Disorder Agnostic Network Structure of Psychopathology Symptoms in Youth

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Abstract

Background: Youth mental health disorders are strong predictors of adult mental health disorders. Early identification of mental health disorders in youth is important as it could aid early intervention and prevention. In a disorder agnostic manner, we aimed to identify influential psychopathology symptoms that could impact mental health in youth.

Methods: This study sampled 6,063 participants from the Philadelphia Neurodevelopmental Cohort and comprised of youth of ages 12-21 years. A mixed graphical model was used to estimate the network structure of 115 symptoms corresponding to 16 psychopathology domains. Importance of individual symptoms in the network were assessed using node influence measures such as strength centrality and predictability.

Results: The generated network had stronger associations between symptoms within a psychopathological domain; overall had no negative associations. A conduct disorder symptom eliciting threatening others and a depression symptom - persistent sadness or depressed mood - had the greatest strength centralities (β = 2.85). Fear of traveling in a car and compulsively going in and out a door had the largest predictability (classification accuracy = 0.99). Conduct disorder, depression, and obsessive-compulsive disorder symptoms generally had the largest strength centralities. Suicidal thoughts had the largest bridge strength centrality (β = 2.85). Subgroup networks revealed that network structure differed by socioeconomic status (low versus high, $p = 0.04$) and network connectivity patterns differed by sex ($p = 0.01$), but not for age or race.

Conclusions: Psychopathology symptom networks offer insights that could be leveraged for early identification, intervention, and possibly prevention of mental health disorders.

Keywords: psychopathology, comorbidity, mixed graphical model, youth, network analysis

Introduction

Over the last few decades, the definitions of mental illnesses and mental health have changed dramatically (Manderscheid et al., 2010). Perhaps most revealing is the growing distinction between physical and mental health disorders. When treating physical illnesses, common cause theory provides an underlying structure for developing effective treatments. The central tenet of common cause theory is that by determining the key symptoms associated with a physical illness, it is feasible to address important biological mechanisms to better treat the disease itself. Most physical symptoms generally exist independently of one another and therefore there is a direct and distinct path between illnesses and symptoms such that a change in one symptom should not affect other symptoms.

In contrast to physical illnesses, mental health disorders are attributed to multiple contributory factors, and it is not always possible to identify biological mechanisms as a catalyst (Borsboom, 2017). In fact, symptoms of mental health disorders can affect one another directly and indirectly. These symptom relationships add a layer of complexity, making it challenging to intervene upon effectively. An approach to disentangle this complexity is to understand the shared symptomatology across disorders (Borsboom, 2008; Fried et al., 2017). In contrast to most leading theories of mental disorders, network theory provides a useful framework to study symptom relationships as it recognizes the shared symptomatology across disorders (Borsboom, 2017; Borsboom et al., 2018; Borsboom et.al., 2021). Network theory posits mental disorders as the result of activation in a symptom network. Symptoms arise, and in turn may cause other symptoms to manifest. These coupled symptoms often synchronize and maintain each other, resulting in a cluster of psychopathology symptoms that lead to the diagnosis of a mental disorder and/or comorbid conditions (Borsboom, 2017).

Comorbidity in mental disorders occurs frequently and is important to study, as those individuals who have more symptoms tend to have poorer prognoses and higher suicide rates, experience an increased impact on daily function, and require more help from a clinician (Cramer et al., 2010). Bridge symptoms – symptoms with a multidirectional relationship to more than one disorder (Borsboom & Cramer, 2013; Cramer et al., 2010) – can help elucidate the way comorbidities develop and offer insight into why they are more prevalent in certain populations (Jones et al., 2018). A bridge symptom linked strongly to multiple disorders may be a risk factor for other illnesses (Fried et al., 2017). Investigating which symptoms are more strongly related could inform clinical prevention and intervention strategies aimed at addressing the burden of comorbidity (Fried et al., 2017).

Most mental health disorders emerge in childhood, adolescence, or in early adulthood (De Girolamo et al., 2012). Almost half of all lifetime mental health disorders begin before age 14, and ~75% before age 24 (Kessler et al., 2005). A large study (N = 10,123) of adolescents aged 13-18 in the continental US showed that 49.5% met criteria for a class of mental disorders (Merikangas et al., 2010). Within this group of adolescents, 20% (40% of those with a diagnosable mental disorder) also met criteria for a mental illness from at least one additional class (Merikangas et al., 2010).

