A Network Analysis of Obsessive-Compulsive Disorder and Its Common Comorbidities

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Abstract

Obsessive-compulsive disorder (OCD) commonly co-occurs with other psychiatric conditions. In recent years, network analysis has been employed to investigate the relationship between OCD and some of its comorbidities. The objective of the current thesis was to explore the comorbidity network of OCD in relation to seven other psychiatric conditions, some of whose interactions with OCD have not been investigated by the former network analysis papers. The thesis made use of an open-source data which was collected from patients who registered to the Behavioural Health Partial (BHP) hospital program at McLean Hospital, Massachusetts between 30 November 2018–16 October 2019. The final sample consisted of 532 people. Their responses to four measures, namely Obsessive-Compulsive and Related Disorders Dimensional Scales, Patient Health Questionnaire, Generalized Anxiety Disorder Scale, Drug Alcohol Craving Scale were analysed using network analysis. In total, we estimated two regularized partial correlation networks. The first network consisted of eight nodes representing eight psychiatric conditions. Differing from the former network in one way, the second one represented OCD and depression at a symptom level. Network 1 showed that OCD was connected to all other obsessive-compulsive and related disorder (OCRD)'s and generalized anxiety disorder (GAD) but not to depression and drug alcohol craving. In this network, OCD was only linked to depression through other OCRD's and GAD. Further, our results highlighted the importance of fatigue as it was one of the most central nodes in Network 2.

Keywords: obsessive-compulsive disorder, comorbidity, network analysis

Scientific Background

Obsessive-compulsive disorder (OCD) is known to have high comorbidity rates (American Psychiatric Association, 2013). The lifetime prevalence of any anxiety disorder and any depressive/bipolar disorder in the adult OCD patient population is at 76% and 63%, respectfully (American Psychiatric Association, 2013). To inquire about the lifetime comorbidity rates at an individual disorder level, one can consult the study by Brakoulias et al. (2017). In their large-scale study which included over 3700 participants from multiple OCD treatment centres across seven countries, the researchers found that the most common five co-occurrent disorders were major depressive disorder (MDD) (50.5%), obsessive-compulsive personality disorder (OCPD) (44.5%), social phobia (26.4%), specific phobia (25.5%), and generalized anxiety disorder (GAD) (24.0%) (Brakoulias et al., 2017). Furthermore, some psychopathologies are more common in OCD patient population than in the general public, with some of such pathologies being body dysmorphic disorder (BDD), hair pulling disorder (HPD) and skin picking disorder (SPD) (American Psychiatric Association, 2013). It is worth mentioning that these three conditions are grouped together with OCD in the DSM-5 chapter named obsessive-compulsive and related disorders (OCRDs). This chapter includes obsessive-compulsive disorder (OCD), body dysmorphic disorder (BDD), hoarding disorder (HD), hair pulling disorder (HPD), skin-picking disorder (SPD), substance/medication-induced obsessive-compulsive and related disorder, obsessive-compulsive and related disorder due to another medical condition, other specified obsessive-compulsive and related disorder, and unspecified obsessive-compulsive and related disorder (American Psychiatric Association, 2013).[1]

According to the network theory, mental disorders are conceptualized as networks of interacting individual symptoms that cluster together syndromically and comorbidities as the result of symptom-level links between two separate clusters (Cramer et al, 2010). This perspective has been used to explore how OCD interacts with several other clinical problems; namely autism (Ruzzano et al, 2015), depression (McNelly et al, 2017; Jones et al, 2018; Klein et al, 2020; Cervin et al, 2020), hoarding (Timpano et al, 2020), eating disorders (Meier et al,2020; Vanzhula et al, 2021) and anxiety disorders (Cervin et al, 2020). Five of these articles are

[1] In the remainder of this paper, the term OCRDs will refer to OCD, BDD, HD, HPD, and SPD, that is excluding substance-induced, medical condition-induced, otherwise specified, and unspecified OCRDs.

investigating the intersyndromic interactions relevant to and testable with the pre-existing dataset we will be using. Please refer to *table 1* for an overview of these five articles and to the methods section for information regarding our dataset.[2] First, however, the following paragraphs will provide a brief introduction to network analysis with its jargons. That is in order to make the review of these five papers easily understandable.

In network analysis, variables are termed 'nodes' and associations between them are termed 'edges' (McNally, 2016). Another important jargon in this field is the 'node centrality' which is the measure of a node's importance to its network (McNally, 2016). The different ways of being important is reflected in different measures of node centrality that exists in network analysis (McNally, 2016). In the methods section, these different centrality measures will be explained in more detail.

When symptoms belonging to different disorders overlap perfectly, to a degree where they can be considered a single entity, Cramer et al. (2010) propose to name such single entity a bridge symptom. Nowadays, however, two different definitions exist that of a bridge symptom, as classified by Castro et al. (2019). According to this classification, the first definition relies on the perfect overlap described above thus relies on the overlapping symptom (the bridge symptom) to be included in the diagnostic criteria of all disorders bridged by it. Whereas the second one considers any symptom which plays a role in connecting distinct disorders as a bridge symptom, including the cases where this symptom does not belong to any specific disorder. Throughout this paper, the latter definition will be used when referring to a bridge symptom.

[2] Note that the networks that represented OCD with multiple nodes corresponding to different forms in which the disorder can manifest (washing, ordering, checking etc) for different individuals were not considered during the literature search. This was because their field of inquiry is different from ours given that our dataset contains information regarding different components of the disorder (such as: avoidance caused by, time consumed by or control over symptoms) regardless of the form the disorder took for a given individual.

Table 1

Overview of Five Articles Reviewed in This Thesis

Study	Participants	Nodes
McNally et al, 2017	408 OCD patients (adults)	OCD severity (10 nodes) Depression symptoms (16 nodes)
Jones et al, 2018	87 OCD patients (adolescents)	OCD severity (10 nodes) Depression symptoms (16 nodes)
Klein et al, 2020	290 OCD patients (adults)	OCD severity (10 nodes) Depression symptoms (10 nodes)
Cervin et al, 2020	352 OCD patients (adolescents)	OCD severity (10 nodes) Depression symptoms (9 nodes)
Timpano et al, 2020	217 HD patients +130 HC (adults)	Anxiety (1 node) Depression (1 node) Social Anxiety (1 node) OCD (1 node) Hoarding features (3 nodes) Impairment (2 nodes) Hoarding motives (4 nodes)
	217 HD patients (adults)	
	130 HC (adults)	

Four studies investigated the comorbidity network of OCD and depression at an item level (McNally et al, 2017; Jones et al, 2018; Klein et al, 2020; Cervin et al, 2020). McNally et al. (2017) reported over a dozen intersyndromic connections between two disorders, the strongest one among them being between distress caused by obsessions and sadness. Similarly, the link between distress caused by obsessive thoughts and sadness was also present as a bridging edge in the study by Jones et al. (2018). There were two other bridging edges in their network which were between time occupied by obsessive thoughts and impairment in concentration/decision making, and between difficulty controlling obsessions and guilt. Klein et al. (2020) reported several edges linking OCD and depression, two strongest among them being between interference due to obsessive thoughts and lack of energy, and between distress associated with obsessive

thoughts and fear. Finally, Cervin et al. (2020) reported the presence of four edges linking the syndromic clusters and these edges appeared between time occupied by obsessions and worry, time occupied by obsessions and sadness, difficulty controlling obsessions and failure, distress caused by compulsions and failure. Overall, there seems to be some discrepancies regarding what the bridge symptoms were for OCD-depression comorbidity. Although, distress caused by obsessions and sadness were rather consistent in emerging as bridge symptoms. It is also important to note that, in these four studies the items of the obsession subscale emerged as bridge symptoms more than the items of the compulsion subscale. Regarding centrality, fatigue followed by distress caused by obsessions and sadness were the most consistent central nodes across these studies and the different measures of centrality they employed.

