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The network structure of schizotypal personality traits in a population-based sample

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ABSTRACT

Outcomes for people with schizophrenia-spectrum disorders (SSDs) are generally poor, making it important to understand risk states and illness transition. The network approach, which conceptualizes psychopathology as a network of causally interacting symptoms, may hold promise in this regard. Here, we present a network analysis of schizotypal personality traits (i.e., schizophrenia-like cognitive, perceptual, affective, interpersonal, and behavioral anomalies that may index one's vulnerability for a SSD) using an international sample. We analyzed data from 9505 participants between the ages of 14–70 who completed the Schizotypal Personality Questionnaire-Brief on TestMyBrain.org. In line with other research, we find that the network of schizotypal traits is densely connected, characterized by three communities of items—interpersonal (I), disorganized (D), cognitive-perceptual (CP)—with I and D features exhibiting the greatest centrality (z-scored M strength: I = 0.56, D = 0.29, CP = −0.84; expected influence: I = 0.54, D = 0.33, CP = −0.84) and predictability (M I = 0.37, D = 0.43, CP = 0.23). Importantly, within our sample, we found the estimated network to be replicable (Network Comparison Test: network structure difference: $M = 0.304$, $p = .420$; global strength difference: $S = 0.904$, $p = .530$), and estimates of node centrality to be stable (correlation-stability coefficient = 0.75). Further, we find network differences between certain groups differing in levels of SSD risk as a function of age (network structure: difference $M = 0.562$, $p < .001$; global strength difference: $S = 3.483$, $p = .012$) and ethnic minority status (global strength difference: $S = 11.488$, $p = .004$). Together, these findings demonstrate the utility of using network approaches to understand SSD risk states as well as the replicability of network findings on schizotypal personality traits and related SSD risk concepts.

1. Introduction

Outcomes for people with schizophrenia-spectrum disorders (SSD) are generally poor, and worse than for other forms of psychiatric illness (Harrow, 2005; McGlashan, 1986). These outcomes include increased rates of social and occupational functioning impairments (Bellack et al., 2007; Skodol et al., 2002), physical morbidity (Leucht et al., 2007), and early mortality (Saha et al., 2007), among many others, which carry a significant burden on patients, families, and society (Knapp et al., 2004). Such associations highlight the importance of understanding the state of being at risk for SSDs and factors that contribute to illness onset.

One method for increasing our understanding of vulnerability for SSDs is by studying schizotypal personality traits, which may be understood as the phenotypic expression—among many other possible expressions—of schizotypy; a personality organization denoting one's latent liability for schizophrenia-spectrum pathology (Kwapil and Barrantes-Vidal, 2015; Lenzenweger, 2018, 2015, 2010; Meehl, 1962). In line with this view, though most individuals with schizotypal traits are not expected to develop a SSD, elevated reports of schizotypal personality traits is associated with elevated risk for SSDs, including schizotypal personality disorder and psychotic disorders (Debbane et al., 2015; Kwapil et al., 2013; Salokangas et al., 2013). Further, schizotypal personality traits have been shown to increase positive predictions of SSDs beyond clinical high risk criteria (Mason et al., 2004). Thus, a better understanding of schizotypal personality traits may yield a better understanding of the etiology and prevention of SSDs (Barrantes-Vidal et al., 2015).

Towards that goal, much prior work has aimed to elucidate the phenomenological nature and latent structure of schizotypal personality traits, which include schizophrenia-like cognitive, perceptual, affective, interpersonal, and behavioral anomalies. Much of this work has used the Schizotypal Personality Questionnaire (SPQ; Raine, 1991) and its brief form (SPQ-B; Raine and Benishay, 1995), which are self-report

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measures that assess a range of schizotypal traits described in the DSM-III-R criteria for schizotypal personality disorder. Using these questionnaires, studies have shown that schizotypal personality traits are multidimensional, and while there exists disagreement about their latent structure (e.g., Compton et al., 2009; Gross et al., 2014; Stefanis et al., 2004), studies generally support a three-factor model comprised of cognitive-perceptual (i.e., ideas of reference, magical thinking, perceptual aberration, paranoid ideation), interpersonal (i.e., social anxiety, lack of close friends, blunted affect, paranoid ideation), and disorganized (i.e., odd speech and behavior) dimensions (Fonseca-Pedrero et al., 2018b, 2018d; Raine and Benishay, 1995). In these models, schizotypy is understood to be a latent entity causing the associated cognitive-perceptual, interpersonal, and disorganized disturbances, and that the co-occurrence of these disturbances is the result of them having a common etiological cause.

Recently, researchers have offered an alternative conceptualization of psychopathology based on the interrelation between symptoms in causal networks. In this network model approach, symptoms do not *reflect* a latent common cause, such as a psychiatric illness, but instead, *comprise* the illness through their dynamic, causal interactions (Borsboom, 2017; Borsboom and Cramer, 2013; McNally, 2016). For example, in the case of a SSD, experiencing an auditory hallucination in the form of a voice saying "it's not safe" may lead to paranoia, odd safety-seeking behavior, and social withdrawal. Here, according to the network conceptualization, the disturbances are not independently caused by a SSD, but by each other in a mutually reinforcing way. Thus, in contrast to traditional methods of assessing the structure of psychopathology, network analysis provides a way for examining how individual and clusters of symptoms interact, and how these potentially causal interactions give rise to psychopathological states. As such, network analysis allows for the identification of those experiences or symptoms that are most central (i.e., important) in a psychopathological state. This information could be used to devise more effective methods for assessing SSD risk, as well as provide crucial information regarding the etiology and pathophysiology of SSD risk states, which may in turn aid in illness prevention and treatment.

