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Deconstructing trait anxiety: a network perspective

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ABSTRACT

Background and objectives: For decades, the dominant paradigm in trait anxiety research has regarded the construct as signifying the underlying cause of the thoughts, feelings, and behaviors that supposedly reflect its presence. Recently, a network theory of personality has appeared. According to this perspective, trait anxiety is a formative construct emerging from interactions among its constitutive features (e.g., thought, feelings, behaviors); it is not a latent cause of these features.
Design: In this study, we characterized trait anxiety as a network system of interacting elements.
Methods: To do so, we estimated a graphical gaussian model via the computation of a regularized partial correlation network in an unselected sample ($N = 611$). We also implemented modularity-based community detection analysis to test whether the features of trait anxiety cohere as a single network system.
Results: We find that trait anxiety can indeed be conceptualized as a single, coherent network system of interacting elements.
Conclusions: This radically new approach to visualizing trait anxiety may offer an especially informative view of the interplay between its constitutive features. As prior research has implicated trait anxiety as a risk factor for the development of anxiety-related psychopathology, our findings also set the scene for novel research directions.

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The distinction between psychological states and traits has a long and occasionally controversial history. Some scholars have dismissed the distinction as arbitrary (Allen & Potkay, 1981), whereas others have defended it in diverse ways (e.g., Allport, 1966; Carr & Kingsbury, 1938; Zuckerman, 1960; Zuckerman, 1983). After conducting an illuminating analysis of these issues, Fridhandler (1986) concluded that psychological states and traits are best construed as *occurrent* and *dispositional* concepts, respectively (Ryle, 1949, p. 112). A psychological state designates an experience that occurs in time, often characterized by observable manifestations evident to others. Psychological states vary in duration depending on the presence of the provocative context. Hence, someone can suffer pain for seconds, hours, or days.

In contrast, a psychological trait is not a state that persists for a long time. Rather, it designates an unobservable, inferred disposition to experience certain psychological states (e.g., Allport, 1966; McCrae & Costa, 1995). Although a disposition is never observed, its if-then logical structure specifies how its realization is observable. For example, the disposition of fragility characterizes Waterford crystal; if struck, then it will shatter. Fragility has a material basis, evinced by the microstructure of crystal that renders it subject to shattering upon impact. Likewise, psychological traits designate

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propensities to experience certain psychological states under certain circumstances, and these propensities are presumably instantiated in neural tissue (e.g., Bishop & Forster, 2013; Mikheenko et al., 2015).

The distinction between state and trait anxiety is critical to anxiety research (e.g., Eysenck, 1983; Spielberger, Gorsuch, Vagg, & Jacobs, 1983). State anxiety denotes an emotional episode provoked by the anticipation of threat, whereas trait anxiety denotes the disposition to experience heightened state anxiety in response to threat. Accordingly, among people who encounter similar levels of threat in their lives, those high on trait anxiety are more likely to experience more frequent, intense, and prolonged episodes of state anxiety than are those low on trait anxiety. Yet in the absence of threat, individuals differing in their degree of trait anxiety should not differ in their levels of state anxiety. That is, to say that someone has high trait anxiety does not necessarily mean that they are continually experiencing episodes of state anxiety.

Spielberger et al.'s (1983) State-Trait Anxiety Inventory (STAI) is the most common instrument for measuring anxiety in its occurrent and dispositional forms. The state form (STAI-S) comprises 20 questions, such as "I am tense" and "I feel upset," answered on a 4-point scale ranging from 1 ("not at all") to 4 ("very much so"). Some items (e.g., "I feel satisfied") are reversed scored, and the questionnaire score is the sum of the 20 items. Respondents are told to respond in reference to how they are feeling at the moment. The trait form (STAI-T) comprises 20 questions, such as "I feel nervous and tense" and "I feel inadequate," answered on a scale ranging from 1 ("almost never") to 4 ("almost always"). Some items (e.g., "I am happy") are reverse scored, and the questionnaire score is the sum of the 20 items. Respondents are told to respond in reference to how they generally feel.

Spielberger et al. (1983, p. 1) discussed the concepts of state and trait anxiety in a manner consistent with Ryle's occurrent versus dispositional distinction, likening state and trait anxiety to kinetic and potential energy, respectively. However, they measure trait anxiety via a self-reported, ordinal measure of frequency of dispositional realization. Hence, in response to the item "I worry too much about something that doesn't really matter," individuals indicate 1 ("almost never"), 2 ("sometimes"), 3 ("often"), or 4 ("almost always"). They justify treating frequency of occurrence of state anxiety as a measure of the disposition of trait anxiety by reasoning that people high on trait anxiety are likely to interpret a wider range of situations as threatening than are those low on trait anxiety. Accordingly, the opportunities for realization of the disposition of trait anxiety will be especially frequent among those high on this trait.