Timpano et al (2020) investigated the comorbidity network of hoarding disorder (HD) in three adult samples: HD patients, healthy controls, and the full sample. The nodes representing the comorbidities of HD (OCD, anxiety, depression and social anxiety) clustered together in all three networks. This cluster was connected to the HD related nodes most consistently through the edge between depression and social impairment caused by hoarding. In addition to the aforementioned findings, the article (Timpano et al., 2020) also reveals that OCD was connected most strongly to anxiety in the first and the second network. Moreover, in both networks anxiety was the pathway through which OCD was linked to depression, although a very weak direct link between OCD and depression existed. Whereas, in the case of the healthy comparison network OCD was connected to depression and the hoarding feature ‘acquire’ approximately as strongly as it is to anxiety.

Research Objectives

Currently, there is no investigation from the network perspective on how OCD relates to the alcohol/substance craving nor to three out of the five obsessive-compulsive and related disorders (OCRDs) namely, body dysmorphic disorder (BDD), hair pulling disorder (HPD), skin picking disorder (SPD). Further, already-investigated comorbidity networks of OCD need more research for their findings to be considered well-replicated.

This thesis aims to examine the comorbidity network of OCD in relation to other OCRDs (BDD, HD, HPD, and SPD) as well as in relation to depression, GAD, and alcohol/substance craving. The motive for this research is 1) applying network analysis to not formerly investigated comorbidities for its exploratory value and 2) replicating the former studies which were on how OCD relates to depression, GAD, and HD. It is important to note, however, that direct replication is not possible as the measurement, design, and subject characteristics of the former studies differ from those that resulted in the current data. What is aimed with this thesis instead is conceptual replication which would enable one to see if the propositions reached by the former research have validity across different methods (Schmidt, 2009).

Hypotheses

The current thesis will mainly conduct exploratory research on how OCD relates to some of its common comorbidities. In addition, however, two plausible hypotheses that emerged after the literature review will be tested as well.

Hypothesis 1

The high centrality of fatigue in OCD-depression comorbidity networks was the most consistent finding throughout the literature review. Therefore, our first hypothesis is that PHQ item 4 (*feeling tired or having little energy*) will be one of the most central nodes in the second network that we will estimate (please refer to the methods section *table 3* for a list of all the nodes present in Network 2). It is important to note that the earlier studies that investigated the item level interactions between OCD and depression (McNally et al., 2017; Jones et al., 2018; Klein et al., 2020; Cervin et al., 2020) did not control for other psychological conditions. Whereas our network will include additional six nodes each representing the total score of one of six conditions (HD, BDD, SPD, HPD, GAD and alcohol/substance craving) when investigating the item level interactions between OCD and depression.

Hypothesis 2

One other hypothesis is that, in our first network (please refer to the methods section *table 2* for a list of all the nodes present in Network 1) HD will be linked to the cluster of OCD, depression, anxiety mainly by having a direct connection with depression rather than OCD or

anxiety. The reason why we are predicting this link to be direct is that, unlike the previous study (Timpano et al., 2020), we do not have separate nodes representing HD and social impairment caused by it. Instead, the node representing HD in our network corresponds the total score of a measure which includes an item addressing social impairment (*How much do these symptoms interfere with school, work or your social or family life?)*.

Methods

Procedure

The current thesis is using data available on the website of Open Science Framework (OSF). The data is from the study 'Transdiagnostic Dimensions in Obsessive Compulsive and Related Disorders: Associations with Internalizing and Externalizing Symptoms' (Snorrason et al. 2020). We thank the authors for making their data public.

The authors of the study report that the participants completed OCDR-DS on the second day and the other study questionnaires on the first day of the program as a part of the routine clinical evaluation. As the study was using an existing de-identified dataset, the hospital's IRB approved it as an exempt protocol (Snorrason et al. 2020). The authors state that all procedures contributing to their work comply with the ethical standards of the relevant national and institutional committees on human experimentation and with the Helsinki Declaration of 1975, as revised in 2008.

Participants

During 30 November 2018–16 October 2019, 544 new patients registered to the Behavioral Health Partial (BHP) hospital program at McLean Hospital in Belmont, Massachusetts. From which, 532 were included in the study after the exclusion of 25 that did not complete the study measures and 4 that completed with unreliable responses. 53.2% of the sample (n= 283) were female, 44.9% (n=239) male and 1.9% (n=10) transgender or non-binary. The average age was at 34, the range being 18-72 and the standard deviation being 14.2 (Snorrason et al. 2020).

BHP hospital program offers intensive 1 to 3 week intervention for patients presenting with acute symptoms. Referrals to the program, about half of the time, are from inpatient hospitalization and for the other half of the time from outpatient providers. According to the study conducted by Snorrason et al. (2019) on a previous cohort, patients of the BHP program had diagnoses including major depressive episode (61%), GAD (46%), social anxiety disorder (34%), panic disorder (19%), post-traumatic stress disorder (13%), OCD (19%), and BDD (8%) (Snorrason et al. 2020).

Measures

Obsessive-Compulsive and Related Disorders Dimensional Scales *(OCRD-DS; LeBeau et al. 2013)*

OCRD-DS is a self-report questionnaire designed by DSM-V OCRD workgroup. It contains five modules, each assessing one OCRD. In every module, information about the disorder is provided together with 5 items assessing different aspects of its severity. The items can be rated from 0 to 4, with the total score (possible range being 0 to 20) indicating the level of severity. OCRD-DS was modelled after the 5-item severity scale of Florida Obsessive Compulsive Inventory (FOCI; Storch et al., 2007). FOCI severity scale as well as the four new scales adapted from it namely, BDD-D, HD-D, HPD-D, SPD-D have high internal consistency scores at 0.89 (FOCI; Storch et al.,2007), and at 0.80, 0.82, 0.89, 0.88 (LeBeau et al., 2013), respectfully.

Patient Health Questionnaire *(PHQ-9; Kroenke et al. 2001)*

PHQ-9 assesses symptoms of major depressive episode in the past two weeks with 9 items, each to be rated on a 4-point scale (0 to 3). A higher score indicates greater severity, the highest score possible being 27. Kroenke et al, (2001) reports the internal reliability of the questionnaire as high, that is between 0.86 and 0.89.

General Anxiety Disorder Scale *(GAD-7; Spitzer et al. 2006)*

GAD-7 assesses symptoms of generalized anxiety disorder in the past two weeks. It has 7 items on a 4-point scale (0 to 3) thus a possible total score ranging from 0-21, higher the score

greater the severity. According to Spitzer et al., (2006), GAD-7 has high internal consistency with Chonbach's alpha being 0.92.

Drug Alcohol Craving Scale *(adapted from the Cocaine Craving Scale; Weiss et al. 2003 by Snorrason et al. 2020)*

Drug Alcohol Craving Scale assesses the craving felt for drugs or alcohol currently and in the last week with 3 items that are all on a 10-point scale. The final score is calculated by taking the average, meaning that the highest possible score is 10 indicating the greatest craving. Snorrason et al. (2020) reports the Cronbach's alpha to be 0.80 for their, thus our, sample.

Statistical Analyses

In this thesis we will estimate two networks. First will be comprised of eight nodes (*table 2*) each of which corresponds to the total score of one condition. The second network, on the other hand, will be comprised of twenty nodes *(table 3)*. While six of these twenty nodes will still correspond to the total score of one condition, the second network, unlike Network 1, will represent the conditions OCD and depression at an item level with five and nine nodes, respectfully. While the power is somewhat compromised in Network 2, we will be able to compare our results with some those of former research which we reviewed in the introduction section *(table 1)*.