In line with these ideas, network analysis has provided novel insights into the relative importance of and causal interaction between symptoms associated with many forms of psychopathology (see McNally, 2016 for a review), including schizotypal personality traits (Fonseca-Pedrero et al., 2018c), other manifestations of schizotypy (Christensen et al., 2018a, 2018b), and related SSD-risk concepts (Murphy et al., 2018; Wigman et al., 2017). Most relevant to the current study, analyzing responses on the SPQ from a massive international sample ($N = 27{,}001$), Fonseca-Pedrero et al. (2018c) found that the schizotypal personality trait network was strongly interconnected, comprised of three clusters of items—Cognitive-Perceptual, Interpersonal, Disorganized—that corresponded to the SPQ's original factor structure, with items indexing behavioral eccentricity, suspiciousness, and interpersonal dysfunction exhibiting the greatest importance in the network. Further, they found patterns of node importance and connectivity suggestive of possible network differences between North American and Chinese participants. Similar three cluster structures have been found in other network analyses using other measures of schizotypy (Christensen et al., 2018a).

Recent research has questioned the replicability of network analysis findings (Forbes et al., 2017) generating much debate in the field (Borsboom et al., 2017; Guloksuz et al., 2017) as well as robust statistical methods that allow for a better assessment of reliability (Epskamp et al., 2018a). Given the growing interest in network models and their potential to inform the study of SSD risk assessment, etiology, and prevention, the importance of evaluating the reliability of findings cannot be overstated. Thus, in this study, we analyzed the network structure of schizotypal personality traits in a large population-based sample, including a more geographically diverse sample of a wider age-range, assessed on a different measure of schizotypy than in the one prior study of the schizotypal personality trait network (Fonseca-Pedrero et al., 2018c). This allowed us to evaluate the replicability of the schizotypal personality trait network in addition to expanding on the extant literature by providing novel tests evaluating network differences between groups of individuals with different levels of SSD risk.

Our analysis followed that of other network analyses (e.g., Fonseca-Pedrero et al., 2018c). Specifically, we estimated an undirected network (i.e., we did not model the direction of causality) comprised of nodes—representing schizotypal personality traits—and edges—representing trait associations that hold even after controlling for the effect of all other nodes. To further elucidate the schizotypal personality trait network structure, we performed two methods for identifying highly connected clusters (i.e., communities) of nodes. To evaluate the relative importance (i.e., centrality) of the nodes, we provide two standard metrics: strength and expected influence, which represent how well a node is connected to other nodes. We also evaluate node predictability or the extent to which a given node can be predicted by all other nodes in the network. To evaluate network differences in groups of people differing in SSD risk, we used a novel permutation test described in van Borkulo et al. (2017). Finally, towards assessing the accuracy and within-sample reliability of the network structure and node centrality, we used a family of bootstrapping methods described in Epskamp et al. (2018a).

Based on the findings of Fonseca-Pedrero et al. (2018c) and other network analyses of related SSD-risk constructs (Christensen et al., 2018a, 2018b; Murphy et al., 2018; Wigman et al., 2017), we expected to find the following: (1) three communities of nodes corresponding to the SPQ-B's factor structure (i.e., cognitive-perceptual, interpersonal, disorganized); (2) higher centrality and predictability for interpersonal and disorganized nodes; and (3) network differences between groups of people differing in levels of SSD risk.

2. Methods

2.1. Participants

Participants were an international sample, representing over 140 different countries (see Supplemental materials), of 9505 Internet-users between 14 and 70 years old who visited the non-profit citizen-science research website TestMyBrain.org between March 2012–March 2018 (Table 1). The majority of our sample was female, completed some college or more, non-Hispanic and White/European, and from predominantly White/European, English-speaking countries (i.e., United States of America, Canada, Great Britain, Ireland, Australia, New Zealand). Participants completed the SPQ-B as part of a battery of other assessments unrelated to the current study, and voluntarily provided demographic information after completing the assessments. Participants who reported technical difficulty while completing the questionnaire or reported completing the questionnaire more than once were excluded from analysis. The study and consent procedure was approved by the Harvard University Committee on the Use of Human Subjects in Research.

2.2. Schizotypal personality traits

Schizotypal personality traits were assessed with the Schizotypal Personality Questionnaire-Brief (SPQ-B; Raine and Benishay, 1995), a 22-item *Yes*/*No* self-report questionnaire that assesses the presence of cognitive-perceptual (8 items; e.g., ideas of reference, mind-reading, perceptual aberrations), interpersonal (8 items; e.g., social guardedness, diminished emotional expression), and disorganized (6 items; e.g., odd speech and behavior) aspects of schizotypal personality, based on DSM-III-R criteria for schizotypal personality disorder (Raine, 1991). The SPQ-B has been validated for use with adolescents as young as 14 years old (Fonseca-Pedrero et al., 2009) and has been used with older adults (Fonseca-Pedrero et al., 2018a). The SPQ-B's psychometric properties

Table 1
Participant characteristics.

Factor	Level	*n* (%)	*M* (*SD*) [min–max]
Age		9505	33.1 (13.6) [14–70]
Gender	Male	3867 (40.7)	
	Female	5584 (58.8)	
	Unknown/not reported	54 (0.6)	
Country	Predominantly English-speaking and White/European ethnicity[a]	6394 (67.3)	
	Non-predominantly English-speaking and White/European ethnicity	3111 (32.7)	
Ethnicity	Non-Hispanic	4300 (45.2)	
	Hispanic	320 (3.4)	
	Declined/unsure/not reported	4885 (51.4)	
Race	American Indian/Alaskan native	73 (0.8)	
	Asian	1198 (12.6)	
	Asia not specified[b]	195 (2.1)	
	East Asian[b]	414 (4.4)	
	Middle Eastern[b]	165 (1.7)	
	South Asian[b]	424 (4.5)	
	African/Black	295 (3.1)	
	Native Hawaiian/Pacific Islander	16 (0.2)	
	European/White	6331 (66.6)	
	Multiracial	524 (5.5)	
	Biracial[b]	397 (4.2)	
	More than two[b]	127 (1.3)	
	Declined/not reported	1068 (11.2)	
Education	Middle school	133 (1.4)	
	High school	1469 (15.5)	
	Some college	2334 (24.6)	
	College	2303 (24.2)	
	Graduate school	2469 (26.0)	
	Other/declined/not reported	797 (8.4)	

[a] This category included the United States of America, Canada, Great Britain, Ireland, Australia, and New Zealand.
[b] Indicates that group is a subsample of larger category (i.e., Asian race or Multiracial).

have been well-studied and are considered adequate (Fonseca-Pedrero et al., 2018b).

