A Brief Exploration of Youth Mental Health Symptom Networks

Philip Nguyen

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1 Introduction

Mental illness remains poorly understood despite its prevalence and impact on people and society [16]. This may be due in part to how it has been studied, that is in light of medical disease or latent variable models where the symptoms of an illness are solely the result of common underlying factors [12]. Recent evidence suggests that this framework may be overly simplistic and fail to capture the underlying complexity involved in characterizing mental illness and its development [3, 5, 12].

Researchers have begun to address these issues by utilizing complex systems and network science approaches in understanding the structure and dynamics of mental disorders [4, 7, 15]. These perspectives are aligned with how clinicians view and treat mental disorders, and they provide a more holistic account that considers the nuanced interplay of biological and environmental factors, which are surely implicated in overall wellbeing [4].

1.1 The Present Study

Mental health problems begin to emerge in late childhood and early adolescence and affect approximately 10-20% of youth worldwide [14]. Many studies of youth mental health have been conducted using cross-sectional data and small sample sizes, which limits the scope of generalization and the understanding of how mental health evolves as a function of risk and resilience. The ABCD Study was thus created to better understand this process in light of biological, neural, and environmental factors [13]. The study aims to follow a large sample of youth starting at ages 9 and 10 for approximately 10 years, collecting a wealth of data including neuroimaging, cognitive, biospecimen, behavioral, environmental, parent self-report, and youth self-report measures across 21 data-collection sites in the U.S. [10].

In this project I construct and examine the symptom networks of a sample of youth using data from the ABCD Study. The long-term goal is to understand how these networks evolve as a function of cultural, environmental, and other factors related to mental health. Here I begin with a brief and preliminary exploration.

2 Methods

2.1 Data

The ABCD Study is currently ongoing and consists of data from 11,875 participants across several time points. The bulk of the data are collected during annual in-person visits with fMRI scans taking place every other year, followed by brief six-month follow-up phone calls [10]. The data are released to the public and researchers annually, with the current iteration being the 4th release.

For this study I use data from the youth self-report Brief Problem Monitor (BPM) survey [2]. The BPM assesses mental health-related symptoms over the past week using 19 items from the Child Behavior Checklist, Teacher Report Form, and Youth Self-Report [1]. Each item is scored on a 0-2

Likert scale ('Not True', 'Somewhat True', 'Certainly True') and falls under one of three domains (Attention, Internalizing, Externalizing). Two items were combined ("I have trouble concentrating or paying attention/I am inattentive or easily distracted" and "I disobey my parents/I disobey at school") due to similarity.

A single symptom network was constructed using BPM data at the 3-year follow-up time point in constructing the symptom network since this project is concerned with the general structure of symptom networks, and not (yet) how they evolve over time. Cases with missing values were dropped, leaving a sample size of 6239 with a mean age of 12.89 years.

2.2 Psychological Networks

In psychological networks, nodes represent observed psychological variables (e.g. responses to questions about mood in the past week) and edges denote a statistical relationship between them, typically after controlling for all other variables [8]. Unlike other commonly studied networks, the edges of psychological networks must be estimated from the data, usually with Ising models for binary data, Gaussian graphical models (GGM) for continuous data, and mixed graphical models (MGM) for mixed data [6]. As with statistical models in general, estimated networks are subject to sampling variation and should be assessed for accuracy and stability before valid conclusions can be made. Methods addressing these issues are discussed in further technical detail here [9, 4], though they generally involve bootstrapping methods. Since this is an exploratory project, I estimate an undirected network model where the edges lack arrows, thus lacking direction of effect (to be considered in future work).

2.3 Modeling

To simplify the modeling, BPM responses were transformed to a binary format where 'Not True' responses are coded as -1 and 'Somewhat True' and 'Certainly True' responses as 1. This allowed me to fit an Ising model to the data, which is commonly used to construct symptom networks [12, 4]. The model was fit using the 'IsingFit' estimator with the Bootnet package in R.

What is estimated are edge weights that indicate the strength of association between two nodes, after accounting or controlling for all the other nodes in the system. Specifically, they represent regularized nodewise logistic regression coefficients [6], which give us an idea of the relationship between symptoms. Once the edge weights are estimated, we can compute centrality measures to determine which nodes are most influential in the system based on network theory metrics. Centrality in symptom networks is often summarized using expected influence (EI), which is computed by summing the values of the edges connected to each symptom [11].

Once the model is fitted, edge weight accuracy and stability was assessed by computing 95% confidence intervals around each edge weight using nonparametric bootstrapping with 500 iterations. Statistically non-significant edges (those with p-values greater than $\alpha = 0.01$) were removed to increase the sparsity of the network since they tend to indicate weak associations. Additionally, case-drop bootstrapping was used to estimate correlation stability (CS) coefficients to determine the stability of centrality indices [11].