As true of many constructs in personality psychology, trait anxiety is conceptualized as a dimension along which people vary. Hence, different levels of trait anxiety can be invoked to explain why people differ in the frequency, intensity, and duration of episodes of state anxiety. Additionally, Allport (1966) argued that a trait can also be viewed as a property within the person possessing causal powers to generate thoughts, emotions, and behaviors. Thus, one can also invoke trait anxiety to explain intraindividual consistency in the frequency, intensity, and duration of state anxiety episodes, whereas intraindividual variability must be attributable to other, situational variables. In this way, trait anxiety is similar to neuroticism, one of the Big Five personality dimensions deemed universal by many theorists (e.g., McCrae, Terracciano, & Members of the Personality Profiles of Cultures Project 2005). This view holds that constructs, such as neuroticism and trait anxiety, function as latent dimensional variables that act as the common cause of the emergence and covariance of their observable manifestations (e.g., nervousness, feeling inadequate; McCrae & Costa, 1995). As Borsboom and colleagues observed (e.g., Borsboom, 2008; Borsboom & Cramer, 2013; Schmittmann et al., 2013), this constitutes a *reflective model* of the relation between a latent dimension and its indicators (Bollen & Lennox, 1991; Edwards & Bagozzi, 2000) such that trait anxiety presumably causes episodes of state anxiety. Alternatively, a *formative model* conceptualizes a trait as a convenient term that merely summarizes indicators just as income, occupational status, and educational level constitute the measures that form the construct of socioeconomic status (SES); SES is not the cause of its indicators.

As an alternative to the latent dimensional perspective, Cramer et al. (2012a) advanced a network theory of personality. In their perspective, rather than regarding, say, neuroticism as the underlying, latent cause of the thoughts, feelings, and behaviors that supposedly reflect its presence, they attributed the emergence and covariance of its elements to direct interactions among them. That is, the trait of neuroticism is the emergent consequence of the interactions among its constitutive elements (Schmittmann et al., 2013). Similarly here, the relation of the constitutive elements of trait anxiety to trait anxiety *per se* is not one of cause and effect; it is *mereological* – part(s) to whole (Borsboom, 2008).

Interestingly, clinical psychologists know from experience that the different features of trait anxiety, as denoted in the STAI-T, interact with one another (e.g., the frequency of experiencing disturbing thoughts increases the frequency of feeling tense; the frequency of feeling like a failure increases the frequency of self-deprecation). Consistent with such intuitive observations, reconsidering trait anxiety from a network perspective can quantify and clarify how these features interact, causing and maintaining each other. Hence, rather than forbidding such interactions, as the latent variable perspective does (when statistically modeling the relationship between a hypothesized latent variable and a set of indicators, it is mathematically assumed that the observable indicators cannot be directly related—a phenomenon called the *assumption of local/conditional independence*; for further discussion and mathematical details, see Borsboom, 2008; Holland & Rosen, 1986; Junker & Sijtsma, 2001), the network approach embraces the notion that each feature may possess independent causal powers that influence other features (Borsboom & Cramer, 2013; Cramer, Waldorp, van der Maas, & Borsboom, 2010). Moreover, this point is of critical importance as features of trait anxiety may organize differently in people with the same "score" on the STAI-T scale.

Although the perspective of a network theory of personality, as advanced by Cramer et al. (2012a), has been applied to different personality dispositions (e.g., Costantini & Perugini, 2016; Watters, Taylor, Quilty, & Bagby, 2016) and mental disorders (for a comprehensive review, see Fried et al., 2017), whether the constitutive features of trait anxiety can also be conceptualized as intertwined nodes embedded within a network system of interacting elements remains unexplored. In the study reported here, we conducted network analyses of the items comprising Spielberger et al.'s (1983) trait anxiety scale. The networks comprised nodes (i.e., items from the STAI-T) and edges (i.e., associations between pairs of items; for a recent tutorial on network methodology, see Epskamp, Borsboom, & Fried, 2017).

We had several aims. First, we endeavored to elucidate the relations between pairs of elements to disclose the connections among features constitutive of trait anxiety. Second, we computed centrality metrics to determine the most influential elements in the networks. Third, an important property of a 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). To test whether the features of trait anxiety cohere as a single large network system or constitute distinct communities of nodes, we conducted modularity-based community detection procedures.

Method

Participants

The de-identified archival data came from adults who had enrolled in a research program about social self-beliefs (Heeren, Wong, Ceschi, Moulds, & Philippot, 2014). The sample consisted of 611 French-speaking individuals (410 women, 67.1%) from the general community. Within the sample, 57.4% (n = 351) were from Switzerland, 17.5% ($n = 107$) from France, 13.3% ($n = 81$) from Belgium, 11.1% (n = 68) from French-speaking African countries, and .7% ($n = 4$) from Canada (i.e., Quebec). Their ages ranged from 18 to 74 years ($M = 31.16$, $SD = 12.18$) and their education completed after primary school from 0 to 12 years ($M = 9.36$, $SD = 1.57$). The initial study was approved by the local ethical committee of and conducted according to the Declaration of Helsinki. Informed consent was obtained from all participants in the study.

Measures

Trait anxiety

The STAI-T (Form Y; Spielberger et al., 1983) is a 20-item scale that measures trait anxiety. We relied on Spielberger et al.'s (1983) measure because it is the most common instrument for measuring trait anxiety (e.g., Bados, Gomez-Benito, & Balaguer, 2010; Balsamo et al., 2013; Bishop & Forster, 2013). Participants rate each of the items on a 4-point Likert-type scale, (1, *Almost Never*; 2, *Sometimes*; 3, *Often*; 4, *Almost Always*). We used the validated French version of this scale (Bruchon-Schweitzer & Paulhan, 1993). Items denoting the absence of anxiety (e.g. I feel rested) were reverse scored. As a result, higher scores on any item correspond to more severe anxiety. The internal reliability of the STAI-T was high in the current sample, with a Cronbach's alpha of .87. Total scores ranged from 26 to 68 ($M = 45.03$, $SD = 7.98$).