Studies on children and adolescent mental health have consistently found that childhood mental health symptoms are strong predictors of adult mental illness. In a prospective longitudinal study of 1,037 participants, more than half of adult anxiety, depression, and substance use disorders were seen in individuals that met diagnostic criteria for a mental disorder before age 15 (Kim-Cohen et al., 2003). In this same sample, conduct disorder and/or oppositional defiant disorder was seen across every group of diagnoses, showing heterotypic continuity by preceding the onset of more than just antisocial personality disorder (Kim-Cohen et al., 2003). A sample of 1,365 participants in a cohort from the Netherlands provided data that suggested childhood aggression, delinquent behavior, and anxious/depressed problems were the strongest predictors for later psychopathology at the 24-year follow-up (Reef et al., 2009). In another study of 142 children with obsessive-compulsive disorder (OCD) in the UK, 41% had OCD at follow-up and 70% had a Diagnostic and Statistical Manual Axis 1 or ICD-10 diagnosis (Micali et al., 2010).

Despite the abundance of findings related to continuity of psychopathology into adulthood, adolescents and young adults receive treatment for mental disorders at lower rates than adult populations (De Girolamo et al., 2012). Young people tend not to seek mental health treatment, deal with issues surrounding access to treatment, and face barriers related to strict policies that can delay treatment (De Girolamo et al., 2012). There is a critical need for early identification to facilitate prevention and early treatment to reduce disease burden in this group (De Girolamo et al., 2012).

The goal of this study was to identify the most influential psychopathology symptoms and to further examine how psychopathology symptom associations impact mental health disorders in youth. We employ network analysis to study these symptom associations. A network model is advantageous over other approaches as it provides a way to map the complex network of relationships between symptoms and can help reveal the underlying relationships between these symptoms (Borsboom & Cramer, 2013; Borsboom, 2017; Bringmann et al., 2013). A variety of psychiatric symptom constructs have been modeled using network analysis, including those for post-traumatic stress disorder (PTSD), obsessive-compulsive disorder (OCD), autism, anxiety, depression, mania, and suicidal ideation and schizotypal personality traits among others (Fonseca-Pedrero et al., 2018; Fried et al., 2018; Isvoranu et al., 2016; Rath et al., 2019; Ruzzano et al., 2014; Weintraub et al., 2020). In this study, we use network theory to model psychopathology symptoms from multiple domains in a disorder agnostic single network to identify influential symptoms and their interdependencies in a community sample of youth.

Methods

Data for this study was obtained from the Philadelphia Neurodevelopmental Cohort (PNC). PNC is a community sample of 9,498 youth between the ages of 8-21 years from the Philadelphia area. Please refer to Calkins et al., 2015 for details on the PNC study. Briefly, the psychopathology assessment in PNC was administered using a structured computerized interview tool for evaluation designed to provide high-level screening of major psychopathology symptoms, to be assessed at the same study visit (Calkins et al., 2015). Psychopathology screening focused on major domains such as mood, anxiety, behavior, psychosis, and suicidal behavior. Questions were adapted from a modified version of the NIMH Genetic Epidemiology Research Branch Kiddie-SADS (Merikangas et al., 2009). In order to measure psychosis spectrum, PRIME Screen-Revised instrument for positive sub-psychotic symptoms, modified K-SADS for positive threshold psychotic symptoms, and the Structured Interview for Prodromal Symptoms for negative or disorganized symptoms were used by the original investigators (Kobayashi et al., 2008; Miller et al., 2003). This project was approved by the IRB at The University of North Carolina at Chapel Hill.

Measures

This study analyzed 115 symptom variables corresponding to 16 common psychopathology domains clinically assessed among youth (attention deficit hyperactivity disorder [ADHD], agoraphobia, conduct disorder, depression, generalized anxiety disorder, mania, OCD, oppositional defiant disorder [ODD], panic disorder, phobia, psychosis, post-traumatic stress disorder [PTSD], separation anxiety, psychosis prodromal symptoms, social anxiety and suicide). List of symptoms assessed are available here. Each variable corresponded to a question elucidating whether the participant had experienced a specific symptom. The PRIME Screen-Revised instrument used to score positive sub-psychotic prodromal symptoms rates symptoms from 0 (absent) to 6 (extreme) on an ordinal scale (Kobayashi et al., 2008). All other psychopathology domains were scored categorically as 0 (no) and 1 (yes). Subgroup analysis was performed on key demographic variables – sex (assigned at birth, male or female), race (White, Black or Other), age group (12-17 or 18-21 years) and socioeconomic status (low, middle or high). Socioeconomic groups were created by categorizing a standardized neighborhood socioeconomic score into tertiles. The youngest age group from 8-11 years was excluded as they did not self-report symptoms, rather their symptom ratings were provided by parents or caregivers.

Statistical Analysis

Missing Data Analysis

The total sample consisted of 6,063 youth, 4,798 of which had complete data. Individuals with at least one instance of missing or unknown data were removed prior to analysis as mixed graphical models (MGM) do not handle missing data. We used the R package *MissMech*

(Jamshidian, Jalal, & Jansen, 2014) to identify the missing data mechanism. Data was not missing completely at random ($p < 0.001$). We subsequently evaluated the effects of removing missing data on subgroups by performing chi-square and t-tests. Results are provided in Table 1. All data were analyzed using the programming language and free software environment R. Codes used for all analysis are available here.

