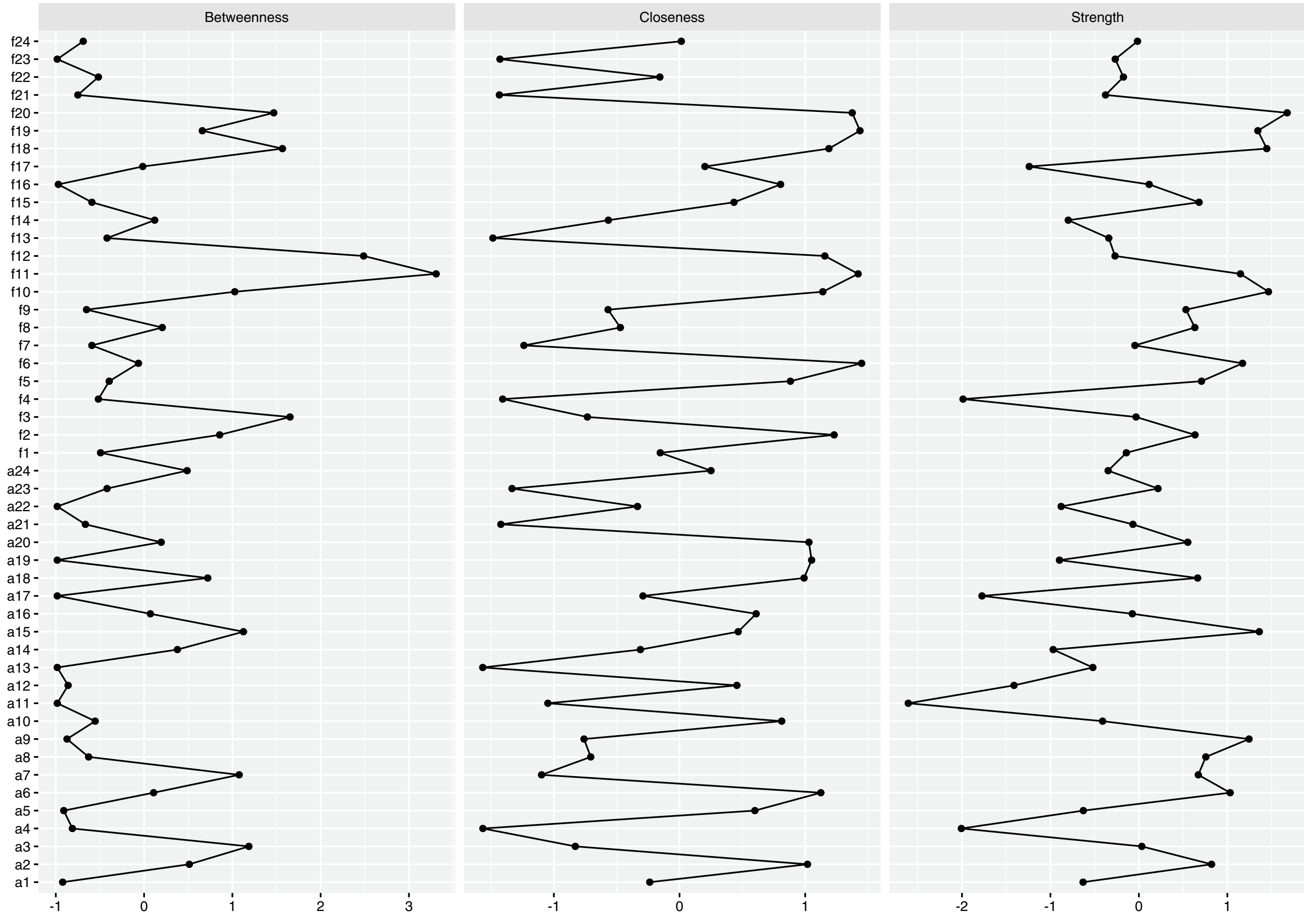

Fig. 2 Centrality plots for graphical LASSO network depicting the betweenness, closeness, and strength of each node (symptom) among individuals with social anxiety disorder (SAD). Each social situation from the LSAS is designated by a number ranging from 1 to 24 that is accompanied either by a letter “f” or “a”, representing fear and avoidance, respectively. Social situations are listed in Table 1

strong. Community detection analysis indicated that this network constitutes a single system without subnetworks. The centrality plot of the comparison group is in Fig. 4. Several nodes that were among the highest on strength centrality in the SAD network were also among the most central ones in the healthy comparison group (e.g., fear of meeting strangers; avoidance of writing while being observed).