Data analytic plan

Network estimation and visualization

We used the R package *qgraph* to compute and visualize the network (Epskamp, Cramer, Waldorp, Schmittmann, & Borsboom, 2012). Node placement was determined by Fruchterman and Reingold's (1991) algorithm; nodes that are nearer to the center of the graph have the strongest connections to other nodes.

We estimated a network via a Graphical Gaussian Model whereby edges signify conditional independence relationships among the nodes (i.e., partial correlations between pairs of nodes controlling for the influence of all other nodes; e.g., Epskamp, Borsboom, et al., 2017). A thicker edge denotes a larger association. Green lines represent positive partial correlations, whereas red lines represent negative partial correlations.

Because networks involving the estimation of many parameters are likely to produce some false-positive edges, we regularized our model by running the graphical LASSO (Least Absolute Shrinkage and Selection Operator; Friedman, Hastie, & Tibshirani, 2008). The aims of this regularization procedure are twofold. 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 *qgraph* (Epskamp et al., 2012) that automatically implements the graphical LASSO regularization in combination with extended Bayesian Information Criterion (EBIC) model selection (Foygel & Drton, 2011). This selection method includes a two-step procedure. First, 100 different network models with different degrees 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 and removing true edges. The hyperparameter γ is usually set between zero and 0.5 (Epskamp, Borsboom, et al., 2017). The closer one chooses a value of γ near 0.5, 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, Heeren, & McNally, 2017; McNally, Heeren, & Robinaugh, 2017), we opted to set γ to 0.5 to be confident that our edges are truly authentic (Epskamp, Borsboom, et al., 2017).

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 1,000 replacements, calculating edges to create a distribution of the edges weights (i.e., regularized partial correlation coefficients between symptom pairs) values. This displays the sampling variation. We accomplished this via the R package *bootnet* (Epskamp, Borsboom, et al., 2017).

Node importance

To quantify the importance of each node in the graphical LASSO network, we computed centrality indices (Freeman, 1978/1979; Opsahl, Agneessens, & Skvoretz, 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.

We then evaluated the stability of the centrality metrics by implementing a subset bootstrap procedure (Costenbader & 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 the R package *bootnet* (Epskamp, Borsboom, et al., 2017). If correlation values decline substantially as participants are removed, then this centrality index would be considered 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. Based on a simulation study (Epskamp, Borsboom, et al., 2017), a minimum CS-coefficient of .25 is recommended for interpreting centrality indices.

Modularity-based community detection

We examined whether the nodes cohere as a single system of mutually interacting element or as multiple interacting subnetworks ("communities"). Following previous studies (e.g., Birkeland & Heir, 2017; Heeren & McNally, 2016, 2018; Robinaugh, LeBlanc, Vuletich, & McNally, 2014), we implemented the spin glass algorithm (Reichardt & Bornholdt, 2006), a modularity-based community detection algorithm suitable for successfully uncovering the structure of relatively small networks (i.e., less than 1000 nodes) with negative edge values (e.g., Traag & Bruggeman, 2009; Yang, Algesheimer, & Tessone, 2016). We used the *spinglass.community* function ($\gamma = 1$, start temperature = 1, stop temperature = .01, cooling factor = .99, spins = 20) of the R package *igraph* (Csardi & Nepusz, 2006).

We also reported the *Q* value for estimating network modularity, as defined by Newman and Girvan (2004). The *Q* value is equal to the sum of the observed number of edges across all communities minus the expected number of edges if placed at random, with the distribution of degrees remaining the same (for a precise mathematical formulation, see Newman, 2006). The Q value is positive if the number of edges within groups exceeds the number expected on the basis of chance, indicating the presence of community structure (Newman, 2006). Modularity reflects the concentration of edges among nodes within modules compared with random distribution of links between all nodes regardless of modules.

Results

For each item, mean, standard deviation, skewness, and kurtosis are available in the supplementary materials (see Table S1).

Graphical LASSO network

Figure 1 depicts the resultant graphical LASSO network, which comprises regularized partial correlations and thereby limits spurious associations. Several features are immediately apparent. Being unable to get disappointments out of one's mind (i18) has strong connections with the presence of intrusive thoughts (i17), getting in state of tension when thinking about concerns and interests (i20), and wishing to be as happy as others seem to be (i4). Strong connections also appear between lack of self-confidence (i12) and the presence of intrusive thoughts (i17); between feeling like a failure (i5) and feeling unable to overcome difficulties (i8); and between the wish to be as happy as others seem to be (i4) and worrying about unimportant things (i9). Strong edges also abound among not making decisions easily (i14), not feeling secure (i13), not being content (i16),