Network analysis was done on (1) complete data as well as (2) imputed data. Imputation was done using the R package *MissForest* (Stekhoven & Bühlmann, 2012). We conducted the following analyses for this study. First, we estimated the network structure using MGM to elucidate the interactions among 115 psychopathology symptoms. In order to identify the most significant symptoms in the network as well as significant bridge symptoms, we estimated centrality and predictability measurements by analyzing the estimated network structure. We then ran network comparison tests (NCT) to perform subgroup analysis stratified by demographic characteristics. Lastly, we assessed stability and accuracy of the estimated networks and associated centrality indices.

Network Estimation

We used MGM to estimate the network structure for a combination of categorical and continuous data (Haslbeck & Waldorp, 2020) in our study sample. In the network structure, symptoms are represented by nodes, and the relationships between symptoms are represented by edges, or the connections between the nodes. Two variables not connected when conditioned on other variables are considered independent (Epskamp et al., 2018). When enough of these nodes and edges are present, it becomes possible to visualize clusters that form between nodes, which may clarify associations between them. MGM estimates regression coefficients representing edge weights via nodewise regression. In order to estimate networks, we utilized a pairwise model (interaction order $k = 2$) and Extended Bayesian Information Criterion (EBIC) to select the LASSO regularization parameter (hyper-parameter = 0.25). We selected EBIC because of its strong performance in selecting sparse networks and its flexibility with categorical variables. The thickness of each edge in the visualized network represents the strength of the association, with thicker edges representing a stronger association (Epskamp et al., 2012).

Network Evaluation

To gain insight into the relative importance of each node, we measured centrality indices, specifically node strength and predictability. We selected the traditional centrality index of node strength in this study as it directly considers edge weights; studies show that strength is the most precisely estimated index and is more appropriate for psychopathology variables in contrast to measures such as closeness and betweenness which are distance-based associations (Barrat et al., 2004; Jones et al., 2019; Opsahl et al., 2010). Node strength, the sum of absolute edge weights connected to a node, is the average strength of the conditional association of a node with other nodes in the network.

We selected predictability as a second measure to assess significance of nodes in the generated network given our primary interest was in assessing co-occurring symptom patterns. In the presence of a large number of observations as is with this study, we used predictability to additionally assess significance of relevant edges in the generated model (Haslbeck & Waldorp, 2018). Predictability measurements, which represent the amount of variance explained by all other nodes in the network, quantifies how relevant a node is by finding how well it can be predicted by all other nodes in a network (Haslbeck & Fried, 2017). We calculated percentages for the explained variance of continuous variables and for the correct classification of categorical variables to show how well a node can be predicted by its neighboring nodes on a scale of 0 to 1; a value of 0 indicates that a node is not predicted by other nodes in the network whereas a value of 1 indicates perfect prediction. We used bridge strength to identify significant bridge symptoms that connected major psychopathology domains by calculating a node's connectivity to other domains (Jones et al., 2019).

Comparison Tests

We conducted NCTs to evaluate network structure differences between subgroup networks. NCTs are permutation-based tests that re-estimate networks to build reference distributions against which test statistics are evaluated (van Borkulo, 2017). An invariant network structure test was first run to check whether the overall network structure differed between two groups by comparing the distributions of edge weights. The global strength invariance test allowed us to compare the connectivity, or weighted absolute sum of edge weights, of two networks (van Borkulo 2017; van Borkulo et al., 2017). NCT results are reported as p-values at a significance level of 0.05 set against the null hypothesis that network structure or connectivity are identical across subgroups. Reference distributions were generated using 1,000 iterations.

Network Accuracy

We conducted network accuracy tests to estimate and analyze the stability of centrality measurements (Epskamp et al., 2018). The centrality index stability is evaluated through case-dropping to find the percentage of nodes that can be dropped to retain stable indices. Strength centrality stability coefficients are calculated to show the maximum proportion of nodes that can be removed to retain a 95% probability that the correlation between original and subset centrality values remain above a default of 0.70 (Epskamp et al., 2018). Ideally, these coefficients should be above 0.50 and no lower than 0.25 to interpret centrality differences (Epskamp et al., 2018). Since centrality indices have shown to have low stability in cross-sectional data (Epskamp et al., 2017), we interpret only those findings with stability coefficients greater than 0.25.

Results

Descriptive and Missing Data Analysis

The final sample (n = 4,798) included 45% males, 57% White youth and 32% Black youth. Approximately 81% of the sample were between the ages of 12-17 years and the remaining 19% were between 18-21 years. Overall differences between all data and complete data are provided in Table 1. We first constructed network models of psychopathology symptoms on complete data followed by imputed data. We also compared network differences across demographic subgroups. Since network estimates remained largely consistent between networks generated on complete data and imputed data, we present results from the complete data network models. NCT results of complete data and imputed data networks are provided in Table 3.