The NCT revealed that the global edge strength was significantly greater in the SAD group (global strength = 26.9) than in the comparison group (global strength = 19.3; $p = .008$). Recent commentators have argued that differential variability (“restricted range”) in symptom severity ratings may distort conclusions about differences in node strength among severe clinical sample (e.g., Terluin et al. 2016). Because the SAD group did exhibit significantly more severe LSAS scores, we thus computed the correlation between the nodes strength and variance in LSAS ratings (McNally et al. 2017). Because the two-tailed Pearson correlation between the variance and strength centrality was nonsignificant, $r(46) = .07$, $p = .66$, differential variability across ratings does not pose a problem for interpreting a symptom’s strength centrality among the SAD group.

Robustness of the Networks Estimates

The bootstrapped CIs for the edges indicate that the edges are fairly stable and a number of edges exhibit values significantly greater than zero, providing an estimate of the certainty and precision of the edges for the SAD (Fig. S1) and the comparison group (Fig. S2). Results indicated that strength centrality was the most stable centrality index, whereas betweenness and closeness centrality were insufficiently stable and should be interpreted cautiously (Figs. S3, S4). For the SAD group, we found CS-coefficients of .05, .21, and .43 for betweenness, closeness, and strength centrality metrics, respectively. For the comparison network, the CS-coefficients for betweenness, closeness, and strength centrality metrics were .05, .13, and .19, respectively.

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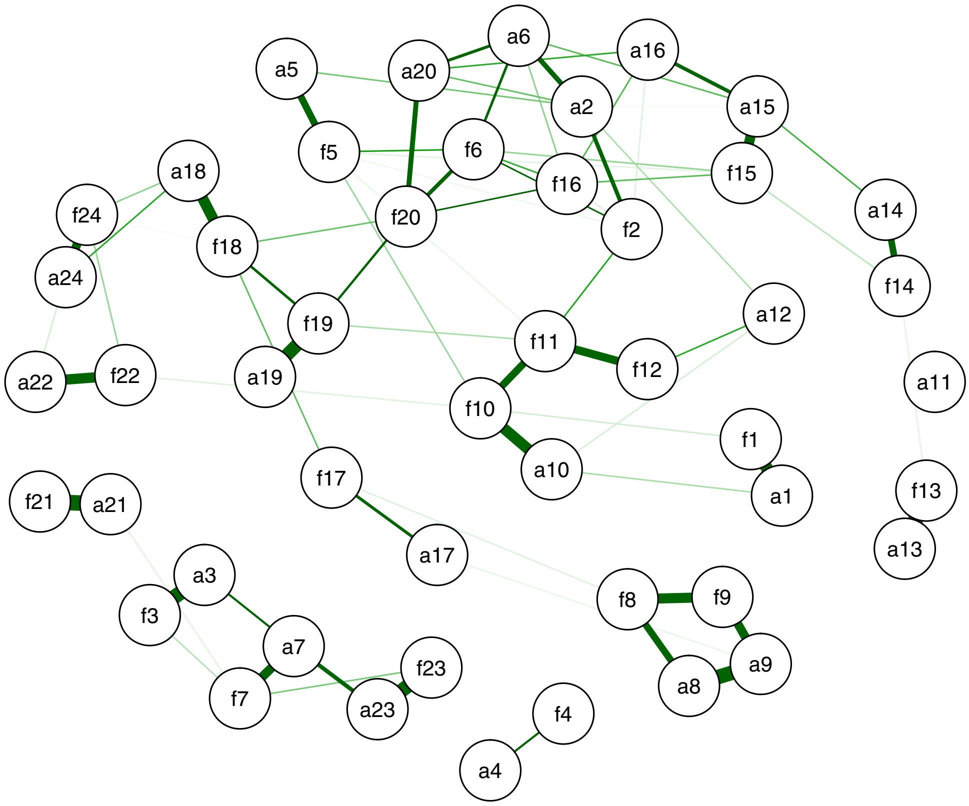

Fig. 3 Networks constructed via the graphical LASSO for the healthy comparison group. The thickness of an edge reflects the magnitude of the association (the thickest edge representing a value of .51). Green lines represent positive regularized partial correlations, whereas red lines represent negative regularized partial correlations. Each social situation from the LSAS is designated by a number ranging from 1 to 24 that is accompanied either by a letter "f" or "a", representing fear and avoidance, respectively. Social situations are listed in Table 1