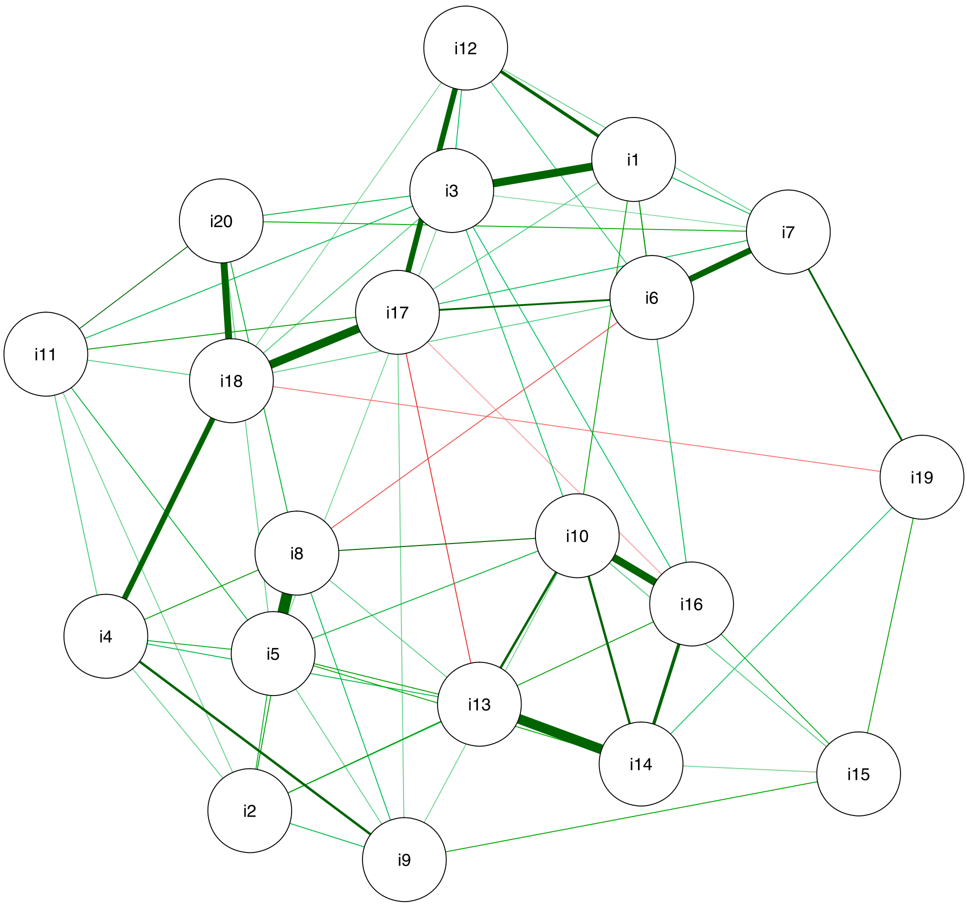

Figure 1. Network constructed via the graphical LASSO. The thickness of an edge reflects the magnitude of the association (the thickest edge representing a value of .29). Green lines represent positive regularized partial correlations, whereas red lines represent negative regularized partial correlations. i1 = "I feel pleasant" (reverse scored); i2 = "I feel nervous and restless"; i3 = "I feel satisfied with myself" (reverse scored); i4 = "I wish I could be as happy as other seems to be"; i5 = "I feel like a failure"; i6 = "I feel rested" (reverse scored); i7 = "I am calm, cool, and collected" (reverse scored); i8 = "I feel that difficulties are piling up so that I cannot overcome them"; i9 = "I worry too much over something that really doesn't matter"; i10 = "I am happy" (reverse scored); i11 = "I have disturbing thoughts"; i12 = "I lack self-confidence"; i13 = "I feel secure" (reverse scored); i14 = "I make decisions easily" (reverse scored); i15 = "I feel inadequate"; i16 = "I am content" (reverse scored); i17 = "Some unimportant thoughts runs through my mind and bothers me"; i18 = "I take disappointments so keenly that I can't put them out of my mind"; i19 = "I am a steady person" (reverse scored), i20 = "I get in a state of tension or turmoil as I think over my recent concerns and interests". For interpretation of the references to color in this figure legend, the reader is referred to the online version of this article.

and not being happy (i10). Finally, the presence of intrusive thoughts (i17) was strongly associated with not feeling rested (i6); and lack of self-confidence (i12) was associated with not feeling pleasant (i1).

The bootstrapped CIs for the edges indicate that the edges are fairly stable as a large number of them exhibit values significantly greater than zero (see Figure S1). Using a bootstrapped difference test (Epskamp, Borsboom, et al., 2017), we tested for significant differences between edge-weights (see Figure S2). Several of the edge-weights were significantly stronger than most others. Among these were the edge-weights between feeling like a failure (i5) and feeling unable to overcome difficulties (i8); being not able to get disappointments out of one's mind (i18) and the presence of intrusive thoughts (i17); making decisions easily (i14) and feeling secure (i13); and between the wish to be as happy as others seem to be (i4) and being unable to get disappointments out of one's mind (i18).