Network Analysis Results

The estimated symptom network is shown in Figure 1a. There were no negative edges in the network. A conduct disorder symptom eliciting if the participant had ever threatened someone had the greatest strength centrality measurement (β = 2.85), followed closely by persistent sadness or depressed mood (β = 2.19), suggesting that they are influential nodes of greater importance compared to other nodes (see Figure 1b). Overall, depression, OCD and conduct disorder domain symptoms had the greatest strength centrality measurements.

Fear of traveling in a car (β = 0.99), compulsively going in and out a door (β = 0.99), and fear of being in an open field (β = 0.98) had the largest predictability values, indicating that they are well predicted by other nodes in the network. Thoughts of suicide (β = 2.85), prolonged feelings of depression (β = 2.66) and auditory hallucinations (β = 2.31) had the largest bridge strength centrality values as shown in Figure 1b, indicating that they had the strongest connections with symptoms from other domains.

Network accuracy tests revealed that relatively narrow 95% CIs were found from bootstrapping edge weights, suggesting a higher accuracy for measured centrality values. The stability coefficients for edge weights and strength centrality were both 0.75, greater than the preferred minimum of 0.50 required to be considered a stable metric (Epskamp et al., 2018). These results suggest that the estimated network is sufficiently accurate and has stable centrality indices.

Subgroup Analysis

Results of subgroup analysis including the top three most central and predictable nodes are provided in Table 4. Subgroup networks are provided as supplementary figures S1-11. NCT was significant for global strength invariance (p = 0.01), but not for network structure invariance (p = 0.90) for the sex subgroups. In contrast, NCT was significant for network structure invariance between low and high socioeconomic groups (p = 0.04) and between middle and high socioeconomic groups (p = 0.05), but not for global strength invariance. NCTs were non-significant for race or age subgroups, indicating that there were no significant differences in network structure or global strength across these subgroup networks. Edge weight correlation stability coefficients and strength centrality correlation stability coefficients were greater than 0.50 for all subgroup networks except for other race youth.

Discussion

We examined the network structure of psychopathology symptoms in a community sample of youth and report influential symptoms and their associations in 12-21 year-old youth. The disorder agnostic symptom network did not have any negative associations. As expected, symptoms within the same psychopathological domain had stronger positive associations than symptoms of different domains. Conduct disorder, depression and OCD symptoms – specifically persistent sadness, obsessions, compulsions and violent behavior – had the highest strength centrality values pointing to its relative importance within the symptom network. Suicide and depression symptoms consistently had high bridge strength centrality values, suggesting strong comorbid relationships.

OCD, Depression and Conduct Disorder Symptoms are the Most Influential

OCD is an influential psychopathology domain in youth associated with a higher risk for developing other mental health disorders if left untreated (Krebs & Heyman, 2015). Individuals diagnosed with OCD are about three times more likely to develop schizophrenia later in life, showing a high co-occurrence between the two disorders (Cederlöf et al., 2015). Network studies of OCD and other disorders, such as depression and autism spectrum disorder, have also shown shared symptom pathways suggesting etiological similarities and comorbidities between these disorders (Cederlöf et al., 2015; Jones et al., 2018; Ruzzano et al., 2014). In our study, we found OCD symptoms to have consistently large strength centrality and predictability values, suggesting strong associations with other psychopathological domains. Similarities observed in networks and centralities across demographic subgroups add robust support to the influence of OCD symptoms on other psychopathology domains such as psychosis and anxiety.

Depression is a common mental health disorder in adolescents that has found to be strongly linked with recurrence as an adult and has similar clinical features in both adolescents and adults (Thapar et al., 2012). Adolescent depression is also a predictor of other disorders later in life, including anxiety disorders and suicidal behavior (Thapar et al., 2012). A depression item elucidating persistent sadness or depressed mood was among the most central in our study and is a criterion symptom for the diagnosis of major depressive disorder. Our results are similar to those reported in previous network analyses of depression and anxiety symptoms (Beard et al., 2016; Kennedy, 2008). Across the spectrum of psychopathology symptoms assessed in community dwelling youth, persistent depression is an important clinical symptom that warrants further examination.

Childhood-onset conduct disorder is found to have high co-occurrence with other anxiety and behavioral disorders such as ADHD and ODD, making it clinically important to identify these conditions early on (Fairchild et al., 2019; Silberg et al., 2015). However, there are fewer studies on symptom-level network structure of conduct disorder. A conduct-disorder symptom – threatening others – was identified to be the most central in the network of our sample and is one of the main clinical features of the disorder (Searight et al., 2001). Our findings add to the existing body of evidence and highlight the strong associations between conduct disorder symptoms and other youth psychopathology.