Table 2

Nodes Belonging to Network 1

Variables		Corresponding Node Names
1.	OCD-D total score	OCD
2.	BDD-D total score	BDD
3.	HD-D total score	HD
4.	HPD-D total score	HPD
5.	SPD-D total score	SPD
6.	PHQ9 total score	PHQ9
7.	GAD7 total score	GAD7
8.	DACS total score	CRAVE

Table 3

Nodes Belonging to Network 2

Variables	Corresponding Node Names
1. OCD-D item 1 (On average, how much time is occupied by these thoughts or behaviours each day?)	OCD_time
2. OCD-D item 2 (How much distress do they cause you?)	OCD_distress
3. OCD-D item 3 (How hard is it for you to control them?)	OCD_control
4. OCD-D item 4 (How much do they cause you to avoid doing anything, going anyplace, or being with anyone?)	OCD_avoidence
5. OCD-D item 5 (How much do they interfere with school, work, or your social or family life?)	OCD_interferance
6. PHQ9 item 1 (Little interest or pleasure in doing things)	PHQ9_1
7. PHQ9 item 2 (Feeling down, depressed, or hopeless)	PHQ9_2
8. PHQ9 item 3 (Trouble falling or staying asleep, or sleeping too much)	PHQ9_3
9. PHQ9 item 4 (Feeling tired or having little energy)	PHQ9_4
10. PHQ9 item 5 (Poor appetite or overeating)	PHQ9_5
11. PHQ9 item 6 (Feeling bad about yourself — or that you are a failure or have let yourself or your family down)	PHQ9_6
12. PHQ9 item 7 (Trouble concentrating on things, such as reading the newspaper or watching television)	PHQ9_7
13. PHQ9 item 8 (Moving or speaking so slowly that other people could have noticed? Or so fidgety or restless that you have been moving a lot more than usual)	PHQ9_8
14. PHQ9 item 9 (Thoughts that you would be better off dead, or thoughts of hurting yourself in some way)	PHQ9_9
15. GAD7 total score	GAD7
16. DACS total score	CRAVE
17. BDD-D total score	BDD
18. HD-D total score	HD
19. HPD-D total score	HPD
20. SPD-D total score	SPD

All networks in this thesis will be regularized partial correlation networks estimated by EBICglasso (Graphical Least Absolute Shrinkage and Selection Operator with Extended Bayesian Information Criterion model selection; Foygel & Drton, 2010; Friedman, Hastie, &

Tibshirani, 2008; Friedman, Hastie, & Tibshirani, 2014). Node centrality incidences will be calculated to derive further information from these networks. Finally, bootstrapping techniques will be performed on the networks to test for accuracy and stability. All missing data will be excluded pair-wise. All analyses will be conducted on the statistical program JASP (JASP Team, 2021).

In the partial correlation networks, also known as Gaussian Graphical Models (GGM), the nodes correspond to variables and the edges correspond to the conditional independence associations, that are the associations between each pair of these variables after accounting for the all the other information available (Epskamp & Fried, 2018). The direction and strength of these associations are reflected in the colour and the thickness of the edges drawn, respectfully (Epskamp et al., 2012). To counterwork potential type 1 errors (false positives) and to enable easier interpretation, the statistical regularization techniques are commonly utilized, one of them being lasso (Least Absolute Shrinkage and Selection Operator; Tibshirani, 1996) (Epskamp & Fried, 2018). The estimator EBICglasso (Graphical Least Absolute Shrinkage and Selection Operator with Extended Bayesian Information Criterion model selection) allows researchers to adjust the degree of regularization manually through setting the hyperparameter (gamma; γ) at a value between 0 – 1 (Epskamp & Fried, 2018). For each network estimation in our study, we will set the gamma value at 0.5 which is the default in JASP.

When addressing the matter of bridge symptom identification, some studies additionally analysed bootstrapped confidence intervals of edge weights in order to separate significant inter-syndromic edges from insignificant ones. In the case of regularized partial correlation networks, however, using bootstrapped confidence intervals of an edge weight to test whether it is significantly different from zero is erroneous since the regularization, a technique to exclude coefficients that are zero, is already applied to these networks (E. Fried, 2018). Thus, in our network estimations we will report all inter-syndromic links that survived the regularization as bridge symptoms.

In network analysis, node centrality metrics are the calculations of how important a given node is for its network (McNally, 2016). A node's expected influence centrality is calculated by summing the weights of all edges attached to that node. The measure of strength centrality, on the other hand, is calculated with one difference; it takes *the absolute values* of these edge weights

before the addition. In regard to the computation of betweenness and closeness centrality, information on the shortest paths between every pair of nodes is needed. While the value of betweenness centrality is acquired through counting the number of times a given node is on the shortest path between a node pair, the closeness centrality denotes the average of the minimum number of steps needed to reach all the other nodes (McNally, 2016). In this thesis, these four centrality measures will be analysed and reported.

In order to investigate the accuracy of edge weights and the stability of centrality indices, we will use the following methods suggested by Epskamp, et al. (2018). Firstly, the edge weights for all resampled data sets will be calculated to draw 95% confidence intervals for each edge using non-parametric bootstrapping. Secondly, case-dropping bootstrapping will be performed to calculate the correlation between centrality indices belonging to the original sample and to all other sub-samples.

Correlation stability coefficient (CS-coefficient) was proposed by Epskamp, et al. (2018) to help researchers interpret the results of case-dropping bootstrap on centrality indices. CS(cor = 0.7) equals the maximum percentage of cases that can be dropped in order for there to be 95% probability that the correlation with the original centrality indices is at least 0.7. To consider a metric stable, the authors recommend a cut-off point of at least 0.5 for the CS-coefficient.

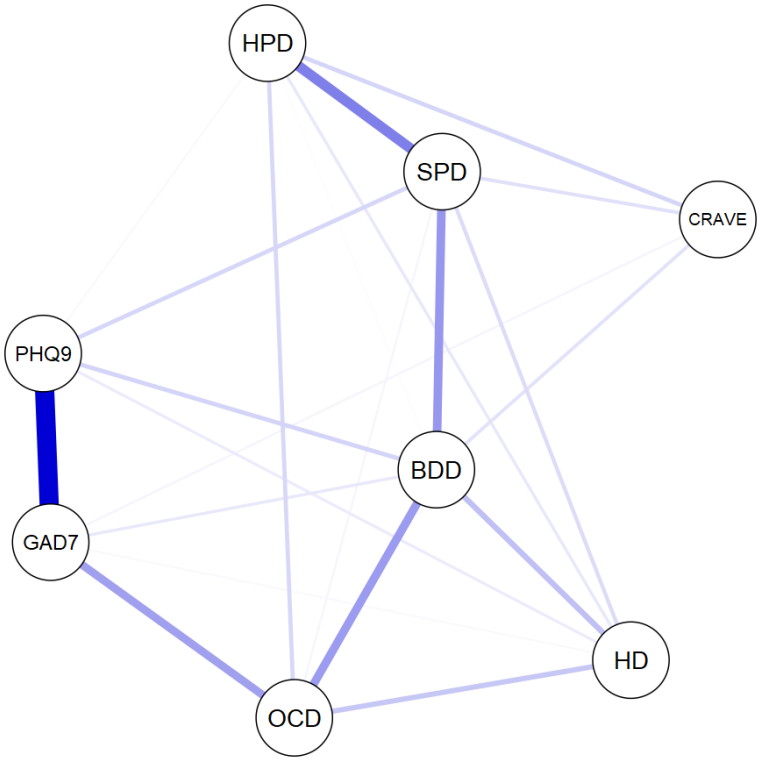
Results

Network 1

All eight nodes belonging to Network 1 (*figure 1*) are connected to at least four other nodes. All the existing edges in the network correspond to positive partial correlations, the strongest ones among them being between GAD and depression (edge weight: 0.561) and HPD and SPD (edge weight: 0.281). HD has a direct yet weak connection to depression (edge weight: 0.045). There is no direct link between OCD and depression. Rather they are connected indirectly, mainly through GAD (edge weights: 0.209(OCD-GAD) and 0.561(GAD-depression)) as well as BDD (edge weights: 0.220(OCD-BDD) and 0.096(BDD-depression)). Further information on exact weights for each edge can be found in the supplement.