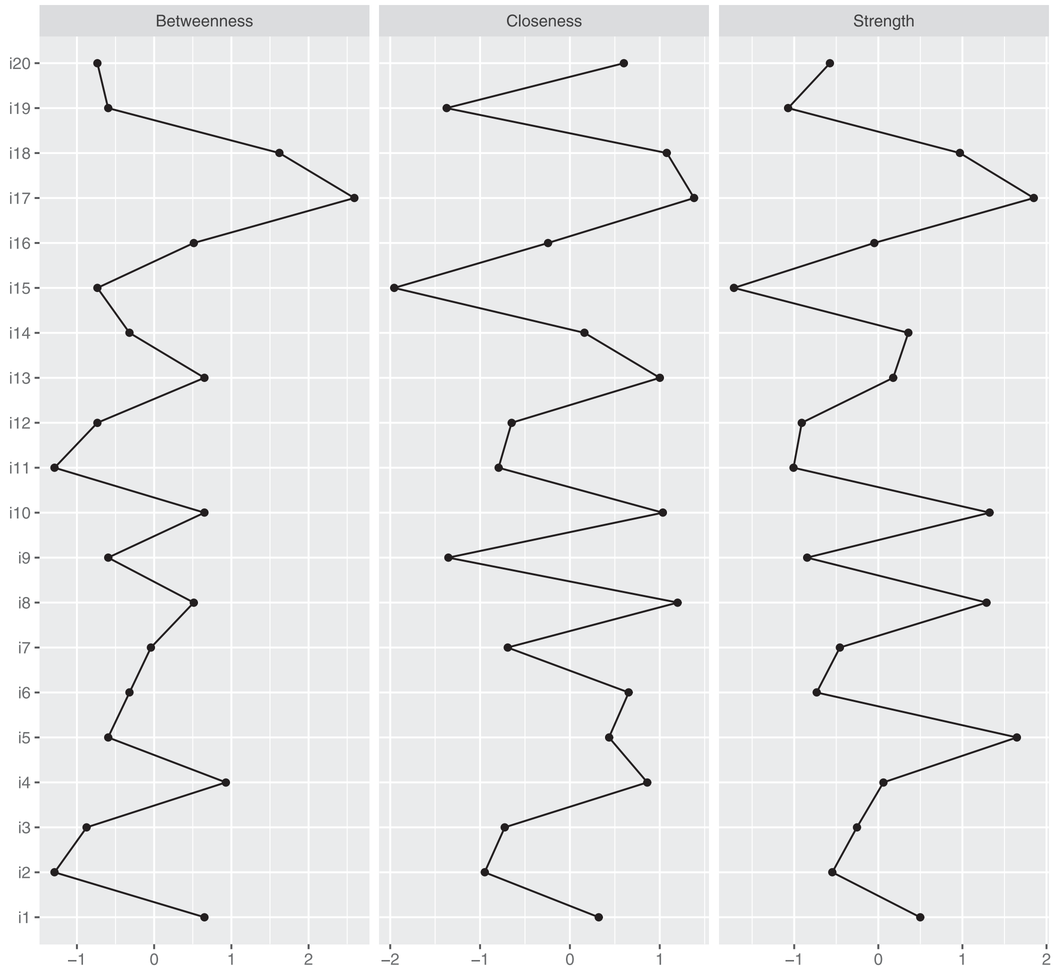

Figure 2. Centrality plots for graphical LASSO network depicting the betweenness, closeness, and strength of each node. i1 = "I feel pleasant" (reverse scored); i2 = "I feel nervous and restless"; i3 = "I feel satisfied with myself" (reverse scored); i4 = "I wish I could be as happy as other seems to be"; i5 = " I feel like a failure"; i6 = "I feel rested" (reverse scored); i7 = "I am calm, cool, and collected" (reverse scored); i8 = "I feel that difficulties are piling up so that I cannot overcome them"; i9 = "I worry too much over something that really doesn't matter"; i10 = " I am happy" (reverse scored); i11 = "I have disturbing thoughts"; i12 = "I lack self-confidence"; i13 = "I feel secure" (reverse scored); i14 = "I make decisions easily" (reverse scored); i15 = "I feel inadequate"; i16 = "I am content" (reverse scored); i17 = "Some unimportant thoughts runs through my mind and bothers me"; i18 = "I take disappointments so keenly that I can't put them out of my mind"; i19 = "I am a steady person" (reverse scored); i20 = "I get in a state of tension or turmoil as I think over my recent concerns and interests".

Centrality indices

These observations are further illuminated by the centrality indices (Figure 2). The node denoting the presence of intrusive thoughts (i17) showed the highest level of betweenness, closeness, and strength, implying that this node may constitute a central hub within the entire network. Being unable to get disappointments out of one's mind (i18) and not being happy (i10) also showed high levels of betweenness, closeness, and strength, Furthermore, feeling like a failure (i5) exhibited a high level of closeness and strength. Finally, the node denoting the wish to be as happy as others seem to be (i4) exhibited a high level of betweenness and closeness.

Consistent with previous studies (e.g., Beard et al., 2016; Bernstein et al., 2017; McNally et al., 2017), the person-dropping bootstrap procedure indicated that strength was the most stable centrality index, whereas betweenness and closeness centrality should be interpreted more cautiously (Figure S3). The CS-coefficients were .59 for strength, .37 for betweenness, and .10 for closeness. Using a bootstrapped difference test (Epskamp, Borsboom, et al., 2017), we also tested whether nodes significantly differ in node strength (see Figure 3). Because strength was the most stable centrality index, we focused only on node strength. A few nodes were significantly more central than most others. Among them, the presence of intrusive thoughts (i17) and being unable to get disappointments out of one's mind (i18) emerged as the two most central ones. Feeling like a failure (i5), not feeling pleasant (i1), and not being happy (i10) also ranked among the most central ones.