In youth, OCD, depression and conduct disorder often go undiagnosed for many years (Fairchild et al., 2019; Krebs & Heyman, 2015; Thapar et al., 2012). Given the strong associations observed between OCD, depression, and conduct disorder symptoms with several other psychopathology domains in our study, we offer that monitoring these symptoms in youth could alert to the onset of not just these disorders but likely others such as psychosis, anxiety and PTSD. Future studies using sociodemographically diverse samples are needed to test the applicability of these findings as screening tools or for early identification of mental health disorders.

Suicidal Ideation is the Strongest Bridge Variable

Suicidal ideation had the highest bridge strength centrality in our symptom network, indicating that it had robust connections with multiple psychopathology domains and may play a role in comorbidity. Suicidal ideation is a direct risk factor for suicide, which is one of the leading causes of death among youth in the United States (Ruch et al., 2019). Studies have found that mental health disorders, especially depression and substance abuse, are some of the strongest risk factors for suicidal attempts, and almost all these disorders are related to suicidal behavior (Franklin et al., 2017). In our study, suicidal ideation was connected to symptoms from several other domains in the network - depression, OCD, PTSD, GAD, panic, and prodromal psychotic symptoms. These findings show that suicidal ideations are present in association with symptoms of several other mental health conditions. Monitoring for suicidal ideations could help not just in prevention of suicide attempts but could also call attention to the presence of other comorbid conditions (Nock et al., 2010) that may require timely intervention.

Networks Across Demographic Subgroups

Network connections across both age groups were sparser when compared to the overall network. Similar to findings from a study of network structure of internalizing symptoms (McElroy & Patalay, 2019), strength centralities remained relatively consistent across age groups in our sample. ODD and depression domains had some of the strongest strength centrality values across age groups (see Supplementary figure S1-2). ODD symptoms are considered some of the earliest and most common to be diagnosed in childhood and are a strong predictor of psychopathology in later adolescence (Mikolajewski et al., 2017).

For sex subgroups, there was a significant difference in global strength but not in network structure, demonstrating that symptom associations were similar in both networks yet with different levels of connectivity (see Supplementary figures S3, S4). The network for female youth had a higher global strength than that for males, indicating that the symptoms were more strongly interconnected in female youth. Depression items were among the most central for both groups but had mostly higher strength centrality values for females, aligning with numerous studies showing that depression is more common in females than males (Albert, 2015; Xia et al., 2018).

A significant difference in network structure was observed between low and high socioeconomic groups but not in global strength, suggesting that overall network structure differed between these groups but not connectivity (see Supplementary figures S5-7). Network research of psychopathology symptoms across socioeconomic groups is limited and our findings call for more research in this area. Considering that the prevalence of psychopathology symptoms vary across communities and populations (Peverill et al., 2021), studies that offer a nuanced assessment of factors associated with different socioeconomic groups that play a role into the onset and/or continuity of mental health disorders is highly warranted.

It is well-established that racial disparities exist in youth mental health research (Alegria et al., 2010), and this extends to psychopathology research using network psychometrics. Our findings were relatively consistent across race subgroups, with OCD and conduct disorder symptoms carrying the highest centrality values. This, in conjunction with the non-significant NCT results, shows that it is highly unlikely that race factors into how psychopathology symptoms manifest during youth.

Node-wise Structural Importance and Clinical Implications

We used both node centralities and predictability values in a complementary manner to infer node wise structural importance. The node strength centralities and predictability values we found for the significant symptoms support each other, with OCD and conduct disorder symptoms in particular having some of the highest measurements for both. The largely consistent measurements for centralities and predictability across demographic subgroups suggest that the identified significant symptoms could be further studied for clinical applications regardless of the individual's demographic background.

Predictability values for agoraphobia symptoms were consistently high; however, this pattern was not seen for strength measurements. Predictability measure is advantageous in being an absolute measure because it shows the extent to which a node can be explained by its neighbors (Haslbeck & Waldorp, 2018). Symptoms with high predictability values are suggested as potential targets for intervening on closely associated neighbor nodes. Given the high predictability values for agoraphobia symptoms that we observed in our network, it may be advantageous to study these symptoms as intervention targets.

In a community sample of youth, we identify conduct disorder, depression, and OCD symptoms as the most influential in youth mental health with suicidality showing bridge associations with several psychopathology domains. Integrating screening for conduct disorder, depression, and OCD symptoms in youth health visits may offer an avenue for early detection of changes in mental health and/or transition to mental health disorders. But given the cross-sectional nature of our study, considerations of depression, OCD, and conduct disorder symptoms either as screening tools or early intervention targets requires further investigation. For suicidal symptoms, in addition to screening for safety, assessment should include screening for comorbid mental health conditions that could affect treatment outcomes and/or require timely interventions.