Figure 1

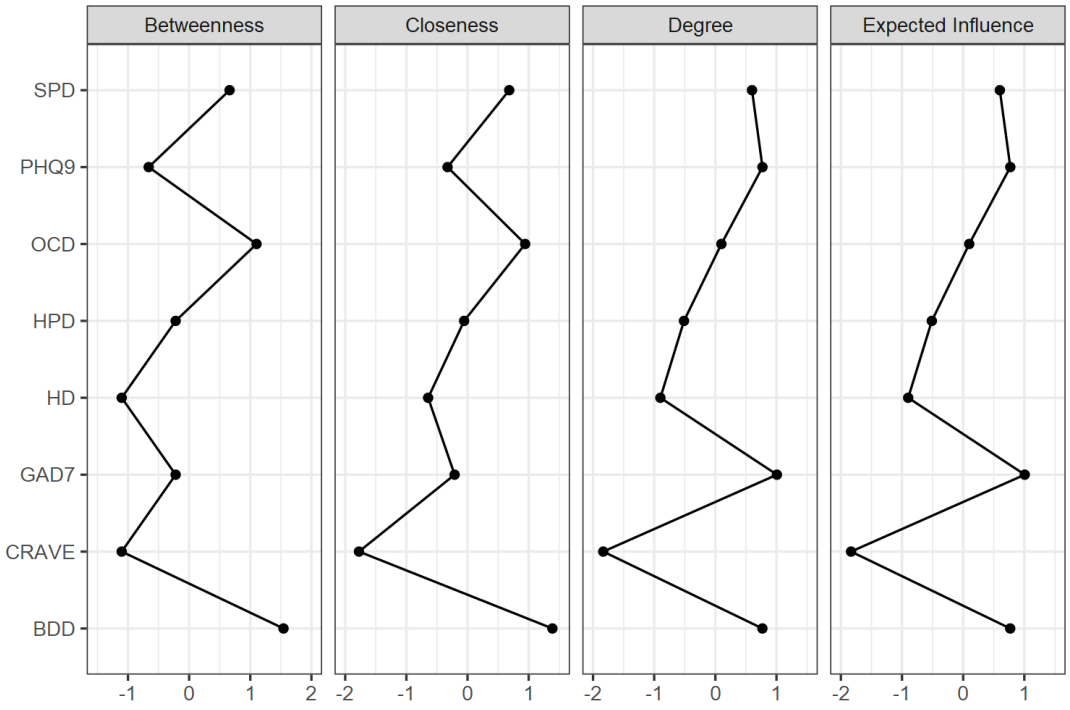
Network of 8 Clinical Conditions Each Represented with 1 node



The centrality indices (normalized) for each node are presented in *figure 2*. As can be seen, the node with the highest betweenness centrality is BDD, followed by OCD, and then by SPD. Likewise, the node with the highest closeness centrality is BDD, followed by OCD, and then by SPD. The node with the greatest strength centrality, on the other hand, is GAD, followed by depression, and then by BDD. As there are no negative associations in this network, therefore the expected influence centrality scores are identical to those of strength centrality.

Figure 2

Centrality Plot belonging to Network 1



Note. The x-axis depicts standardized z-scores.

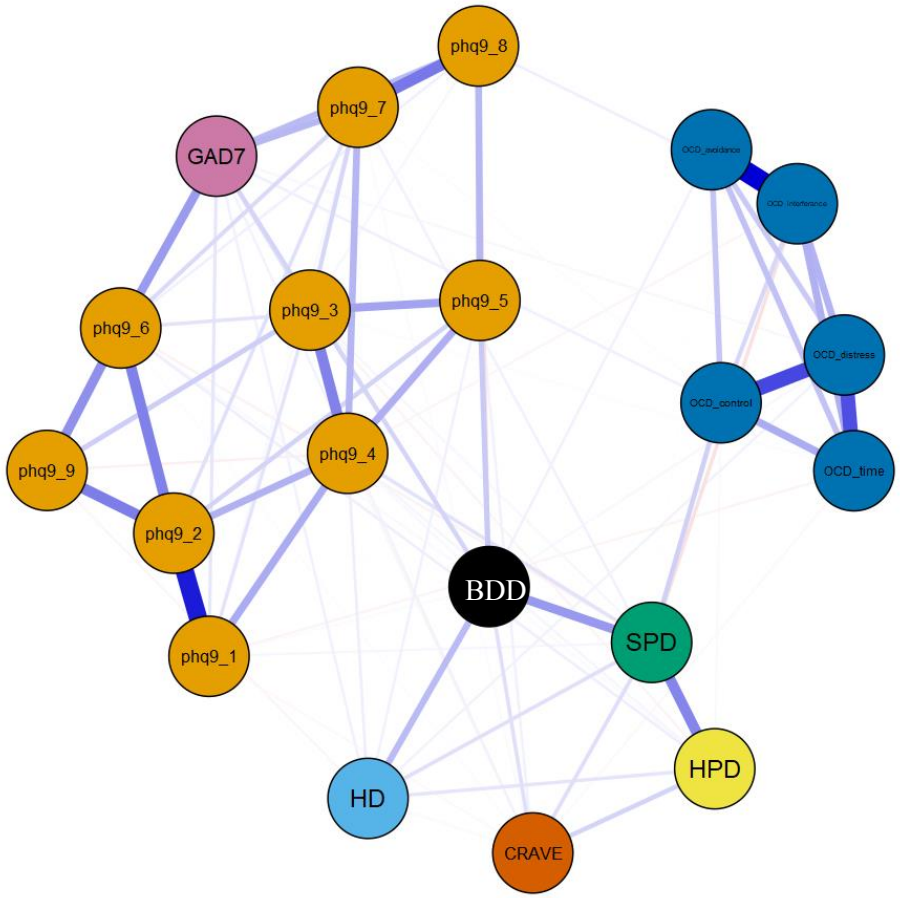
Network 2

As illustrated in *figure 3*, the nodes belonging to Network 2 are well connected to each other with the vast majority of these associations being positive. The strongest edges unsurprisingly emerge within disorder and are between 1) avoidance caused by OCD symptoms and interference caused by OCD symptoms (0.584), 2) anhedonia and depressive mood (0.521), 3) inability to control OCD symptoms and distress caused by OCD symptoms (0.422), and 4) distress caused by OCD symptoms and time consumed by OCD symptoms (0.402). There appear to be a few symptom-level direct links between OCD and depression. However, these links are weak and not all positive. This symptom-level analysis also aids further investigation into the aforementioned finding that OCD is indirectly linked to depression through other nodes. Here, we can see that time consumed by OCD (0.033) and distress caused by OCD (0.015) link the

disorder to GAD which is connected to depression symptoms: feeling bad about oneself (0.227), concentration problems (0.165), motor retardation or restlessness (0.154), and to a lesser extent anhedonia (0.056), and sleeping problems (0.055). The items distress caused by OCD (0.016) and avoidance caused by OCD (0.031) link the disorder to BDD which is connected to five different depression symptoms. Among them, the symptom with the strongest association to BDD is poor appetite or overeating (0.121). On the other hand, anhedonia (0.010), fatigue (0.016), feeling bad about oneself (0.014), and motor retardation or restlessness (-0.065) have weaker links that are not all positive. Information on the exact weights for each edge of this network is provided in the supplement.