Responses were required for all items of the SPQ-B so there were no instances of missing SPQ-B data. Subscale scores, internal consistency, and subscale correlations are depicted in Table 2. See Supplemental materials for item-level descriptive statistics.

2.3. Network analysis

2.3.1. Network structure

To estimate the schizotypal personality trait network, we used the Ising model—a type of pairwise Markov random field model (PMRF) appropriate for binary data (van Borkulo et al., 2015). PMRF networks are composed of nodes, which represent variables (i.e., an item on the SPQ-B), and edges, which represent undirected conditional relationships between two variables. Edges are *undirected* in that they represent an association between nodes without making assumptions about the direction of causality, and *conditional* in that the association holds after controlling for the effect of all other variables in the network. In this way, the network can be interpreted similarly to a network of partial correlations with binary items. Since the data are cross-sectional, causal connections between variables cannot be assumed. However, because associations between variables cannot be explained away by the other variables in the network, they may provide clues regarding causality. Edges in the network are weighted, depicting the magnitude of association between variables with thicker edges representing stronger relations, and signed, depicting whether the relation between variables was positive or negative. In order to deal with the large number of pairwise associations estimated in the network, we implemented a form of regularization known as least absolute shrinkage and selection operator (LASSO), which reduces many of the associations to zero, limiting the number of small/spurious edges, and in turn, producing a sparser and more interpretable network (van Borkulo et al., 2015).

To aid in the visual interpretation of the network, we performed two methods of data-driven item-clustering (see Fried, 2016). First, given the mathematical equivalence between network and latent variable models (Kruis and Maris, 2016), we performed exploratory factor analysis identifying factors based on a Scree plot and evaluating varimax-rotated factor loadings. Second, we used the spinglass algorithm (Reichardt and Bornholdt, 2006). Because the spinglass algorithm is non-deterministic, we ran the algorithm 1000 times. The median number of communities identified ($N = 3$), along with the grouping of items on iterations when three communities were identified, were the same as those identified in the exploratory factor analysis. Thus, we report and visualize this three community structure. Networks are visualized with the R (R Core Team, 2017) package *bootnet* (Epskamp et al., 2018a) using the Fruchterman-Reingold algorithm (Fruchterman and Reingold, 1991) where more strongly-related nodes are placed closer together.

We evaluated the replicability of the network by splitting the dataset in half, re-estimating the network in each half of the dataset, and then performing a permutation-based network comparison test (NCT; van

Table 2
SPQ-B descriptives and subscale correlations.

Scale	*M* (*SD*)	Standardized α	2.[a]	3.[a]
1. Cognitive-Perceptual	3.32 (2.09)	0.66	0.37 [0.35, 0.39]	0.43 [0.42, 0.45]
2. Interpersonal	4.17 (2.45)	0.78		0.47 [0.46, 0.49]
3. Disorganized	2.49 (1.87)	0.71		
Total	9.95 (4.96)	0.82		

[a] Column depicts subscale correlations (Pearson *r* values and 95% CI in brackets).

Borkulo et al., 2017) with 2000 samples to derive reference distributions for test statistics related to two hypotheses: (1) network structure invariance, which concerns the similarity of edge weight distributions, and (2) network global strength invariance, which concerns the overall level of connectivity. We report the following test statistics which speak to the aforementioned hypotheses, respectively: *M*, which is the maximum difference in edge weights, and *S*, which is the difference in global strength. Lack of statistically significant differences ($p > .05$) between the networks suggests that the network is invariant, and thus replicable with respect to edge weight distribution and overall connectivity. The NCT was implemented in the R package *NetworkComparisonTest* (van Borkulo et al., 2017).

2.3.2. Network centrality and predictability

In addition to the structure of the network and relation among the nodes, nodes can be characterized by their importance or *centrality*. We compute and report two related measures of node centrality: *strength* and *expected influence* (EI). Strength centrality is the sum of the absolute edge weights connected to that node and represents how well a node is directly connected to all other nodes. A node high in strength is likely to activate many other nodes, and from a clinical standpoint, may be a good target for intervention (Fried et al., 2017). Because strength is computed based on the absolute magnitude of edge weights, the presence of negative edge weights may distort a node's actual influence on the rest of the network. For example, two nodes with equal strength but differing number of negative edge weights may have the opposite effect on the network. EI deals with this issue by retaining the sign of the edge weight in calculating strength, effectively taking into account positive and negative edge weights (Robinaugh et al., 2016). Others have suggested that node strength and EI may be particularly relevant for the study of psychopathology (McNally, 2016; Robinaugh et al., 2016) and have found that at least node strength exhibit greater stability compared to other centrality estimates (Epskamp et al., 2018a). Nonetheless, for thoroughness, we report two other metrics of centrality—*closeness* and *betweenness*—in the Supplemental materials. Centrality metrics were *z*-scored and calculated with the R package *qgraph* (Epskamp et al., 2012).