Discussion

This study is the first to characterize and compare the network of fear and avoidance of a wide range of interpersonal and social evaluative situations among individuals with and without SAD. Perhaps the most striking result was the confirmation of our prediction that the network of individuals qualifying for the diagnosis of SAD was more strongly connected than that of people free of the diagnosis. Moreover, community detection analyses revealed that the networks of both groups functioned as a single system devoid of subnetworks ("communities"). Our findings suggest that the clinical and nonclinical networks do not differ vis-à-vis their community structure or centrality. Rather, our findings indicated the two networks differ only in terms of overall strength connectivity. Hence, for example, the chief difference between a person with SAD and a shy person without the disorder is that the probability of fearing (and avoiding) one situation more strongly predicts fearing (and avoiding) another situation with the former person than the latter one. It is not as if they fear and avoid entirely different situations.

Our results are consistent with the network theory of mental disorders that assumes that tightly interconnected networks with many strong edges between symptoms are more pathogenic than those with fewer and weaker connections (Borsboom 2017; Borsboom and Cramer 2013; Fried and Cramer 2017). According to this theory, as a result, activation of each node can easily spread to other ones, ultimately producing a cascade of node activation. Our results are also clearly in keeping with previous network studies reporting similar observation among other clinical populations (Pe et al. 2015; van Borkulo et al. 2015; Wigman et al. 2013). Thus, our findings imply that global network strength distinguishes fear and avoidance of social situations in people with SAD versus those without SAD. Although SAD and comparison networks differed in terms of overall strength connectivity, there were no striking differences in their most central nodes. For both groups, the most central nodes concerned situations involving interactions with unfamiliar people (e.g., fear of meeting strangers, fear of expressing a disagreement to disapproval to unfamiliar people, fear of looking at unfamiliar people eye-to-eye). This finding is consistent with developmental models of SAD that hold that uneasiness in social situations involving unfamiliar people figure prominently in the etiology and maintenance of SAD (e.g., Kagan 2014). Follow-up studies including longitudinal or intensive time-series data collection are thus needed to test whether fear of social situations involving unfamiliar people triggers other social fears and avoidance behaviors, and ultimately conspires to increase the overall network connectivity of the SAD network.

Our findings raise questions about how the networks of individuals with SAD become more tightly interconnected than those of healthy individuals. As only fear and avoidance