Figure 3

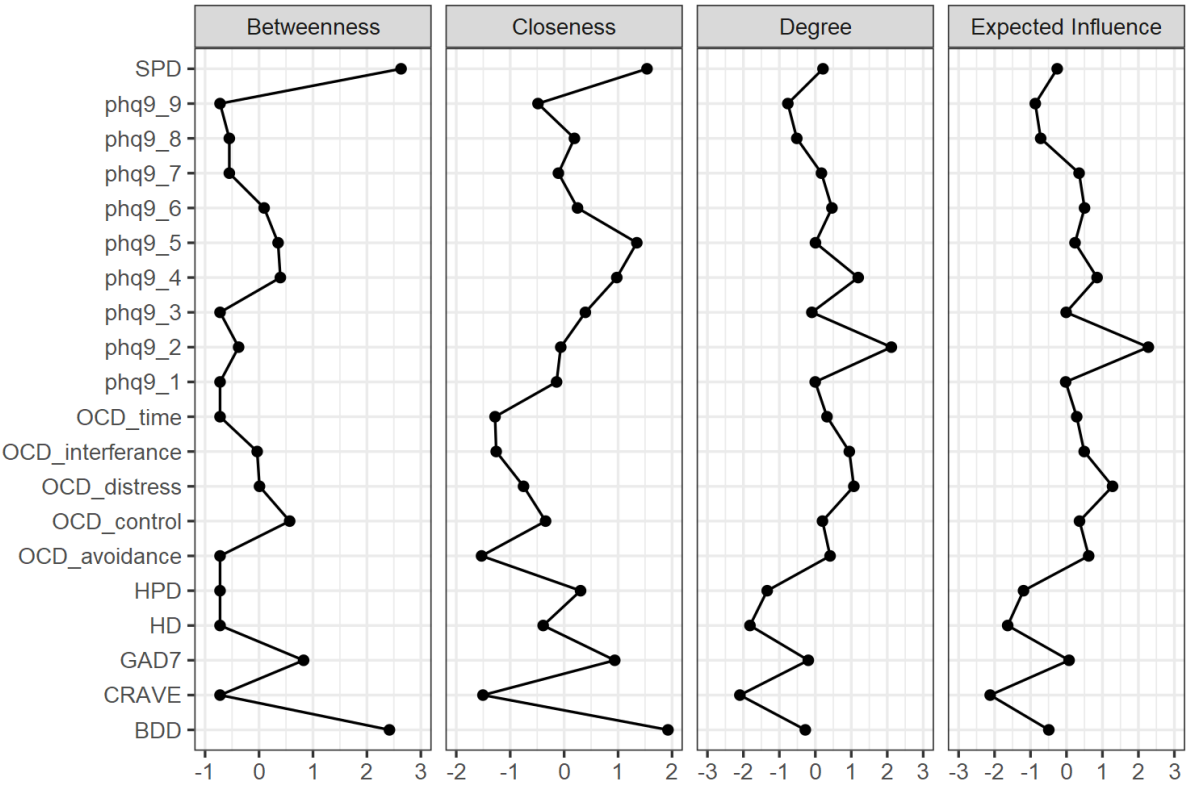
Network of 8 Clinical Conditions 2 of which Represented with Multiple Nodes



As can be seen in *figure 4*, the nodes having both the highest betweenness and the highest closeness centrality are BDD and SPD. Regarding strength centrality, depressed mood appears to have the greatest score, followed by fatigue, distress caused by OCD symptoms, and then interference caused by OCD symptoms. Depressed mood also exhibits the largest expected influence centrality and it is followed by distress caused by OCD, fatigue, and then avoidance caused by OCD.

Figure 4

Centrality Plot belonging to Network 2



Note. The x-axis depicts standardized z-scores.

Accuracy and Stability

The resulting plots from the non-parametric bootstrap with 1000 samples which was applied on both networks are presented in the supplement. As can be seen, there are considerable bootstrapped CIs around the edge weights belonging to both networks. Many of the edges'

confidence intervals overlap, resulting in uncertainties concerning the exact order of these edges (cf. Epskamp et al., 2018). However, the edge between depression and GAD is the strongest one in Network 1 and its confidence intervals does not overlap with those of any other edges.

The case-dropping bootstrap using 1000 samples was performed on both networks and resulted in the plots that can be found in the supplement. For the Network 1, both the closeness and the node strength metrices are stable as their CS-coefficient surpasses the cut-off value. For the Network 2, on the other hand, only the metric node strength has its CS-coefficient above the cut-off thus only the strength centrality indices' order can be considered stable. In this thesis we will base our interpretations only on the centrality metrices that are reported above as stable.

Discussion

In the first network that we estimated, OCD and its seven comorbidities were represented by one node for each. The findings revealed that OCD had edges directly linking it to BDD, GAD, HD, HPD, and SPD. Interestingly, depression was one of only two variables (the other one being substance/alcohol craving) that had no connection to OCD. They were only indirectly connected through BDD, GAD, HD, HPD, and SPD. It is important to note that due to the considerable number of overlaps between the bootstrapped confidence intervals of the edge weights it is not possible to say which of these five comorbidities have the strongest link to OCD. However, it is possible to say with confidence that out of these five comorbidities the one with the strongest connection to depression was GAD, as the bootstrapped confidence intervals of the edge between depression and GAD did not overlap with any other. Although it is important to remember that BDD, HD, HPD, and SPD are all legitimate pathways as they survived regularization, GAD seems to be the main pathway between OCD and depression thus requiring further thought. One hypothesis could be that OCD-depression comorbidity is not related to OCD's unique nature but rather to its anxious component that it shares with GAD.

According to Epskamp, Waldorp et al. (2017) there are three different ways of interpreting an existing edge in GGM's, like our networks. Firstly, the edges could be representing causal interactions issuing from one to another. Two examples could be that GAD is causing both depression and OCD (depression ← GAD → OCD) and that OCD is causing GAD

which in turn causes depression (OCD → GAD → depression). Besides the possibility that the edges are the product of one-way causality, they might also be the product of mutual causality. For instance, GAD could be causing depression and at the same time, depression could be causing GAD (GAD ←→depression). Since we used cross-sectional data, we do not know which direction/s does the causality follow, if there is any causality. The third interpretation could simply be that the connected nodes predict each other after controlling for all the other nodes. What this means for our study is that knowing the level of OCD does not add any predictive value regarding the level of depression and vice versa, when the levels of BDD, GAD, HD, HPD, and SPD are already known.

One of our hypotheses was that HD would be linked to the cluster of OCD, depression, anxiety mainly by having a direct connection with depression rather than with OCD or anxiety. It is not possible to say whether the hypothesis is falsified as the bootstrapped confidence intervals of OCD-HD, anxiety-HD, and depression-HD overlap. However, it is more likely that HD is connected more strongly to OCD as this was the estimation resulting from the edge weight analysis.

With Network 2, we aimed to investigate symptom level interactions between OCD and depression for conceptual replication of the former studies that we reviewed in the introduction section. Our study differed from earlier work in its methods such as sample characteristics and measurement choice but mainly in the fact that we controlled for six other conditions. In the end, our study found no direct link between OCD and depression in Network 1 and only weak symptom level links, which were not all positive, in Network 2. In this symptom level investigation, the edges between avoidance caused by OCD and depressive symptoms were those whose absence were the most surprising, that is given Carvalho and Hopko (2011)'s paper. Carvalho and Hopko (2011) put to the test the mainstream view that avoidance leads to the development and maintenance of depression through reducing positive reinforcement. Their findings supported this view by demonstrating that the relationship between avoidance and depression was significantly mediated by both the behavioural and the self-report indices of reward, even after controlling for anxiety (Carvalho & Hopko, 2011). Thus, we would have expected to see a direct link between depression symptoms and the node representing avoidance (direct since positive reinforcement was not measured for our data). Although we do not have a

node representing the concept of avoidance as a whole but rather avoidance caused exclusively by OCD (*How much do these symptoms cause you to avoid doing anything, going anyplace, or being with anyone?*), the finding is still contrary to the expected.

For Network 2, depressed mood and fatigue were the most central nodes. This finding affirms our hypothesis that the node representing fatigue would be one of the most central in Network 2. If the edges linked to fatigue are reflective of causal influences issuing from it, then deactivating fatigue would induce substantial changes in the network. Even though it is very plausible that fatigue would have a causal influence on sleep problems, concentration impairment, appetite problems, and anhedonia -which are some of the nodes with the strongest association to fatigue in our network- given the correlational nature of our research we cannot draw these causal conclusions rather can only hypothesize about them.

One other hypothesis could be that fatigue would function in the same way as, or through, avoidance in that it could be influencing depression by inhibiting positive reinforcements. Moreover, positive reinforcement is thought to occur after a pleasurable outcome of a behaviour or a sense of achievement experienced after a behaviour is completed (Beck et al., 1979; Lewinsohn, 1974, as cited in Carvalho & Hopko, 2011), both of which ways could plausibly be inhibited by fatigue. For example, fatigue could be a reason for a person to reject a friend's invite to meet up and a reason to neglect schoolwork. Consequently, this individual could be missing out on opportunities to get pleasure or a sense of achievement, in this case from the social interaction and from being successful in completing their schoolwork, respectfully. However, with no node to represent positive reinforcement of any type we cannot test whether fatigue actually has a link to depression through the reduced positive reinforcement. This leads us to the following paragraphs where a discussion will be held on the limitations regarding the variables employed as nodes in our analysis.