We implemented a non-parametric bootstrap procedure with 2000 bootstrap samples to generate 95% confidence intervals (CI) around edge weights and node strength to assess the reliability of differences in edge weights and node strength. We additionally assessed the stability of the centrality estimates through a *case-dropping subset bootstrap* routine, in which centrality measures were repeatedly calculated from subsets of the data with an increasing proportion of observations removed (Epskamp et al., 2018a). Stability is formally assessed with the *correlation stability coefficient* (*CS*-coefficient), which represents the number of observations that can be dropped from the full dataset such that that correlation between centrality estimates from the full dataset and subsetted dataset is 0.7 or higher at 95% probability (Epskamp et al., 2018a). Higher scores denote that a greater number of observations can be dropped without significant changes in the magnitude of centrality estimates. These bootstrapping procedures were conducted using *bootnet* (Epskamp et al., 2018a).

A node high in strength and EI may be strongly connected to many other nodes. However, these other nodes may explain only a small amount of variance in the high strength/expected influence node. Thus, we additionally provide the *predictability* of nodes, which measures on an absolute scale how well a given node can be predicted by all other nodes in the network (Haslbeck and Fried, 2017). Predictability speaks to controllability in that highly predictable nodes are ones that can be controlled by other nodes in the network while low predictable nodes are ones that are largely determined by factors outside of the network (Haslbeck and Waldorp, 2018). As such, predictability may too provide an important metric of clinical relevance in that a highly predictable node is likely to be impacted by changes to connecting nodes (Haslbeck and Fried, 2017). Because edge direction is unknown and may be directed *away* from predictable nodes, predictability should be interpreted as an upper bound estimate (Haslbeck and Waldorp, 2018). We used the R package *mgm* (Haslbeck and Waldorp, 2018) to measure predictability, which was calculated as normalized accuracy (i.e., the accuracy with which a given node can be predicted by other nodes in the network beyond the marginal probability).

2.3.3. Network comparisons between levels of SSD risk

Risk for SSDs has been shown to vary as a function of demographic and sociocultural variables including age, gender, and ethnicity/race (Castillejos et al., 2018; van der Werf et al., 2014). Network characteristics may too vary as a function of SSD risk. To investigate this possibility, we used the NCT to evaluate differences in network structure and overall network connectivity (i.e., global strength) between the following subgroups: (1) peak risk age range (i.e., 14–29; $n = 4712$) versus past peak risk age range (i.e., 30–70; $n = 4793$); (2) males ($n = 3867$) versus females ($n = 5584$); and (3) ethnic/racial minority status (i.e., participants from predominantly English-speaking, White/European race countries—United States of America, Canada, Great Britain, Ireland, Australia, New Zealand—reporting Hispanic ethnicity or non-White/European race, excluding participants reporting more than one ethnicity/race; $n = 900$) and non-ethnic/racial minorities (i.e., participants from those same countries reporting non-Hispanic ethnicity and White/European race; $n = 1841$). We set alpha equal to 0.017 to account for the three NCTs. In the case of a significant difference in network structure, we evaluated which specific edges were different between the groups using a Bonferroni-Holm correction for multiple tests (van Borkulo et al., 2017). Group differences in SPQ-B scores are provided in the Supplemental materials.

2.3.4. Data availability

Data from this study are available on the Open Science Framework at https://osf.io/stw2g.

3. Results

3.1. Network structure

The schizotypal personality trait network is depicted in Fig. 1. Three communities of items were identified that correspond almost exactly to the SPQ-B's original three factor structure with two exceptions: two items within the disorganized subscale—*vague and elusive during conversation* (D3) and *difficulty communicating clearly* (D6)—were included as part of the Interpersonal community. Out of 231 possible edges, 150 (64.9%) were non-zero, of which 9 (3.9%) were negative. All negative edges were between items of different communities, and 6 (66.7%) were between Cognitive-Perceptual and Interpersonal community items. Inspection of the bootstrapped edge weight differences (Fig. 2) suggests that these negative edge weights were reliably smaller in absolute magnitude ($M = 0.12$, $SD = 0.03$) than the positive edge weights ($M = 0.33$, $SD = 0.33$). On average, within-community edge weights (i.e., associations between items within the same community) were highest for the Disorganized community (Table 3), followed by the Interpersonal community, and the Cognitive-Perceptual community. Outside-community edge weights (i.e., associations between items in different communities) were similar (Table 1). Bootstrapped edge weight differences suggested that the strongest edge weights—I3-I7, D2-D5, D1-D2, I3-I5, I4-I8, CP1-CP6—were reliably stronger than most other edge weights (Fig. 2).

Regarding replicability, the two networks derived from splitting the dataset were strongly correlated in terms of edge weights ($\rho = 0.86$, 95% CI [0.82, 0.89]), strength ($\rho = 0.84$, 95% CI [0.65, 0.93]), and EI ($\rho = 0.93$, 95% CI [0.83, 0.97]). The NCT revealed no difference in network structure ($M = 0.304$, $p = .420$) or global strength ($S = 0.904$, $p = .530$) between the two networks suggesting that the estimated network is replicable within the sample.