Limitations

Our study is not without limitations. This study is cross-sectional, and we used a community sample rather than a clinical sample to extract network patterns and identify significant symptoms. As such we do not know if the significant symptoms and their associations to other symptoms we found in our study would be generalizable to clinical samples or samples that our demographically different from the PNC. Our inclusion choice for psychopathology symptoms in this study were limited to those symptoms that were consistently answered by all or most participants. This resulted in us excluding eating disorder symptoms in the analysis. Further, it is possible that participants may have not disclosed certain symptoms due to stigma. These are significant limitations of our study.

Since data for this study was extracted from PNC, the limitations of that study apply here as well, especially in terms of sample representativeness. The sample was representative of the recruitment pool in terms of sex and age group but not race (Calkins et al., 2015). Additionally, the youngest age group encompassing ages 8-11 was not included due to a lack of self-reported symptoms. Lastly, the structured and abbreviated nature of the assessment may have decreased sensitivity to some clinically relevant symptoms. These factors should be accounted for when generalizing study findings to other populations. Future research is needed to test the screening and clinical applications of findings from our study and should ideally be of a longitudinal design.

Conclusion

In conclusion, our study examined the associations among psychopathology symptoms in youth across 16 common psychopathology domains. Our work expands upon previous studies of specific disorders in youth by focusing on network structure of common mental health symptoms. We identify influential symptoms that could be tested for mental health screening in general health settings. Our findings offer insights into youth psychopathology and avenues for further study to test clinical applicability of symptom-based early detection and interventions.

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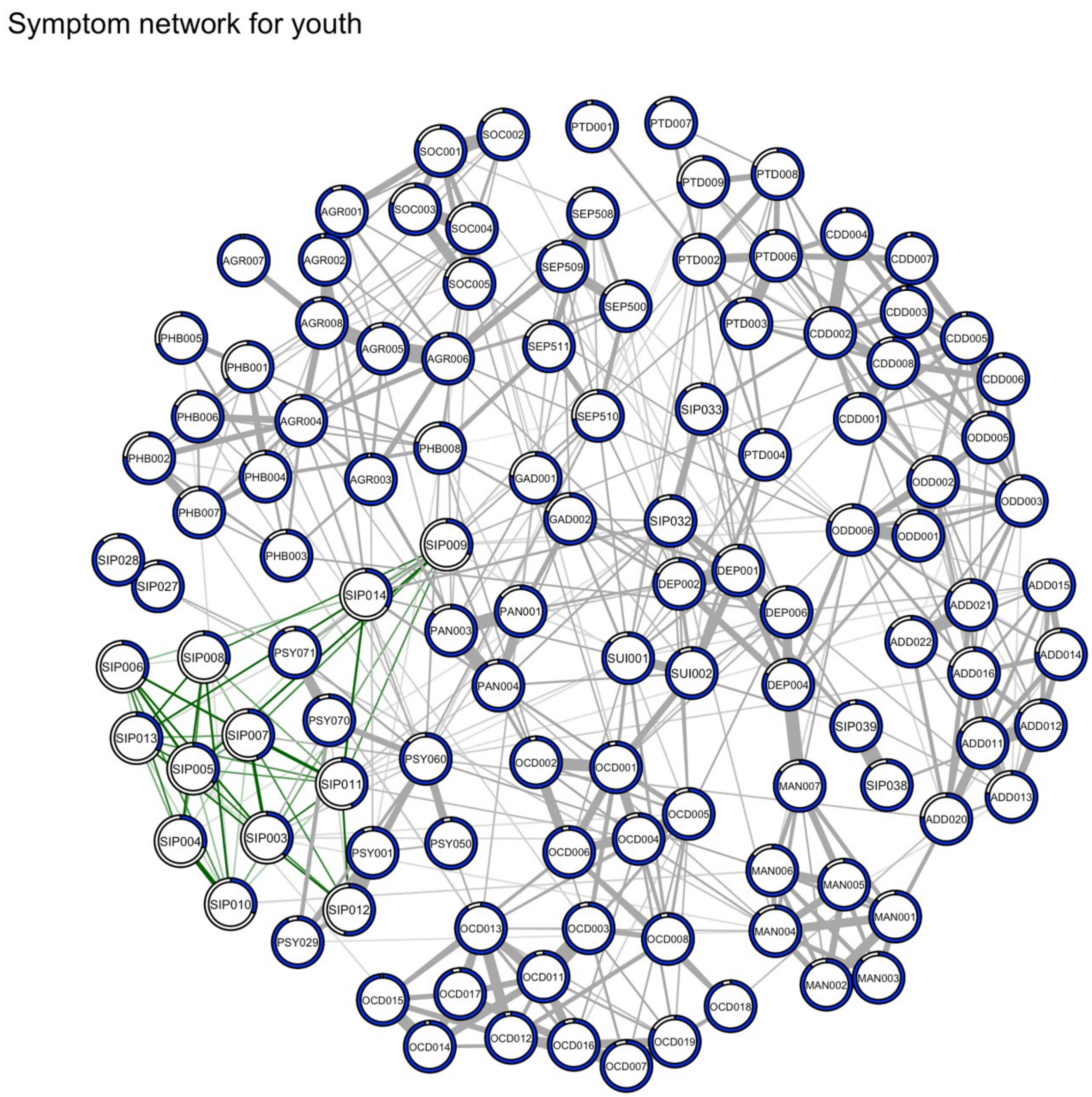