As a start, our networks may not include all relevant variables defined as those whose absence would result in an incorrect representation of the true network structure (Fried & Cramer, 2017). Potentially relevant yet absent ones are 1) some common comorbidities of OCD, 2) some syndromic components that may or may not be listed as symptoms in the DSM (Fried & Cramer, 2017) and 3) some variables that are not part of one specific syndrome (Fried & Cramer, 2017). For the former category, obsessive-compulsive personality disorder (OCPD) which is present in

23 to 32 percent of the OCD patient population could be a good example (American Psychiatric Association, 2013). To come up with ideas for what might make suitable candidates for the latter two categories, on the other hand, we can consult Fried & Cramer (2017). In this article, the authors list a few variables likely to be relevant in psychopathological networks namely, impairment of functioning, cognitive processes, positive/negative social interactions per day, rejection events, physical activities, substance abuse, and specific to anxiety disorders the authors further add distress and approach/avoidance behaviours (Fried & Cramer, 2017). It is worth noticing that some of these suggestions (mainly positive social interactions and psychical activity) are closely related to positive reinforcement which was highlighted above.

For OCD, our second network includes nodes representing distress (*How much distress do these symptoms cause you?*), avoidance behaviours (*How much do these symptoms cause you to avoid doing anything, going anyplace, or being with anyone?*) as well as impairment of functioning (*How much do these symptoms interfere with school, work or your social or family life?*). However, it does not include separate nodes for obsessions and compulsions which are the two symptoms of the disorder. Whereas for depression, our second network includes nine separate nodes for nine symptoms of depression as defined by DSM-5 (American Psychiatric Association, 2013). However, it does not include nodes for other relevant components of depression. Apart from these missing components of OCD and depression, components of some other disorders, that we previously only represented with one node, would also be good candidates for inclusion. This is especially true for GAD which, in our network estimation, seems to be the most important variable to understand the nature of OCD-depression comorbidity.

Lastly, it is also important, while trying to include all relevant variables, to ensure that the nodes are neither conceptually overlapping nor too many in number (Fried & Cramer, 2017). While the first warning guards against biases in centrality estimates and spurious causal claims between conceptually overlapping variables, the second one primarily addresses the concerns over power (Fried & Cramer, 2017). Overall, the minimum number of mutually exclusive nodes should be used to study a chosen phenomenon as comprehensively as possible.

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Supplement

Network 1

Summary of Network

Number of nodes	Number of non-zero edges	Sparsity
8	22 / 24	0.214

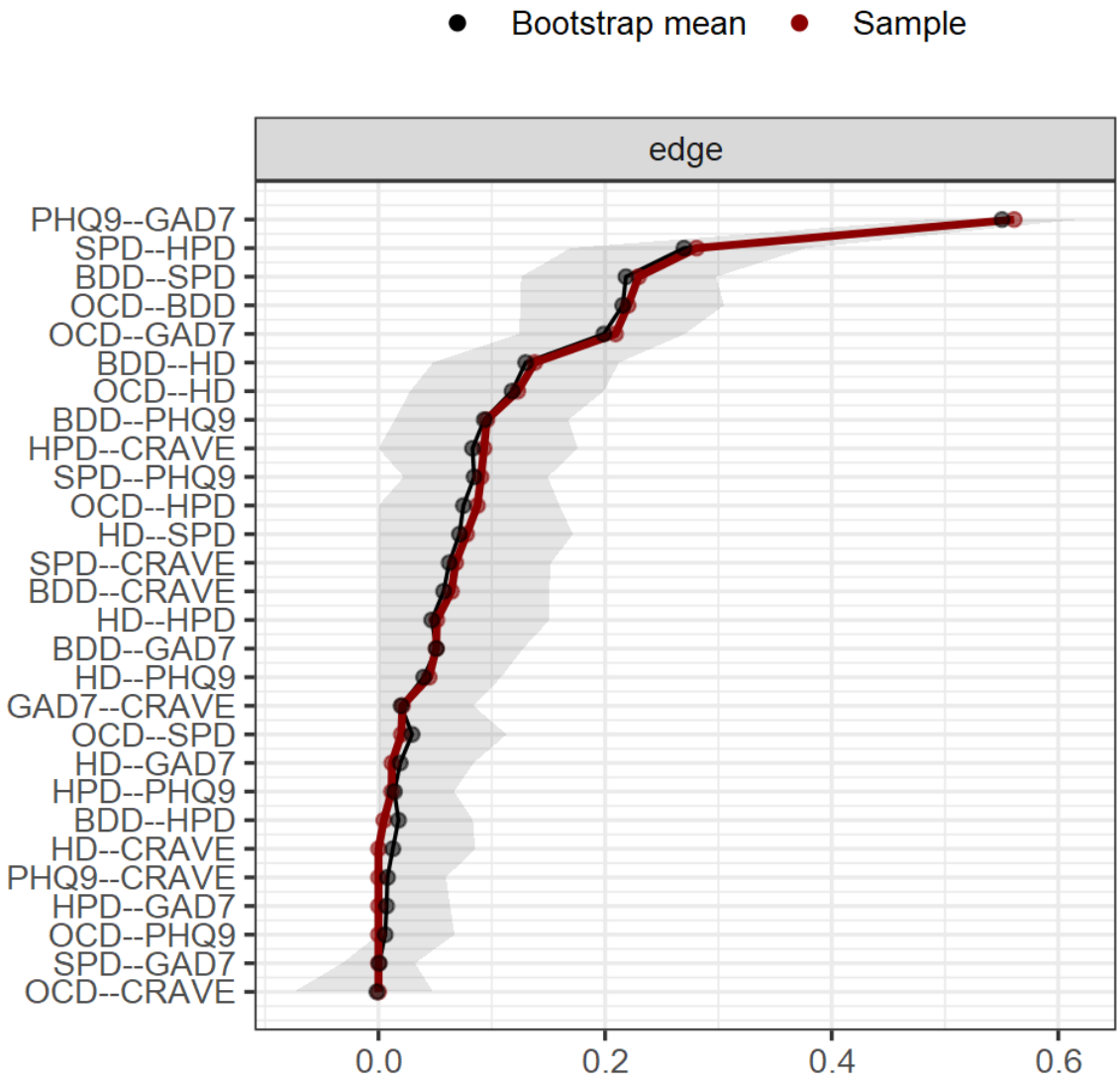
Centrality measures per variable

	Network			
Variable	Betweenness	Closeness	Strength	Expected influence
OCD	1.102	0.942	0.099	0.099
BDD	1.543	1.388	0.769	0.769
HD	-1.102	-0.644	-0.899	-0.899
SPD	0.661	0.682	0.599	0.599
HPD	-0.220	-0.055	-0.513	-0.513
PHQ9	-0.661	-0.327	0.771	0.771
GAD7	-0.220	-0.211	1.007	1.007
CRAVE	-1.102	-1.775	-1.833	-1.833