3 Results

Figure [1] shows the thresholded symptom network of ABCD youth at year-3 follow-up. The edge weight estimates are generally stable as shown in Figure [2a], with the majority of confidence intervals having small to moderate ranges. A correlation stability coefficient of 0.52 [LB: 0.44, UB: 0.59] was estimated, indicating that up to 0.52% of the samples can be dropped before the Estimated Influence centrality measure becomes unstable when recalculated in future samples. A centrality plot is shown in

Figure [2b], indicating the most 'important' nodes in the network at a global level, which should by complemented by the symptom network visualization.

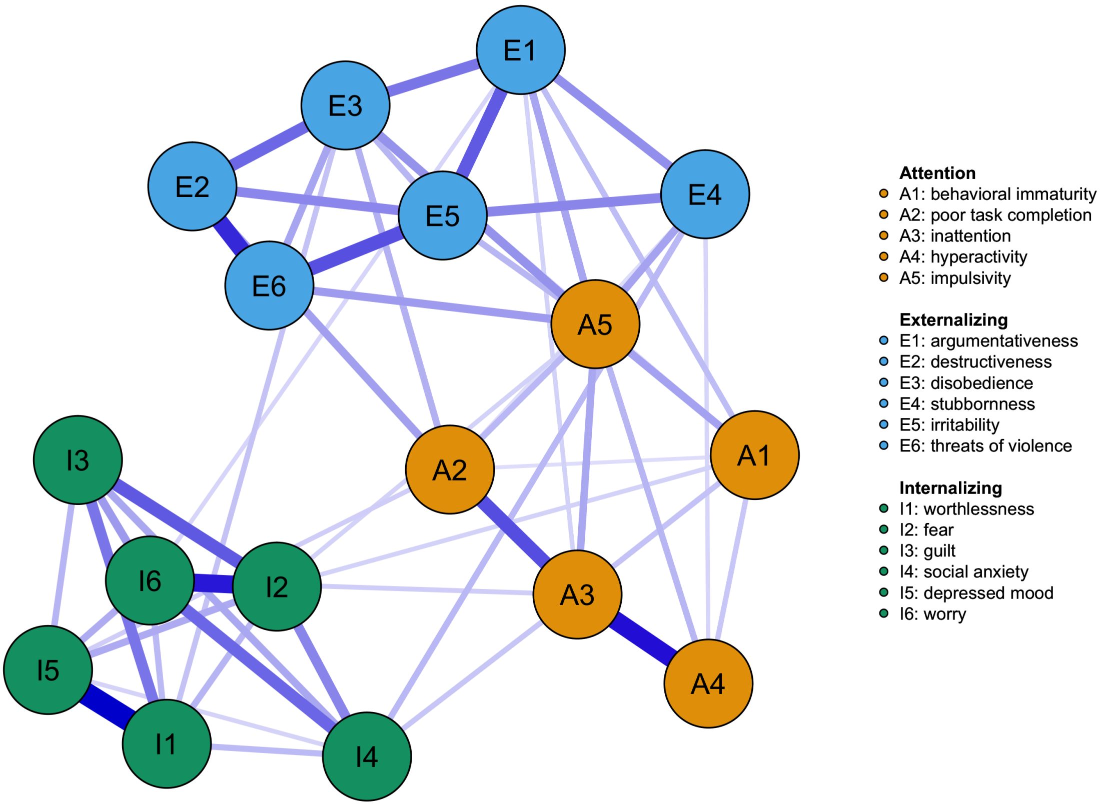
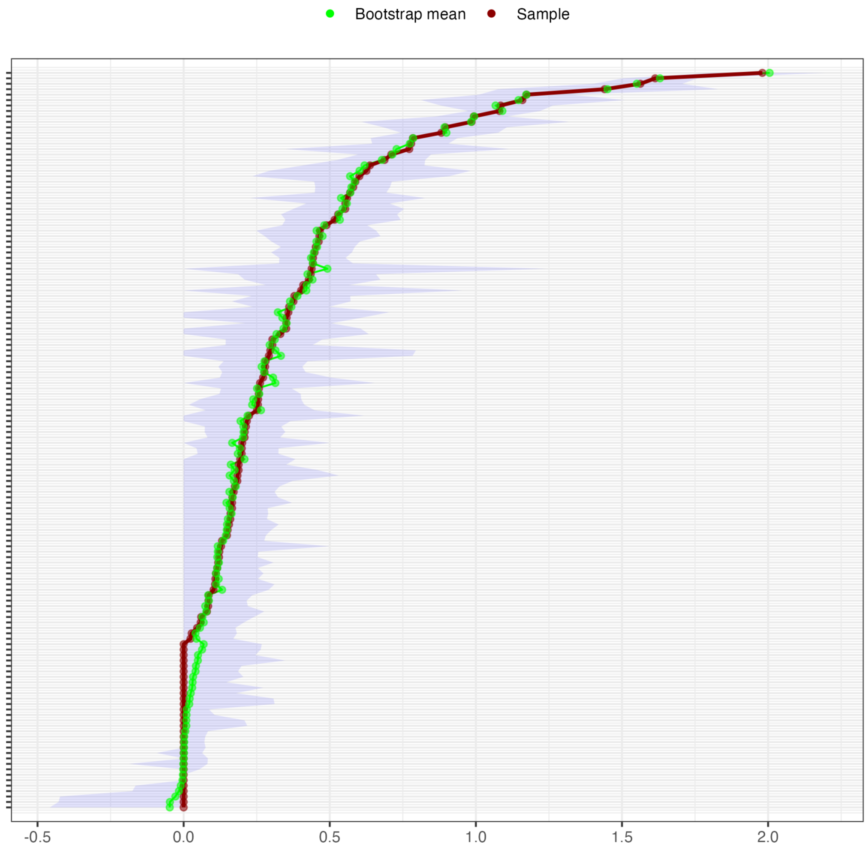