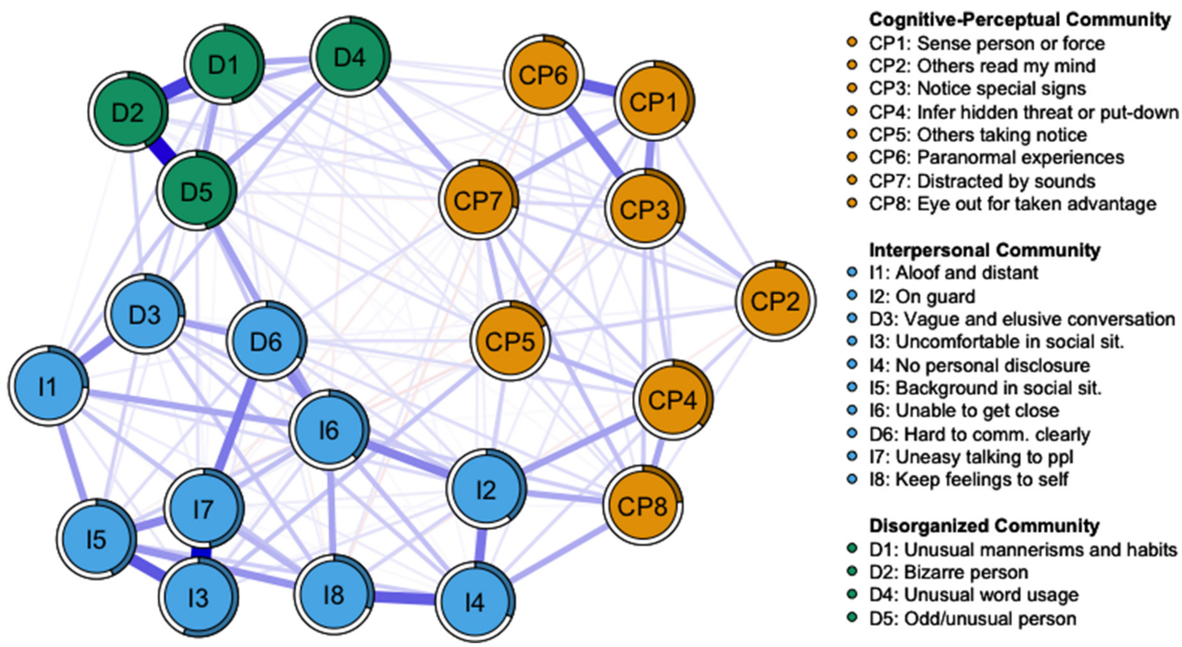

Fig. 1. Each item is represented by a node in the network named and numbered by the subscale (I = interpersonal, D = disorganized, CP = cognitive-perceptual) and colored by the community. Lines between nodes represent edges weights, with thicker lines depicting larger edges weights. Positive edge weights are depicted in blue; negative edge weights are depicted in red. The colored circle around each node depicts predictability with fuller circles meaning that the node is more predictable. See Supplemental material for additional item information.

3.2. Network centrality and predictability

Node centrality is depicted in Fig. 3. Node strength and EI were strongly correlated (ρ = 0.96, 95% CI [0.90, 0.98]). The most central nodes ($zs \geq 1$) were *odd and unusual person* (D5), *unable to get close to others* (I6), *uneasy talking to people* (I7), and *being on guard* (I2). On average, Interpersonal community nodes had the highest strength (Table 3) and EI, followed by Disorganized community nodes, and Cognitive-Perceptual community nodes exhibiting the least amount of centrality. In fact, all Cognitive-Perceptual community nodes were in the bottom 50% of the distribution in terms of node centrality. Inspection of the bootstrapped node strength estimates suggested that the highest strength nodes (D5, I6, I7, I2) and the lowest strength nodes (CP2, CP6, D4, CP5) were reliably different in strength from most other nodes (Fig. 3). Regarding strength stability, the *CS*-coefficient was 0.75 suggesting that node strength estimates were highly stable (Fig. 3).