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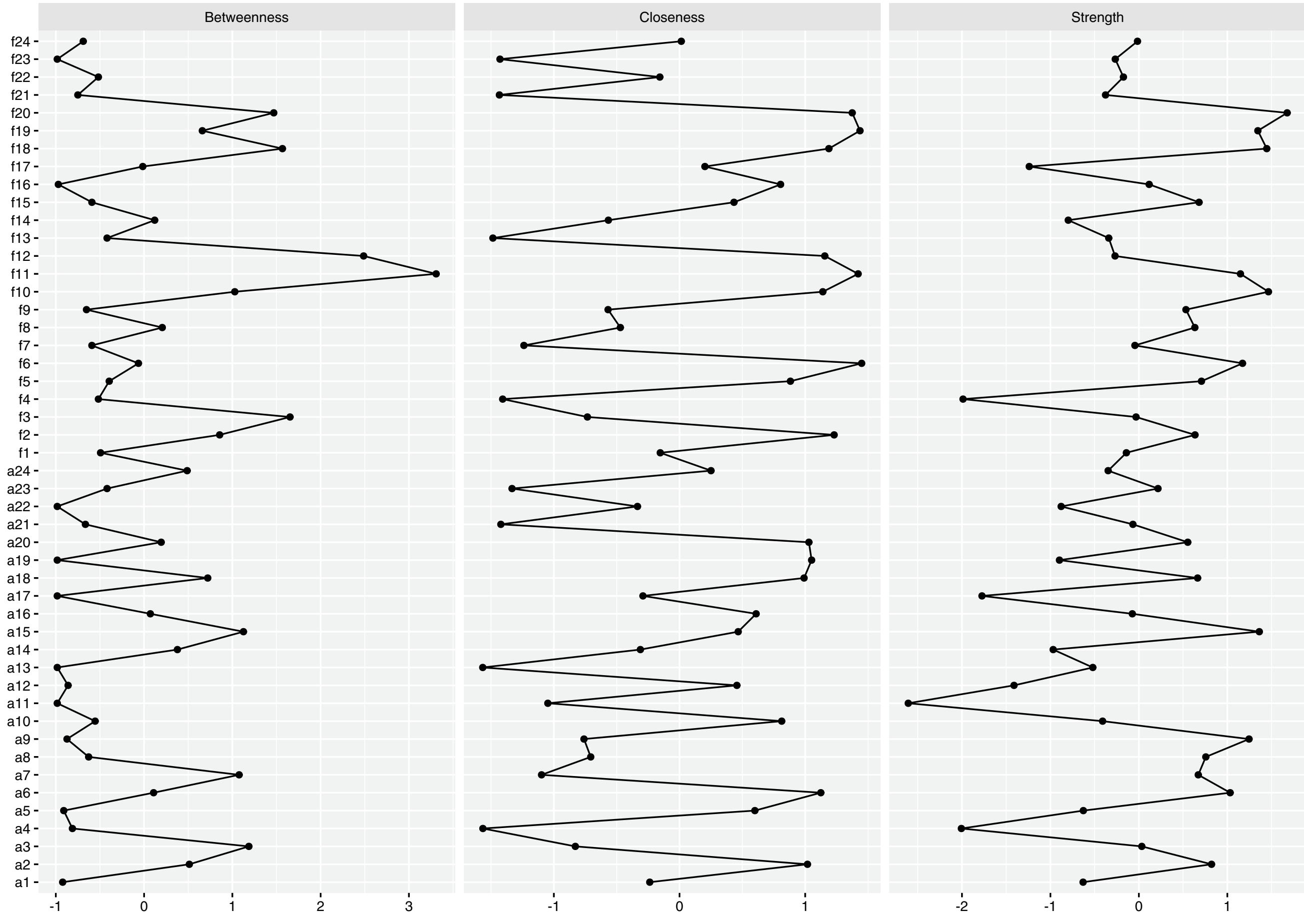

Fig. 4 Centrality plots for graphical LASSO network depicting the betweenness, closeness, and strength of each node (symptom) for the healthy comparison group. Each social situation from the LSAS is designated by a number ranging from 1 to 24 that is accompanied either by a letter "f" or "a", representing fear and avoidance, respectively. Social situations are listed in Table 1

of social situations were tested in the present study, one cannot rule out the possibility that the network is densely interconnected for threat-related stimuli. Prominent models of SAD have persuasively postulated multiple causal pathways and loops whereby variables increasingly reinforce the threat-value assigned to social evaluative stimuli, thereby fostering the development of secondary processes to further detect and avoid potential threat, culminating in a full-blown episode of SAD (e.g., Wong and Rapee 2016). Accordingly, the threat-value assigned to social evaluative stimuli may constitute a key process that triggers other ones, thereby propagating activation through the whole network. Notably, this hypothesis also dovetails with the notion of fear generalization in which aversive experiences with one stimulus or event renders related cues or situations as threatening (Dymond et al. 2015). Critical next steps will thus be to further explore this issue. Likewise, because theories of SAD posit that several other mechanisms (e.g., postevent processing) also figure in the etiology and maintenance of the disorder (Wong and Rapee 2016), these variables are suitable for inclusion in future studies (for a discussion, see Heeren and McNally 2016a, b; Jones et al. 2017). For example, Heeren and McNally (2016b) expanded network approaches beyond symptoms to include laboratory measures of attention processes and behaviors among individuals with SAD. An important direction will thus be to examine how the overall connectivity of the network denoting fear and avoidance vis-à-vis social situations is related to non-symptom processes implicated in the etiology and maintenance of SAD.

Our findings have several clinical 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; Valente 2012). Consequently, our findings point to the highly central nodes as key targets for prophylactic and therapeutic interventions. Notably, as most central nodes concerned situations

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involving interactions with unfamiliar people, therapists may wish to target such situations via exposure therapy. Likewise, because previous studies indicated that the overall network connectivity can predict the course of mental disorders, our findings set the scene for novel indicators of SAD prognosis. Although the purpose of this study has required the use of a cross-sectional approach to compare the overall network connectivity between groups, the assessment of the overall network connectivity as a prognostic factor would require graphical vector autoregressive modeling (VAR) of intensive time-series data from individual patients (e.g., Wichers et al. 2016). Moreover, VAR enables intraindividual network estimation for individual patients, an approach that does accommodate within-diagnosis heterogeneity in network structure (e.g., Epskamp et al. 2017b; van Borkulo et al. 2016).