Modularity-based community detection

The spin glass algorithm detected one community of nodes in the graphical LASSO network. The modularity was extremely small with a value of $Q = 1.8^{-16}$, corroborating the absence of distinct community structures. Taken together, these results indicate that the network of trait anxiety coheres as a single network system.

Discussion

For decades, the dominant paradigm in trait anxiety research has regarded the construct as signifying the underlying cause of the thoughts, feelings, and behaviors that supposedly reflect its presence (for recent discussions, see McCrae, 2009; Mõttus & Allerhand, in press). Recently, a network theory of personality has arrived (Cramer et al., 2012a, 2012b; Mõttus & Allerhand, in press). According to this perspective, trait anxiety is a formative construct emerging from the interactions among its elements rather than being the latent cause of its observable manifestations (Cramer et al., 2012a, 2012b; Schmittmann et al., 2013). In this study, we examined trait anxiety from this network perspective. Consistent with the network theory of personality (e.g., Cramer et al., 2012a, 2012b), we find that the constitutive features of trait anxiety can indeed be conceptualized as a single, coherent network system of interacting elements.

Perhaps the most striking result was the observation that not all constitutive features were equally important in determining the network structure of trait anxiety. Indeed, when considering node centrality, the presence of intrusive thoughts and being unable to get disappointments out of one's mind emerged as the most central features of the trait anxiety network. Moreover, the edges weights associated to these two nodes were ranking among the significantly strongest ones. Interestingly, these findings align with research suggesting that difficulty disengaging attention from concern-related material and the presence of intrusive thoughts are two core transdiagnostic processes across anxiety and mood disorders (e.g., Armstrong & Olatunji, 2012; Clark & de Silva, 1985; Clark & Rhyno, 2005; De Raedt & Koster, 2010) that have been repeatedly associated with trait anxiety (e.g., Bados et al., 2010; Bieling, Antony, & Swinson, 1998).

Notably, network models hold that the pattern of relations among nodes is due to direct, perhaps bidirectional, causal pathways among variables (McNally, 2016; Valente, 2012). If so, then highly