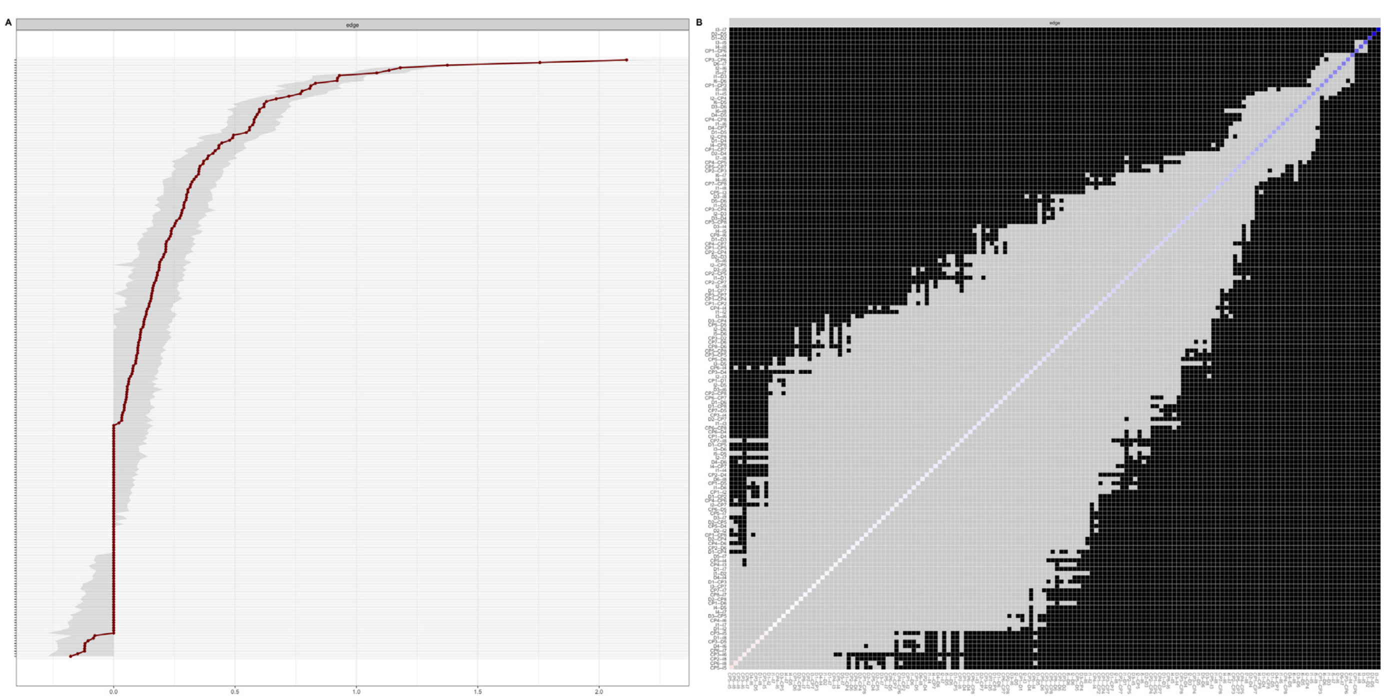

Fig. 2. A) Edge-weight accuracy. The red line depicts the sample edge-weight and the gray bar depicts the bootstrapped confidence interval. B) Edge-weight bootstrapped difference test. Gray boxes denote edges that are not statistically different from one another and black boxes denote edges that are statistically different from one another ($p < .05$, uncorrected). The colored boxes on the diagonal correspond to the color of the edge weights in the schizotypal personality trait network (Fig. 1), with positive edge weights depicted in blue and negative edge weights depicted in red.

Table 3
Network statistics.

Variable	Community	*M*	*SD*
Within-community edge weights	Cognitive-Perceptual	0.37	0.24
	Disorganized	0.89	0.54
	Interpersonal	0.47	0.41
Outside-community edge weights	Cognitive-Perceptual	0.17	0.14
	Disorganized	0.17	0.13
	Interpersonal	0.18	0.15
Strength	Cognitive-Perceptual	−0.84	0.84
	Disorganized	0.29	1.01
	Interpersonal	0.56	0.65
Expected influence	Cognitive-Perceptual	−0.84	0.92
	Disorganized	0.33	1.00
	Interpersonal	0.54	0.59
Predictability	Cognitive-Perceptual	0.23	0.12
	Disorganized	0.43	0.05
	Interpersonal	0.37	0.10

Predictability was strongly correlated with node strength ($\rho = 0.73$, 95% CI [0.44, 0.88]) and EI ($\rho = 0.70$, 95% CI [0.40, 0.87]). Predictability varied substantially across nodes ranging from 0.04 for *others can tell what I'm thinking* (CP2) to 0.56 for *feeling uncomfortable in social situations* (I3) (Fig. 1). Mean predictability was 0.33 ($SD = 0.12$), and was highest for Disorganized community nodes (Table 3), followed by Interpersonal community nodes, and Cognitive-Perceptual community nodes.

3.3. Network comparisons between levels of SSD risk

We compared networks between groups differing in psychosis-risk with respect to age, gender, and ethnic minority status. On age, edge weights were strongly correlated between the low- and high-risk networks ($\rho = 0.84$, 95% CI [0.80, 0.88]). However, the NCT revealed significant differences in global strength ($S = 3.483$, $p = .012$), such that connectivity was higher in the low-risk group, and network structure ($M = 0.562$, $p < .001$). Specifically, 4 of 231 (1.7%) edges differed between the groups (D1-CP6, D3-CP7, I1-I7, D3-I8), with 3 (75%) of these cases involving greater connectivity in the low-risk group due to no node connectivity in the high-risk group.

On gender, edge weights were strongly correlated ($\rho = 0.83$, 95% CI [0.79, 0.87]), and no network differences were observed ($S = 2.470$, $p = .329$; $M = 0.317$, $p = .376$). Finally, on ethnic minority status, edge weights were strongly correlated between the high- and low-risk group ($\rho = 0.71$, 95% CI [0.64, 0.77]). However, the NCT revealed a significant difference in global strength ($S = 11.488$, $p = .004$), characterized by increased global strength in the low-risk group, and no differences in network structure ($M = 0.584$, $p = .344$). The difference in global strength appeared to be driven partly by a larger number of connected nodes in the low- (39.8%) versus high-risk group (29.0%)—as opposed to average edge weight magnitude (low-risk $M = 0.42$, $SD = 0.37$; high-risk $M = 0.41$, $SD = 0.31$)—which was particularly apparent for the Cognitive-Perceptual community (low-risk non-negative edges: 29.3%; high-risk non-negative edges: 16.5%). Because sample size affects network sparsity (van Borkulo et al., 2015), we evaluated the possibility that the large discrepancy in sample size between the low- and high-risk group may have contributed to the observed difference. We re-ran the NCT 10 times using a random sample of 900 participants from the low-risk group each iteration to equal the sample of the high-risk group (Fried et al., 2018). Across iterations, global strength was higher in the low-risk group (range $S = 4.684–10.752$), with the mean difference relatively similar in magnitude, although lower, than in the analysis with the full sample ($M_S = 7.788$, $SD_S = 2.139$). These differences were statistically significant ($p < .05$, Bonferroni-corrected) in 7 of the 10 samples suggesting that global strength differences related to minority status were not entirely due to differences in sample size. No differences in network structure were observed ($M_M = 0.638$, $SD_M = 0.037$, range $= 0.589–0.696$, all $ps > .05$).

4. Discussion

In this study, we used state-of-the-art techniques to characterize the schizotypal personality trait network in a population-based sample. In doing so, our study elucidates the complex relation between phenomena that are thought to index one's vulnerability for SSDs. Furthermore, our study critically addresses the replicability of prior network findings on the extended SSD phenotype (Fonseca-Pedrero et al., 2018c), which is an issue that has generated much interest and concern (Borsboom et al., 2017; Forbes et al., 2017; Fried et al., 2018).