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). Second, betweenness and closeness centrality were insufficiently stable and should be interpreted cautiously. This observation dovetails with previous network research in psychopathology reporting that strength centrality was the most stable centrality index (e.g., Beard et al. 2016; Bernstein et al. 2017; McNally et al. 2017). Here, despite the very low stability of betweenness and closeness, we opted to report these two metrics to be consistent with recent guidelines (Epskamp et al. 2017a). Yet, because closeness and betweenness have been more commonly used in other fields (e.g., social networks; Opsahl et al. 2010) and that network approaches are still so novel in psychopathology, it raises questions about how relevant those metrics are in our field (Borgatti 2005). Third, although strength centrality was the most stable centrality index, its CS-coefficient was less than ideal for the healthy comparison network. As such, one cannot guarantee that the centrality features of the healthy comparison network replicate in other healthy samples. Replications are thus clearly warranted. Fourth, to the best of our knowledge, uncertainty still abounds regarding the optimal way to determine the minimum sample size requisite for network computation and comparison (C. D. van Borkulo, personal communication, May 24, 2016). Accordingly, some edges may have been thicker with larger sample sizes. Likewise, the stability of the centrality metrics, especially the strength of the healthy comparison network, may have been greater if we had more participants than we did. Indeed, although sample sizes like those of the present study are usually not regarded as small for clinical studies, networks models estimate a very large number of parameters. Cross-sample validations in large samples are thus required to draw firm conclusions. Fifth, we only included patients with the generalized form of SAD. However, some individuals with SAD fear and avoid a more circumscribed set of situations (i.e. the performance-only subtype in DSM-5; APA 2013). We suspect that the networks of these of these individuals to be less highly interconnected than those of individuals with the generalized subtype. Sixth, we checked the DSM-IV criteria by using the MINI. This instrument only provides a cursory assessment. On the other hand, this instrument has very high correlations with in-depth structured interviews (e.g., *kappa* values ranging between .60 and .70 for SAD; Lecrubier et al. 1997; Sheehan et al. 1997). Likewise, some of the initial studies related to the current convenience sample included the assessment of a part of the interviews by a second independent assessor (e.g., Heeren et al. 2011, 2012b). Inter-agreement for the diagnosis was good, with *kappa* values ranging from .83 to .85. Seventh, although the internal reliability of the LSAS was high, all the variables of the present network analysis came from a single scale, with each variable assessed by a single item. Finally, we focused on individuals with SAD. However, many papers on network approaches to psychopathology have suggested that network methodologies offer a way to transcend current psychiatric nomenclatures (e.g., Curtiss and Klemaski 2016; Fried et al. 2016; Hofmann et al. 2016). Accordingly, future research could examine the network structure of fear and avoidance of social situations across different clinical populations.

In conclusion, these limitations notwithstanding, this study is the first to provide evidence that SAD can be conceptualized as a densely interconnected network of fear and avoidance of social situations. Our findings dovetail with the network theory of mental disorders that conceptualizes networks with strong between-symptom connections as more pathogenic than similar networks with weaker connections (Borsboom 2017). As prior network studies indicated that global network strength can predict prognosis of mental disorders, our findings pave the ways for novel indicators of SAD prognosis based on overall network connectivity.

Acknowledgements This work was supported by a Grant (F.R.S.-FNRS #FC78142) from the Belgian National Fund for Scientific Research; a postdoctoral fellowship from the Helaers Foundation for Medical Research; the Belgian Foundation for Vocation (« Vocatio »); and the WBI World Excellence Grant—BioWin: The Competitive Cluster in Health and Life Sciences of Wallonia [Grant Number: sub/2015/228106243177], all awarded to Alexandre Heeren. These foundations did not exert any editorial influence over this article.

Compliance with Ethical Standards

Conflict of Interest Alexandre Heeren and Richard J. McNally declare that they have no conflict of interest.

Informed Consent All procedures followed were in accordance with the ethical standards of the responsible committee on human experimentation (institutional), and conducted according to the Declaration of Helsinki. Informed consent was obtained from all individual subjects participating in the study.

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Animal Rights Statements No animal studies were carried out by the authors for this article.

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