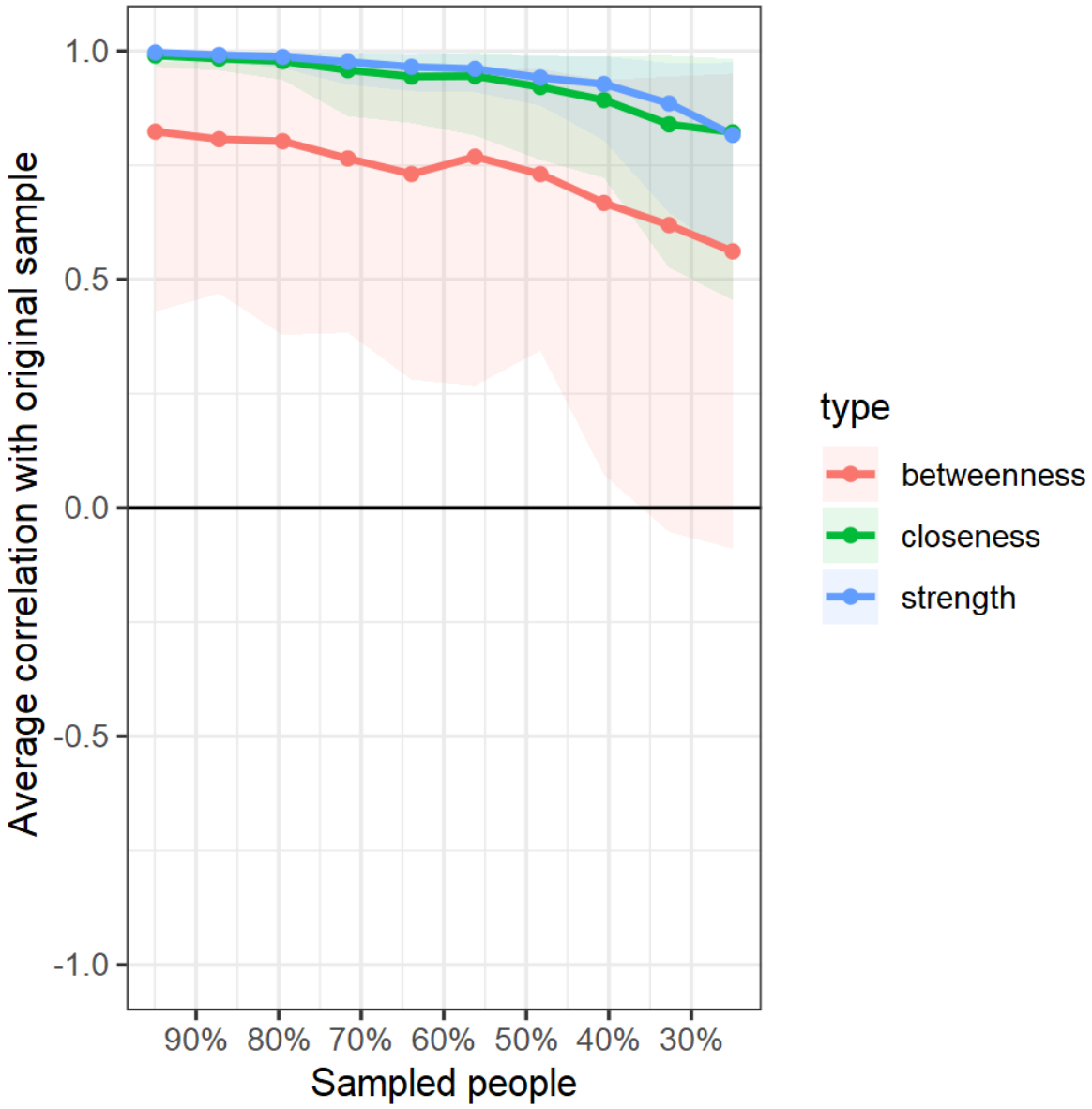
Weights matrix

	Network							
Variable	**OCD**	**BDD**	**HD**	**SPD**	**HPD**	**PHQ9**	**GAD7**	**CRAVE**
OCD	0.000	0.220	0.123	0.020	0.087	0.000	0.209	0.000
BDD	0.220	0.000	0.138	0.230	0.005	0.096	0.051	0.064
HD	0.123	0.138	0.000	0.078	0.051	0.045	0.012	0.000
SPD	0.020	0.230	0.078	0.000	0.281	0.090	0.000	0.068
HPD	0.087	0.005	0.051	0.281	0.000	0.012	0.000	0.093
PHQ9	0.000	0.096	0.045	0.090	0.012	0.000	0.561	0.000
GAD7	0.209	0.051	0.012	0.000	0.000	0.561	0.000	0.021
CRAVE	0.000	0.064	0.000	0.068	0.093	0.000	0.021	0.000

Edge Stability



Centrality Stability



Network 2

Summary of Network

Number of nodes	Number of non-zero edges	Sparsity
20	94 / 180	0.505

Centrality measures per variable

	Network			
Variable	**Betweenness**	**Closeness**	**Strength**	**Expected influence**
BDD	2.418	1.925	-0.278	-0.492
HD	-0.723	-0.389	-1.817	-1.636
SPD	2.633	1.536	0.213	-0.258
HPD	-0.723	0.304	-1.338	-1.195
GAD7	0.826	0.938	-0.195	0.072
CRAVE	-0.723	-1.505	-2.098	-2.123
OCD_time	-0.723	-1.281	0.325	0.284
OCD_distress	0.009	-0.753	1.071	1.280
OCD_control	0.568	-0.344	0.199	0.362
OCD_avoidance	-0.723	-1.531	0.411	0.617
OCD_interferance	-0.034	-1.260	0.945	0.492
phq9_1	-0.723	-0.140	-0.003	-0.023

Centrality measures per variable

Variable	Network			
	Betweenness	**Closeness**	**Strength**	**Expected influence**
phq9_2	-0.379	-0.063	2.114	2.276
phq9_3	-0.723	0.393	-0.096	-0.010
phq9_4	0.396	0.976	1.192	0.850
phq9_5	0.353	1.347	0.004	0.237
phq9_6	0.095	0.248	0.462	0.502
phq9_7	-0.551	-0.107	0.170	0.350
phq9_8	-0.551	0.190	-0.515	-0.718
phq9_9	-0.723	-0.485	-0.764	-0.868

Weights matrix

Variable	Network																		
	BDD	**HD**	**SPD**	**HPD**	**GAD7**	**CRAVE**	**OCD_time**	**OCD_distress**	**OCD_control**	**OCD_avoidance**	**OCD_interference**	**phq9_1**	**phq9_2**	**phq9_3**	**phq9_4**	**phq9_5**	**phq9_6**	**phq9_7**	**phq9_8**	**phq9_9**
BDD	0.000	0.156	0.233	0.010	0.096	0.070	0.000	0.016	0.000	0.031	0.000	0.010	0.000	0.000	0.016	0.121	0.014	0.000	-0.065	0.000

Weights matrix

	Network																		
Variable	**BDD**	**HDD**	**SPD**	**HPD**	**GAD7**	**CRAVE**	**OCD_time**	**OCD_distress**	**OCD_control**	**OCD_avoidance**	**OCD_interference**	**phq9_1**	**phq9_2**	**phq9_3**	**phq9_4**	**phq9_5**	**phq9_6**	**phq9_7**	**phq9_8**	**phq9_9**
HD	0.156	0.100	0.070	0.006	0.030	0.009	0.000	0.028	0.000	0.000	0.000	0.000	0.000	0.000	0.038	0.030	0.000	0.002	0.000	-0.021
SPD	0.233	0.207	0.000	0.280	0.000	0.073	0.000	0.000	0.105	-0.005	-0.065	0.020	0.000	0.018	0.064	0.000	-0.026	0.000	0.000	0.004
HPD	0.010	0.016	0.280	0.000	0.000	0.097	0.000	0.000	0.012	0.000	0.000	0.000	0.000	-0.024	0.020	0.000	0.035	0.030	0.000	0.000
GAD7	0.009	0.003	0.000	0.000	0.000	0.028	0.033	0.015	0.000	0.000	0.000	0.056	0.000	0.055	0.000	0.000	0.227	0.165	0.154	0.000
CRAVE	0.070	0.009	0.073	0.097	0.028	0.000	-0.014	0.000	-0.002	0.000	0.000	-0.014	0.000	0.000	-0.020	0.030	0.007	0.008	0.000	0.000