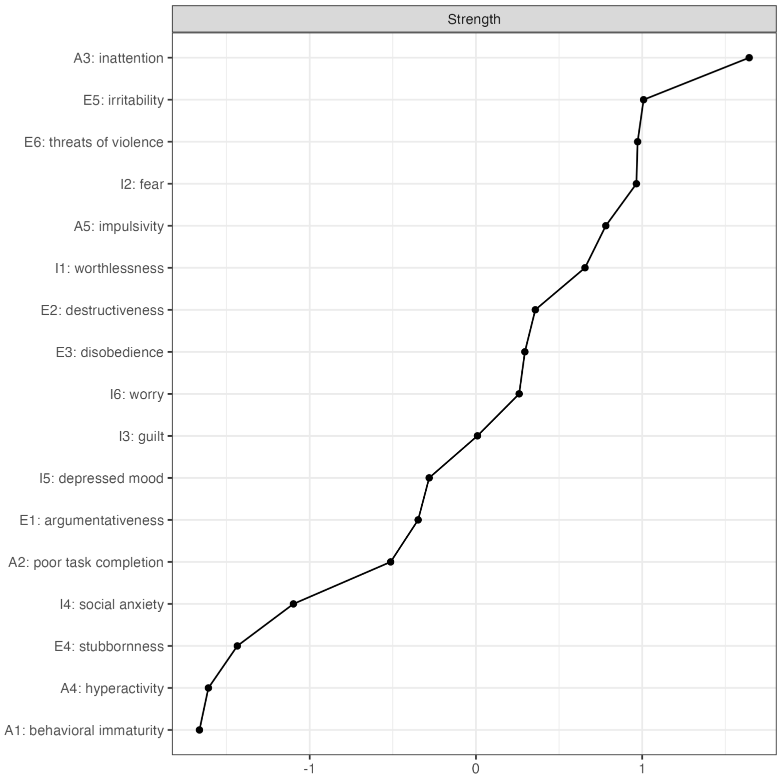
Figure 1: Estimated symptom network using 3-year follow-up CBCL data.

Nodes were colored according to whether they belonged to the Attention, Externalizing, or Internalizing group and placed using a force-directed network layout. Thicker edges denote stronger associations between symptoms. In the Internalizing cluster the strongest belong to I1 ("I feel worthless or inferior") and I5 ("I am unhappy, sad, or depressed"), and I2 ("I am too fearful or anxious") and I6 ("I worry a lot"). In the Externalizing cluster it's E2 ("I destroy things belonging to others") and E6 ("I threaten to hurt people"). In the Attention cluster it's A3 ("I have trouble concentrating or paying attention/I am inattentive or easily distracted") and A4 ("I have trouble sitting still"). We can also see how symptoms are associated across clusters, though these relationships tend to be weaker.

The most central nodes as measured by Estimated Influence is A3 ("I have trouble concentrating or paying attention/I am inattentive or easily distracted"), along with A1 (" I act too young for my age"), A4 (" I have trouble sitting still"), and E4 ("I am stubborn"). Again it should be emphasized that Estimated Influence is a global network measure. It doesn't indicate anything about particular relationships between symptoms.



(a) 95% confidence intervals for edge weights.



(b) Centrality plot of Estimated Influence (standardized to z-scores).

4 Discussion

This brief project was an exploration of how a network science approach could be applied to understand the structure of mental health symptoms in large sample of youth. The results indicate that associations between symptoms within the same cluster are stronger than those across cluster, though the relationships between symptoms across clusters are retained even after statistical pruning of edges and a fitting procedure using LASSO regularization. Having a large sample size addresses some of the common fitting issues associated with estimating psychological network structures, however other methods such as Mixed Graphical Models may have yielded better results [6, 4]. For example, Mixed Graphical Models allow the addition of covariates such as income or parental education to the model, which is likely to improve the validity and generalizability of the current results. Additionally, BPM data were available across multiple time points and could have been utilized to draw stronger directional relationships between symptoms. However, due to time constraints and the exploratory nature of the project, this avenue is left for future research. At the very least the network approach is complementary to latent variable models and has opened up new research questions into the nature of mental health [8]. I personally find this an exciting topic and look forward to ongoing explorations and applications of complex systems and network science in understanding adolescent development.

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