Figure 1a. Symptom network across 115 symptoms from 16 psychopathological domains for youth, 12-21 years of age. Green edges represent positive associations between nodes, and grey edges show positive relationships between categorical variables. There were no negative associations in the network. The navy-blue ring around the nodes is the predictability or the amount of variance explained by all other nodes in the network for continuous variables; for categorical variables, the ring indicates classification accuracy.

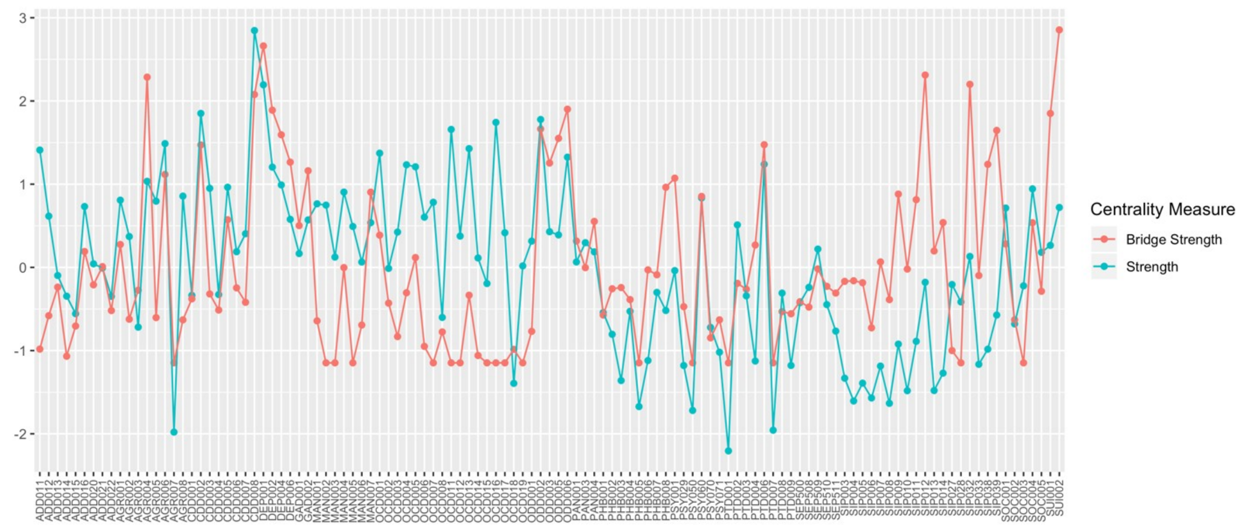

Figure 1b. Strength and bridge strength centralities for the symptom network. Centrality values on y-axis are z-scores

Table 1

*Demographic Characteristics of Subgroups*X	**All participants (*n* = 6063)**		**Complete data (*n* = 4798)**		**Analysis**	
Variable	**Mean**	**SD**	**Mean**	**SD**	***t***	***p-value***
Age (years)	16.47	2.34	16.32	2.26	3.35	<0.001
Socioeconomic status	0	1.00	0.03	0.99	-1.55	0.12
	Frequency (%)		**Frequency (%)**		**χ^2**	***p-value***
Sex					0.01	0.93
Male	45.08		45.19			
Female	54.92		54.81			
Race					1.73	0.42
White	56.16		57.42			
Black	33.28		32.35			
Other	10.56		10.23			
Age (years)					21.70	<0.001
12-17	77.00		80.70			
18-21	23.00		19.30			
Socioeconomic status					2.50	0.29
Low	33.33		31.95			
Middle	33.47		33.83			
High	33.20		34.22			

Note. N = 6063 for all participants and n = 4798 for final sample with complete data.

Table 2

Network Comparisons Test between Demographic Subgroups

	Network Invariance		Global Strength	
Groups	***p-value***	***Test Statistic M****	***p-value***	***Test Statistic S***[#]
Sex				
Male vs. Female	0.90	0.52	0.01	12.16
Race				
White vs. Black	0.44	0.71	0.53	14.62
White vs. Other[a]				
Black vs. Other[a]				
Age (years)				
12-17 vs. 18-21	0.82	0.68	0.88	33.04
Socioeconomic status				
Low vs. Middle	0.56	0.67	0.88	0.53
Low vs. High	0.04	1.10	0.26	4.25
Middle vs. High	0.05	1.42	0.32	3.71

[a] Test not run due to limited variance.