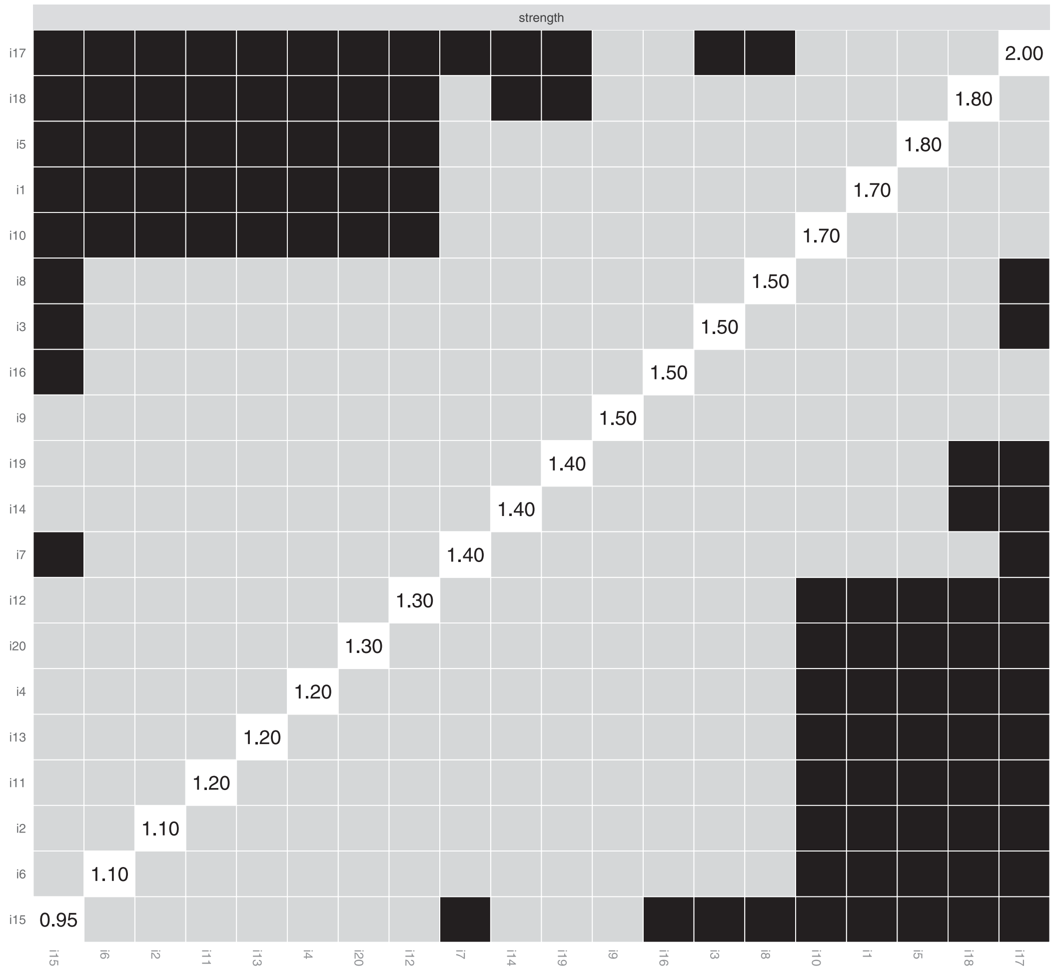

Figure 3. Bootstrapped difference tests between node strengths. Gray boxes indicate nodes that do not differ significantly from one another and black boxes represent nodes that do differ significantly from one another. White boxes show the value of the standardized node strength. i1 = "I feel pleasant" (reverse scored); i2 = "I feel nervous and restless"; i3 = "I feel satisfied with myself" (reverse scored); i4 = "I wish I could be as happy as other seems to be"; i5 = "I feel like a failure"; i6 = "I feel rested" (reverse scored); i7 = "I am calm, cool, and collected" (reverse scored); i8 = "I feel that difficulties are piling up so that I cannot overcome them"; i9 = "I worry too much over something that really doesn't matter"; i10 = "I am happy" (reverse scored); i11 = "I have disturbing thoughts"; i12 = "I lack self-confidence"; i13 = "I feel secure" (reverse scored); i14 = "I make decisions easily" (reverse scored); i15 = "I feel inadequate"; i16 = "I am content" (reverse scored); i17 = "Some unimportant thought runs through my mind and bothers me"; i18 = "I take disappointments so keenly that I can't put them out of my mind"; i19 = "I am a steady person" (reverse scored); i20 = "I get in a state of tension or turmoil as I think over my recent concerns and interests".

central nodes are thus especially important in determining the network structure and its dynamic flows (Costantini et al., 2015; Valente, 2012). Indeed, when a highly central node is activated (i.e., the personality characteristic is present), it is likely to activate others, both directly and indirectly (e.g., via paths through other nodes), thereby producing the activation of the entire network system. As numerous psychopathologists have argued that trait anxiety acts as a potential hidden "generator" that renders individuals more vulnerable to the development of anxiety and mood psychopathology (e.g., Bishop & Forster, 2013; Eysenck, Derakshan, Santos, & Calvo, 2007; Mathews & Mackintosh, 1998; Weems et al., 2007; for a review see, Gidron, 2013), future research may be most fruitful if it focuses on the causes, consequences, and malleability of highly central nodes rather than overall trait anxiety scores. The latter may obscure critical causal relationships. Clinically, this could mean that practitioners may wish to foster widespread and possibly even lasting change in the entire network by turning off such highly central nodes (Borsboom & Cramer, 2013; Costantini et al., 2015; Valente, 2012). On the other hand, nodes may be highly central by virtue of being strongly affected by other nodes while having only limited outgoing influence (Valente, 2012). As such, prior to initiate translational research, follow-up studies including intensive time-series data collection and experimental methods should ensure that those two nodes do conspire to trigger other ones.

Aside from node centrality, an important property of a complex network system is community structure. Indeed, many real-world networks, such as those involving routers and computers connected by physical links or neural networks within the brain contain communities or subnetworks (Han, Li, & Deng, 2016). With respect to trait anxiety, our community detection analyses revealed that features of trait anxiety did cohere as a single large network devoid of subnetworks ("communities"). In other words, it implies that the features of trait anxiety do not divide naturally into groups of nodes with dense connections internally and sparser connections between groups. This observation has strong practical implications. Indeed, in the presence of distinct subnetworks, it can be more important to identify central nodes within communities than to identify central nodes within an entire network.

Interestingly, our findings yield implications regarding the STAI-T. Researchers tally all items to achieve an unweighted sum score as an index of trait anxiety. However, items vary in terms of their centrality, and hence importance to the network (Fried & Nesse, 2015). In this way, prior network research has shown that weighting the presence of depressive symptoms based on their strength values improves the predictions regarding the onset of major depression (e.g., Boschloo, van Borkulo, Borsboom, & Schoevers, 2016). Accordingly, one could weight each item of the STAI-T by using its standardized strength value in the graphical LASSO network (e.g., Borsboom, 2008; Boschloo et al., 2016). Likewise, research on short-from development of the STAI-T might implement item-selection strategies based on the five features of trait anxiety—i.e., the presence of intrusive thoughts, being unable to get disappointment out one's mind, feeling like a failure, not feeling pleasant, and not being happy—that were significantly more central than most others.

Several issues require further examination. First, we assessed only trait anxiety, precluding strong inferences vis-à-vis the generalization of our findings to state anxiety. Future research is thus clearly needed to examine the potential network structure of state anxiety. Moreover, because individuals high on trait anxiety are more likely to experience more frequent, intense, and prolonged episodes of state anxiety than are those low on trait anxiety, the critical next step will thus be to explore how the trait and state anxiety can be linked from a network perspective. For example, does the network structure differ between individuals high on trait anxiety versus those low on trait anxiety (e.g., Heeren & McNally, 2018; van Borkulo et al., 2015)? Are certain trait anxiety nodes particularly influential in activating state anxiety? Likewise, whereas trait anxiety denotes the disposition to experience heightened state anxiety in response to threat, state anxiety denotes an emotional episode provoked by the anticipation of threat. As such, follow-up studies testing regarding how the presence (*versus* the absence) of threat in the immediate environment can affect the connections between trait and state anxiety networks.