We found that the schizotypal personality trait network is densely connected with predominantly positive connections, and can be characterized by three communities of items—Cognitive-Perceptual, Interpersonal, Disorganized—that closely mirror the SPQ's factor structure. The small number of negative edges we did observe was largely between Cognitive-Perceptual and Interpersonal community items, suggesting a possible dynamic attenuating effect of some aspects of social distance on odd/magical beliefs. On average, both as a community and individual nodes, Interpersonal and Disorganized phenomena exhibited the greatest within-network connectivity and centrality, with items indexing personal/behavioral eccentricity, difficulty with interpersonal interaction/relationships, and paranoid ideation being most central. Connectivity was weakest and nodes were least central within the Cognitive-Perceptual community. In line with these findings, node and community predictability showed a similar pattern of results with overall predictability at 0.33, which is extremely similar to prior predictability estimates of the schizotypal personality trait and other SSD risk networks (Fonseca-Pedrero et al., 2018c; Haslbeck and Fried, 2017).

Tests of within-study stability, reliability, and replicability suggested that these findings are robust. Moreover, these findings are consistent with other network analyses of schizotypy and psychosis-proneness. Using the SPQ in a large international sample, Fonseca-Pedrero et al. (2018c) uncovered the same community structure, similar negative connections between certain cognitive-perceptual and interpersonal items, and similar patterns of connectivity within- and between communities, which have also been observed using other measures of psychosis-proneness (Murphy et al., 2018) and in an adolescent sample (Wigman et al., 2017). The three-community structure we uncovered also converges with that of other network analyses that uncovered positive, negative, and disorganized communities using a different analytic technique and a different measure of schizotypy (Christensen et al., 2018a). Our finding that interpersonal and disorganized phenomena including paranoia and eccentric behavior was most central, and cognitive-perceptual phenomena was least central, is also consistent with these prior findings. Thus, through an entirely web-based sample representing over 140 different countries and the use of a different measure of schizotypal personality traits, our findings extend the generalizability of network findings on SSD risk states.

Together, these findings highlight the importance and interconnection of interpersonal and disorganized phenomena in schizotypal personality traits. The finding that cognitive-perceptual phenomena were less central and less predictable suggest that these experiences may be relatively independent of interpersonal and disorganized traits, and/or more strongly influenced by out-of-network factors not measured here (Haslbeck and Fried, 2017). The notion that cognitive-perceptual traits may be somewhat independent from interpersonal and disorganized traits is supported by other network analyses (Christensen et al., 2018a) and factor analyses (Kwapil et al., 2018b, 2007) demonstrating minimal associations between positive and negative schizotypy factors, which may superficially map onto the SPQ-B's cognitive-perceptual and interpersonal/disorganized communities (although see Gross et al., 2014 and Discussion below). Another possibility is that cognitive-perceptual phenomena are well connected to and can

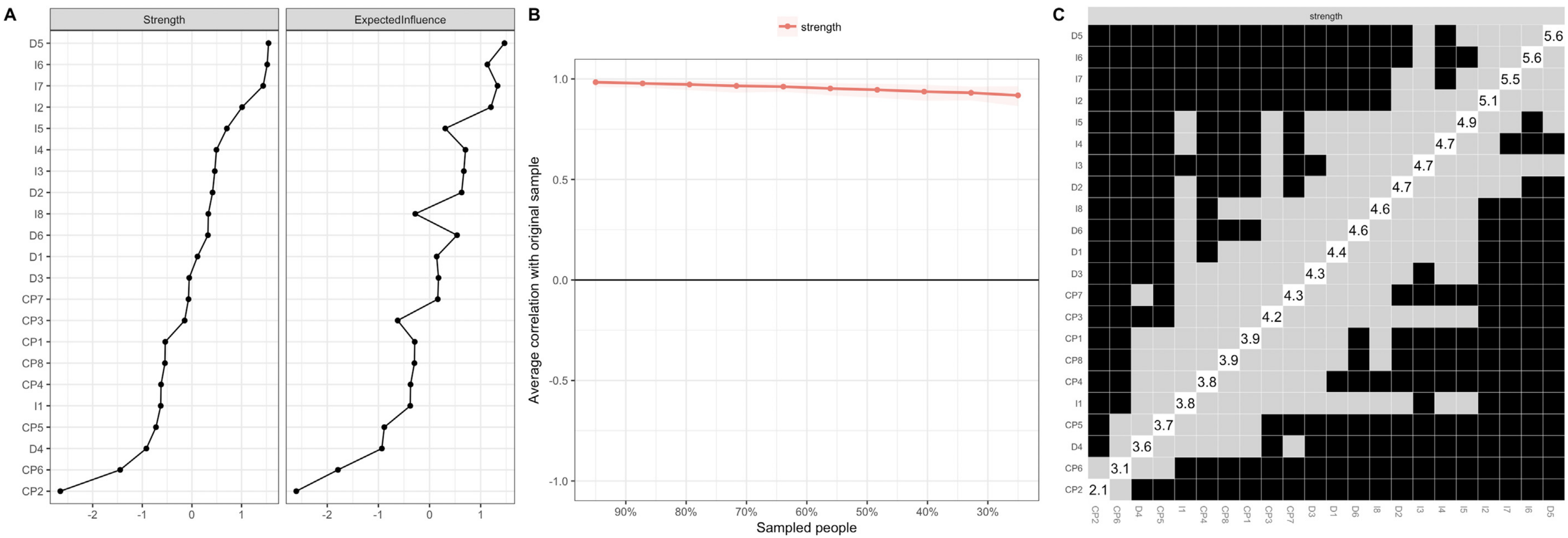

Fig. 3. A) Node strength (z score) is depicted on the left; Expected Influence (z score) is depicted on the right. B) Strength stability. The red bar represents the average correlation between strength in the full sample and subsetted sample with the red area depicting the 2.5th quantile to the 97.5th quantile. C) Strength bootstrapped difference test. Gray boxes denote edges that are not statistically different from one another and black boxes denote edges that are statistically different from one another ($p < .05$, uncorrected). White boxes on the diagonal depict node strength.