* *M* statistic is the largest difference in edge strength between the networks.
# *S* statistic is the difference in global strength.

Table 3

Network Comparisons Test between Imputed and Complete data by Subgroups

	Network Invariance		Global Strength	
Groups	***p-value***	***Test Statistic M****	***p-value***	***Test Statistic S***[#]
Sex				
Male	1.00	0.34	0.35	8.12
Female	0.98	0.44	0.43	8.02
Race				
White	1.00	0.35	0.21	8.96
Black	1.00	0.38	0.38	9.27
Other	1.00	0.61	0.69	4.68
Age (years)				
12-17	1.00	0.30	0.60	5.13
18-21[a]				
Socioeconomic status				
Low	1.00	0.33	0.31	9.99
Middle	1.00	0.51	0.29	8.99
High	1.00	0.47	0.71	4.52

[a] Test not run due to limited variance.

* *M* statistic is the largest difference in edge strength between the networks.

\# *S* statistic is the difference in global strength.

Table 4

Significant Symptoms in Demographic Subgroup Networks

			Symptom	Centrality (β)	Symptom	Predictability*
Sex	Male	1	CD - Threatening others	2.30	AGR - Fear of traveling in a car	0.99
		2	DEP - Persistent sadness/depressed mood	1.99	PTD - Upset by being forced to do something sexual	0.99
		3	OCD - Arranging or ordering	1.80	AGR - Fear of being in an open field	0.99
	Female	1	CD - Threatening others	2.49	OCD - Going in and out a door repeatedly	0.98
		2	CD - Rule breaking	2.38	AGR - Fear of traveling in a car	0.98
		3	OCD - Cleaning or washing	2.05	CD - History of setting fires, breaking into cars or destroying property on purpose	0.98
Age Group	12-17 years	1	CD - Threatening others	2.64	AGR - Fear of traveling in a car	0.99
		2	DEP - Persistent sadness/depressed mood	2.21	OCD - Going in and out a door repeatedly	0.98
		3	CD - Rule breaking	1.97	AGR - Fear of being in an open field	0.98
	18-21 years	1	CD - Threatening others	2.76	OCD - Going in and out a door repeatedly	0.99
		2	MAN - Hyperenergetic with difficulty stopping	2.02	AGR - Fear of being in an open field	0.98
		3	OCD - Arranging or ordering	2.02	AGR - Fear of traveling in a car	0.98

Race Groups	White	1	CD - Threatening others	2.80	OCD - Going in and out a door repeatedly	0.99
		2	OCD - Cleaning or washing	2.52	AGR - Fear of traveling in a car	0.99
		3	OCD - Arranging or ordering	2.43	AGR - Fear of being in an open field	0.99
	Black	1	CD - Threatening others	2.43	AGR - Fear of traveling in a car	0.98
		2	OCD - Fear over unintentionally doing or saying something bad	2.43	OCD - Going in and out a door repeatedly	0.98
		3	ADHD - Difficulty paying attention	2.01	PTD – Experienced natural disaster where thought would die/be hurt	0.97
	Other	1	OCD - Getting dressed over and over again	3.31	AGR - Fear of being in an open field	0.98
		2	MAN – Elevated mood without special event	2.52	OCD - Getting dressed over and over again	0.98
		3	MAN - Hyperenergetic with difficulty stopping	2.01	AGR - Fear of traveling in a car	0.98
SES	Low	1	OCD - Fear over unintentionally doing or saying something bad	3.02	AGR - Fear of traveling in a car	0.98
		2	CD - Threatening others	2.59	OCD - Going in and out a door repeatedly	0.97
		3	DEP - Persistent sadness/depressed mood	1.99	PTD – Experienced natural disaster where thought would die/be hurt	0.97
	Mid	1	OCD - Arranging or ordering	3.03	OCD - Going in and out a door repeatedly	0.99
		2	OCD – Concern over harming others/self	2.83	AGR - Fear of traveling in a car	0.99
		3	ADHD - Difficulty paying attention	1.88	AGR - Fear of being in an open field	0.98
	High	1	OCD - Cleaning or washing	2.42	CD - History of trying to hurt someone with a weapon	0.99
		2	ADHD - Difficulty paying attention	2.26	OCD - Going in and out a door repeatedly	0.99
		3	CD - Threatening others	2.17	AGR - Fear of traveling in a car	0.99

Note. CD – Conduct disorder, OCD – Obsessive-compulsive disorder, AGR – Agoraphobia, PTD – Post-traumatic stress disorder, ADHD – Attention deficit hyperactive disorder, DEP – Depression, MAN – Mania.

*Predictability is the proportion of correct classification accuracy. Values range from 0 – 1, where 0 is symptom not explained by other symptoms in the network and 1 indicates symptom is perfectly predicted by other symptoms in the network.