Weights matrix

	Network																		
Variable	**BDD**	**HDD**	**SPD**	**HPD**	**GAD7**	**CRAVE**	**OCD_time**	**OCD_distress**	**OCD_control**	**OCD_avoidance**	**OCD_interference**	**phq9_1**	**phq9_2**	**phq9_3**	**phq9_4**	**phq9_5**	**phq9_6**	**phq9_7**	**phq9_8**	**phq9_9**
OCD_time	0.000	0.000	0.000	0.000	0.033	-0.014	0.000	0.402	0.189	0.141	0.182	-0.024	0.000	0.007	0.000	0.000	0.000	0.000	0.000	0.000
OCD_distress	0.016	0.028	0.000	0.000	0.015	0.000	0.402	0.000	0.422	0.122	0.173	0.000	0.000	0.003	0.000	0.000	0.000	0.000	0.000	1.600e-6
OCD_control	0.000	0.000	0.105	0.012	0.000	-0.002	0.189	0.422	0.000	0.132	0.089	0.000	0.000	0.000	0.000	0.000	0.000	-0.009	0.000	0.000
OCD_avoidance	0.031	0.010	-0.005	0.000	0.000	0.000	0.141	0.122	0.132	0.000	0.584	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
OCD_interference	0.000	0.000	-0.000	0.000	0.000	0.000	0.182	0.173	0.089	0.584	0.000	0.000	0.000	0.000	-0.021	-0.003	0.000	0.000	0.034	0.000

Weights matrix

	Network																		
Variable	**BDD**	**HDD**	**SPD**	**HPD**	**GAD7**	**CRAVE**	**OCD_time**	**OCD_distress**	**OCD_control**	**OCD_avoidance**	**OCD_interference**	**phq9_1**	**phq9_2**	**phq9_3**	**phq9_4**	**phq9_5**	**phq9_6**	**phq9_7**	**phq9_8**	**phq9_9**
phq9_1	0.001	0.000	0.065	0.000	0.056	-0.014	-0.024	0.000	0.000	0.000	0.000	0.000	0.521	0.062	0.189	0.000	0.000	0.013	0.000	0.000
phq9_2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.521	0.000	0.000	0.177	0.098	0.289	0.069	0.000	0.294
phq9_3	0.000	0.000	0.018	-0.024	0.055	0.000	0.007	0.003	0.000	0.000	0.000	0.062	0.000	0.000	0.286	0.210	0.000	0.091	0.018	0.111
phq9_4	0.016	0.038	0.064	0.020	0.000	-0.020	0.000	0.000	0.000	0.000	-0.021	0.189	0.177	0.286	0.000	0.183	0.000	0.167	0.000	-0.032

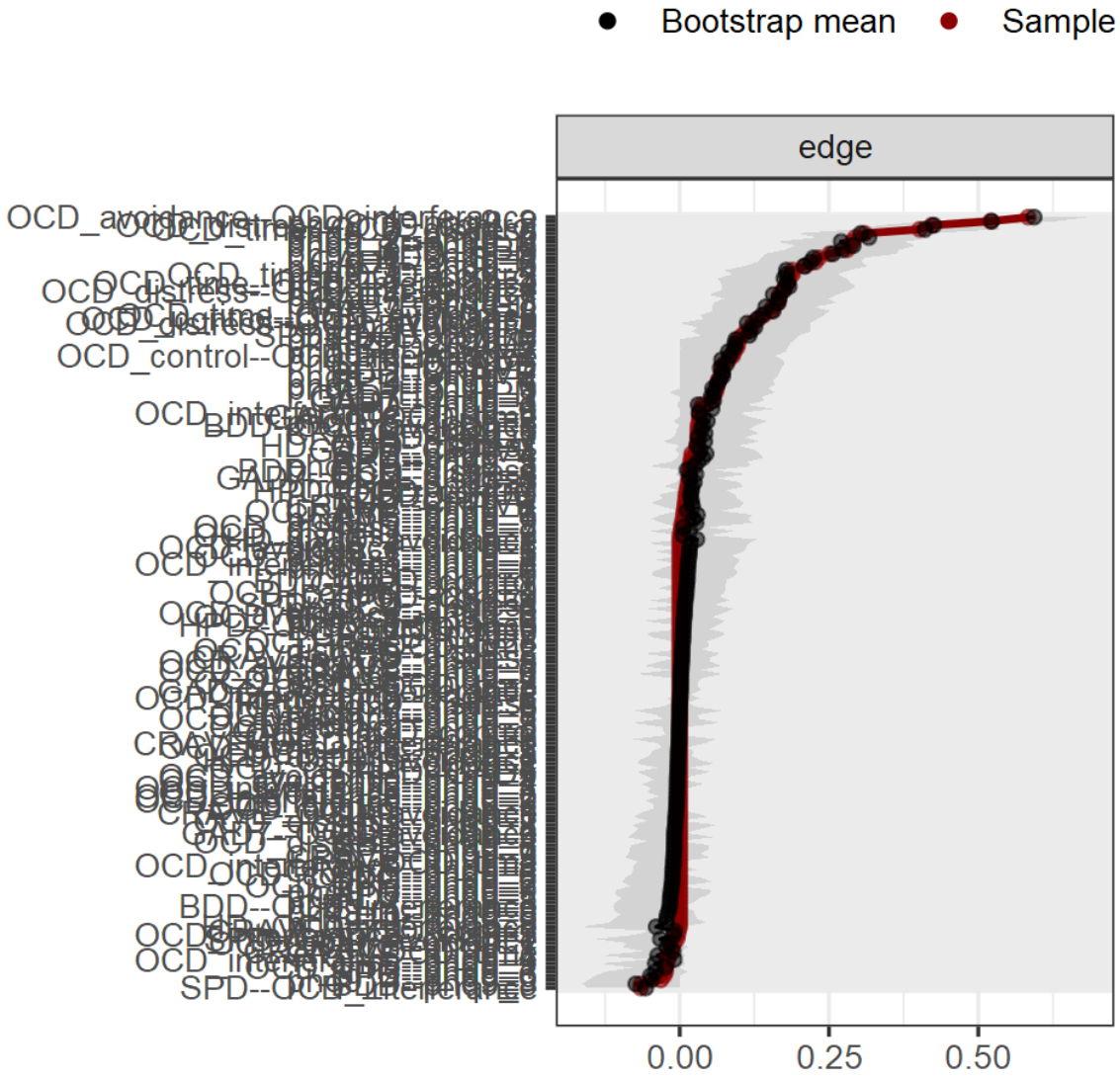
Weights matrix

	Network																		
Variable	**BDD**	**HDD**	**SPD**	**HPD**	**GAD7**	**CRAVE**	**OCD_time**	**OCD_distress**	**OCD_control**	**OCD_avoidance**	**OCD_interference**	**phq9_1**	**phq9_2**	**phq9_3**	**phq9_4**	**phq9_5**	**phq9_6**	**phq9_7**	**phq9_8**	**phq9_9**
phq9_5	0.121	0.030	0.000	0.000	0.0000	0.0030	0.000	0.000	0.000	0.000	-0.003	0.000	0.098	0.210	0.183	0.000	0.063	0.006	0.165	0.000
phq9_6	0.014	0.000	-0.026	0.035	0.2277	0.0007	0.000	0.000	0.000	0.000	0.000	0.000	0.289	0.000	0.000	0.063	0.000	0.082	0.033	0.251
phq9_7	0.000	0.000	0.000	0.030	0.1655	0.0008	0.000	0.000	-0.009	0.000	0.000	0.013	0.069	0.091	0.167	0.006	0.082	0.000	0.309	0.000
phq9_8	-0.065	0.000	0.000	0.000	0.1544	0.0000	0.000	0.000	0.000	0.000	0.034	0.000	0.000	0.018	0.000	0.165	0.033	0.309	0.000	0.000
phq9_9	0.000	-0.000	0.000	0.000	0.0000	0.0000	0.000	1.600e-6	0.000	0.000	0.000	0.000	0.294	0.111	-0.032	0.000	0.251	0.000	0.000	0.000

Weights matrix

Variable	Network																			
	BDD	**HDD**	**SPD**	**HPD**	**GAD7**	**CRAVE**	**OCD_time**	**OCD_distress**	**OCD_control**	**OCD_avoidance**	**OCD_interference**	**phq9_1**	**phq9_2**	**phq9_3**	**phq9_4**	**phq9_5**	**phq9_6**	**phq9_7**	**phq9_8**	**phq9_9**
	0	2	0	0																
	0	1	4	0																

Edge Stability



Centrality Stability