Second, in line with previous trait approaches (e.g., Eysenck, 1983; McCrae et al., 2005), our data were collected at one point in time. As such, they do not reflect how features of trait anxiety trigger each other over time, and therefore may not be interpreted as such (Bos et al., 2017; Maurage, Heeren, & Pesenti, 2013). To best capture the within-person temporal dynamics of individual networks, one would need to apply computational methods that characterize the within- and between-person temporal dynamics of intensive intraindividual time-series data (Epskamp, van Borkulo, et al., 2017). Such an approach will also help to test whether some properties of the network system (e.g., overall network connectivity) act as a predisposition to experience state anxiety. Moreover, techniques from the study of sudden transitions in ecosystems (e.g., Hirota, Holmgren, Van Nes, & Scheffer, 2011) may also help identify when a network system is on the brink of tipping into a high-anxiety state or returning to a low-anxiety one (e.g., Cramer et al., 2016). Such techniques could be especially useful for exploring when the presence of threat triggers an episode of state anxiety, offering radically new perspective for the study of trait and state anxiety.

Third, following previous network studies in psychology (e.g., Costantini & Perugini, 2016; Fried et al., 2017; Heeren, Jones, & McNally, 2018; Watters et al., 2016), we included all items from the STAI-T scale in our network analyses. One may wonder about the potential redundancy among the items. However, a close inspection of the graphical LASSO network suggests that most of the items that have close content do not overlap in the network. For instance, the node denoting having disturbing thoughts is differently connected to other nodes than the one denoting experiencing unimportant thoughts. Likewise, the bootstrapped difference test revealed that most of the nodes denoting items that have seemingly similar content significantly differed in terms of strength centrality. As such, the aggregation of the items that have seemingly similar content would obscure their distinctive roles the in the network. On the other hand, all the variables came from a single scale, each assessed by a single item. Although the STAI-T is the most common instrument to assess trait anxiety, an important direction will thus be to examine the replicability of the present findings by using other distinct reliable measurement tools to assess each feature of trait anxiety (for example of network estimation including non-questionnaire measures, see Bernstein et al., 2017; Heeren & McNally, 2016; Jones, Heeren, & McNally, 2017).

Fourth, following previous network studies in psychology (e.g., Birkeland & Heir, 2017; Heeren & McNally, 2016, 2018; Robinaugh et al., 2014), we relied on the spin glass algorithm to uncover the community structure. Although research has shown that this algorithm is suitable for detecting communities in relatively small networks (i.e., less than 1000 nodes) with negative edge values (e.g., Traag & Bruggeman, 2009; Yang et al., 2016), this algorithm is a nondeterministic one (Reichardt & Bornholdt, 2006). In computational complexity theory, a nondeterministic algorithm is an algorithm that can exhibit different behaviors on different runs (Cormen, Leiserson, Rivest, & Stein, 2009; Floyd, 1967). Unlike a deterministic algorithm that produces only a single output for the same input, nondeterministic algorithms are ones that, at every possible step of a computational path, can allow for multiple continuations (Floyd, 1967). As such, although re-running the algorithm several times on different workstations produced equivalent outputs with our data, one cannot guarantee that this algorithm will produce the equivalent results across distinct workstations, operating systems, or samples. Replications are thus clearly warranted.

Finally, one may wonder about the potential correspondence between community structure and previous factor-analytic approaches to trait anxiety (for a recent overview, see Balsamo et al., 2013). However, although network and factor-analytic approaches both rely on correlation and covariance matrix (Costantini et al., 2015; Goekoop, Goekoop, & Scholte, 2012; Watters et al., 2016), there is a fundamental difference between the two approaches that renders impossible the direct comparison of their outputs. Indeed, the factor analytic approach identifies sets of items that form underlying latent variables through an algebraic analysis of variance; in contrast, network analysis relies on a geometrical analysis of an association matrix. Moreover, mathematical equivalence (interchangeability) between latent variable and network models do not imply ontological equivalence (cf. geocentric versus heliocentric models of the solar system; Galilei, 1615/2012). The former postulate an unobserved cause as the generator of covariance among elements of trait anxiety, whereas the latter do not. As such, although our results offer a radically new approach to visualizing trait anxiety as interacting system, it does not allow us to compare the present findings with traditional factor analytic approaches to trait anxiety (Goekoop et al., 2012; Watters et al., 2016). Current development in computational approaches enabling the combination of network and latent variable models via residual network modeling may help accomplish this aim in future research (Epskamp, Rhemtulla, & Borsboom, 2017).

In conclusion, these limitations notwithstanding, this study is the first to provide evidence that trait anxiety can be conceptualized as a network system. Our findings dovetail with those of Cramer et al. (2012a) who have shown how personality dimensions can be conceptualized in network terms. Given that extensive research has implicated trait anxiety as a risk factor for the development of anxiety disorders, our findings set the scene for novel research directions. As asserted by Allport (1946), "No doors should be closed in the study of personality."[1]

Note

1. We are indebted to Cramer et al. (2012b), who brought this quotation to our attention.

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