be well predicted by other nodes in their network, with their interaction playing out slowly over long periods of time, which we would have been unable to capture with these cross-sectional data. This would be consistent with other research suggesting that social dysfunction and social isolation occurs prior to the onset of illness (Kwapil, 1998; Matheson et al., 2013; Tarbox and Pogue-Geile, 2008; Van Os et al., 2000), and that negative and disorganized features associated with SSDs predict later psychotic experiences (Dominguez et al., 2010). Nevertheless, in line with what others have suggested (Garety et al., 2001; Murphy et al., 2018), these findings could be consistent with two SSD-risk phenotypes and concomitant paths to schizophrenia-spectrum pathology: one that operates through a social disturbance route that may involve isolation/withdrawal (Matheson et al., 2013; Tarbox and Pogue-Geile, 2008), anhedonia (Kwapil, 1998), and interpersonal disorganization (Dominguez et al., 2010), which may over time contribute to the onset of positive symptoms (Hoffman, 2007), and another that operates through a cognitive-perceptual disturbance route that may involve distorted metacognitive processes and appraisals of perceptual experiences (Broyd et al., 2017; Krabbendam et al., 2004).

Regarding possible network differences, we provide converging evidence of similar network connectivity and structure between males and females (Fonseca-Pedrero et al., 2018c), and novel evidence that the schizotypal personality trait network may differ as a function of psychosis-risk relating to age and ethnic minority status. Specifically we observed differences in network structure and global strength as a function of age-related-risk, and differences in global strength as a function of ethnic-minority-status-related-risk.

Several limitations are notable, and those related specifically to network analysis and some of the commonly used analytic techniques have been incisively discussed elsewhere (Christensen et al., 2018b; Fried and Cramer, 2017). First, we emphasize that the associations discussed here cannot be understood as causal. Though conditional associations of the type we present may provide clues regarding causality since they cannot be explained away by other nodes, longitudinal data are needed to infer causal connections. Second, echoing Simpson's paradox, it remains unclear whether the between-persons associations uncovered here hold within-persons (Fried et al., 2017). Ideally, between-persons associations could help to generate hypotheses to be tested within-persons to generate personalized network models (Epskamp et al., 2018b), which will be infinitely more useful in drawing actionable treatment implications. Third, as often the case with psychopathology assessments, many items on the SPQ-B are quite similar, which may have inflated estimates of edge weights and centrality. However, the current findings are consistent with at least one other study that appropriately dealt with this issue (Fonseca-Pedrero et al., 2018c). Fourth, participants were non-randomly sampled leaving open the possibility of self-selection effects that might include differences in schizotypal personality traits between internet-users and non-internet users. That said, scores on the SPQ-B from our sample are generally similar to the SPQ-B scores reported in other studies (Kwapil et al., 2018a; Raine and Benishay, 1995), and findings from prior studies using TestMyBrain.org have been similar to studies using nationally-representative samples (Hartshorne and Germine, 2015). Fifth, schizotypal personality traits were assessed only with self-report. Though SPQ-B scores have been shown to be moderately-to-strongly associated with clinician ratings (Raine and Benishay, 1995), self-reporting schizotypal traits is subject to a range of limitations that can impact the accuracy with which those traits are reported (Kendler et al., 1996).

It is also important to note that the SPQ-B assesses one specific expression of schizotypy (i.e., that associated with schizotypal personality disorder) among many possible expressions (Lenzenweger, 2018, 2015). As such, the structure of schizotypal personality traits do not necessarily map onto other, current multidimensional models of schizotypy —comprised of positive (e.g., perceptual aberration, magical ideation, referential thinking), negative (e.g., social disinterest, anhedonia, flat affect, avolition), and disorganized dimensions (e.g., disorganized thought and behavior) (Christensen et al., 2018a; Kwapil et al., 2018b) —in a straightforward manner (Gross et al., 2014). Thus, we caution against extending these findings to schizotypy as a broader construct.

Nonetheless, along with others (Christensen et al., 2018a, 2018b; Fonseca-Pedrero et al., 2018c; Murphy et al., 2018; Wigman et al., 2017) these findings demonstrate the potential utility of network models for drawing novel insights about phenotypes that are related to risk for SSDs. However, it remains unclear whether network models are enough to explain the often protracted and complex process involving genetic, neurodevelopmental, environmental factors, and their interaction, in which individuals transition from a state of risk to a state of active SSD (although see Isvoranu et al., 2017). Indeed, the finding that overall predictability was only 0.33—which is an upper bound estimate—supports that idea that out-of-network factors are strongly at work. Ultimately, hybrid models in which vulnerability (and active illness) is maintained by a network of dynamically interacting phenomena until triggered by some common cause may best explain schizotypy, other conceptualizations of psychosis-proneness, and active SSDs (Fried and Cramer, 2017).

In summary, our findings highlight the relative importance and predictability of interpersonal and disorganized aspects of schizotypal personality traits in a population-based sample, and provide novel evidence of possible network differences between groups of individuals who differ in their risk for SSDs. Importantly, our findings demonstrate consistency of the schizotypal personality trait network both within-study and between-studies (Fonseca-Pedrero et al., 2018c). Thus, we add to a growing literature that network findings appear to be replicable (Borsboom et al., 2017; Fried et al., 2018). We hope our findings can be used for generating and testing hypotheses regarding causal within-persons associations, and that future work test the connection between network models and other experiences that confer risk for SSDs. Ultimately, such research may provide fundamental insights into the nature, prevention, and treatment of SSDs.

Conflict of interest

All authors declare that they have no conflicts of interest.

Contributors

L.G. created the web-based testing platform and performed data collection. D.D.F. developed the study concept and analyzed the data with assistance from A.S. D.D.F. drafted the paper and A.S., L.R., and L.G. provided critical revisions. All authors approved the final version of the paper for submission.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.schres.2019.01.046.

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