Psychological Medicine

www.cambridge.org/psm

A network analysis of how obsessive-compulsive symptoms change during exposure and response prevention treatment

Hyunsik Kim[1], Jeremy Tyler[2], Michael Wheaton[3], Saeri Park[4], Choong-Wan Woo[4,5,6], Edna Foa[2] and Helen Blair Simpson[7,8]

[1]Department of Psychology, Sogang University, Seoul, South Korea; [2]Center for the Treatment and Study of Anxiety, Department of Psychiatry, University of Pennsylvania, Philadelphia, PA, USA; [3]Department of Psychology, Barnard College, New York, NY, USA; [4]Center for Neuroscience Imaging Research, Institute for Basic Science (IBS), Suwon, South Korea; [5]Department of Biomedical Engineering, Sungkyunkwan University, Suwon, South Korea; [6]Department of Intelligent Precision Healthcare Convergence, Sungkyunkwan University, Suwon, Korea; [7]Center for OCD and Related Disorders, New York State Psychiatric Institute, New York, NY, USA and [8]Department of Psychiatry, Columbia University, New York, NY, USA

Original Article

Cite this article: Kim, H., Tyler, J., Wheaton, M., Park, S., Woo, C.-W., Foa, E., & Simpson, H. B. (2025). A network analysis of how obsessive-compulsive symptoms change during exposure and response prevention treatment. *Psychological Medicine*, **55**, e305, 1–9
https://doi.org/10.1017/S0033291725101906

Received: 01 March 2025
Revised: 12 August 2025
Accepted: 10 September 2025

Keywords:
exposure and response prevention; network analysis; obsessive-compulsive disorder; symptom network; treatment response

Corresponding author:
Helen Blair Simpson;
Email: blair.simpson@nyspi.columbia.edu

Abstract

Background. Although exposure and response prevention (EX/RP) is recommended as a first-line treatment for obsessive-compulsive disorder (OCD), responses vary among patients. This study was the first to use network analysis to examine how OCD symptom networks change with EX/RP and vary across different progress trajectories.

Methods. Data from four clinical trials with 334 adults with OCD who received manualized EX/RP were pooled. The Yale-Brown Obsessive-Compulsive Scale (Y-BOCS) was administered at baseline, midpoint, and post-treatment. OCD symptom networks were constructed using individual Y-BOCS items at these three time points, both for the entire sample and for three different progress trajectories (dramatic, moderate, and little-to-no progress) previously identified using growth mixture modeling. Network measures, including global efficiency, modularity, and weighted degree centrality, were computed to quantitatively assess network properties across treatment.

Results. Network analysis revealed two distinct modules at baseline: resistance/control and interference/distress. In the full sample, these two modules became integrated over time, as indicated by significant increases in global efficiency and weighted degree centrality and decreases in modularity; at post-treatment, the network shifted toward a fully connected network, and the strength of associations between nodes increased. These changes were most pronounced in the dramatic progress class.

Conclusions. Our findings indicated that effective EX/RP treatment was associated with more integrated OCD symptom networks, which may serve as an indicator of treatment response. Future research should examine how these shifts in network connectivity correspond to changes in underlying brain circuitry and/or to early identification of treatment responders.

Introduction

Cognitive behavioral therapy consisting of exposure and response prevention (EX/RP) is a first-line treatment for obsessive-compulsive disorder (OCD) (Koran & Simpson, 2013; National Collaborating Centre for Mental Health, 2006). However, responses among patients are heterogenous (Simpson et al., 2006, 2008; Simpson, Foa et al., 2013, 2021). while some achieve remission, others have partial responses, and still others are left with impairing residual symptoms. A limitation of the literature on OCD treatment response to date is that it typically focuses on treatment response or remission rates, often comparing pre- and post-treatment symptom severity. This overlooks the fact that patients' OCD symptoms may interact with each other in different patterns over the course of treatment. To address this gap, our paper examines the relationships among OCD symptoms as they change over the course of EX/RP treatment using network analysis, with the aim of providing insights into how to improve EX/RP treatment outcomes.

Network analysis is an analytical method for studying the interconnectedness of entities within a system, where entities are represented as nodes and their relationships are represented as edges, to uncover patterns, structures, and dynamics within the network (Brandes, 2005; Pósfai & Barabási, 2016). Several network analysis measures are available to characterize the structure of networks and to quantitatively assess the relationship between entities function of networks. Global efficiency assesses the average inverse shortest path length in the network, providing a measure of how efficiently information or resources can be exchanged across the network (Latora & Marchiori, 2001). Modularity quantifies the strength of the division of a network into modules, highlighting the presence of densely connected groups of nodes (Newman & Girvan, 2004).

Degree centrality measures the importance of a node based on the number of direct connections it has, indicating how influential or connected it is within the network (Freeman, 2002).

Network analysis can be used to examine the connections between psychiatric symptoms by representing symptoms as nodes and their relationships as edges within a network (Borsboom & Cramer, 2013; Fried et al., 2017). Thus, it can be used to understand the complex interactions among individual OCD symptoms and their responses to treatment by viewing symptoms as interconnected elements within a dynamic network (Borsboom, 2017; De Boer et al., 2021). This approach also illustrates how symptoms influence each other over time, revealing patterns of mutual reinforcement or inhibition. Identifying how OCD symptoms relate to one another and how these relationships change over time may allow for targeted interventions focusing on specific symptom clusters or central nodes within the network, potentially disrupting the cycle of symptom reinforcement and improving treatment outcomes (Robinaugh et al., 2016; Robinaugh et al., 2020).

Despite the potential utility of network analysis, only a few studies have applied it to the study of OCD and its treatment. Using network analysis, Olatunji et al. (2019) sought to identify which OCD symptoms are central to the OCD symptom network in a clinical population with various psychiatric disorders (n = 264) and a non-clinical population (n = 310). They used the Obsessive-Compulsive Inventory-Revised (Foa et al., 2002) to assess OCD symptoms. They found that negative appraisals of intrusive thoughts were the most central symptoms in the OCD network and predicted co-occurring symptoms of anxiety and depression. However, this network analysis was not conducted in concert with treatment, and so the ways in which the relations among OCD symptoms *change with treatment* were not explored. Using network analysis of 1,343 patients, Kuckertz et al. (2022) examined differences in the OCD symptom network between responders and non-responders to EX/RP treatment. Their results showed a significant difference in the OCD symptom network structure between responders and non-responders, indicating that the initial symptom network structure at baseline can discriminate between individuals who are likely to respond to treatment and those who are not. Although informative, their study focused on individuals in partial or residential treatment, which does not reflect the typical treatment setting for most OCD patients. In addition, their analysis was limited to comparing treatment responders and non-responders, overlooking differential changes in the OCD symptom network across *different treatment trajectories* over time.

Our study addresses this gap by examining *longitudinal* changes in the OCD symptom network during *outpatient* EX/RP, focusing on differences *across treatment response groups*. We pooled data from four clinical trials that involved manualized EX/RP treatment and OCD symptoms assessed using the Yale-Brown Obsessive-Compulsive Scale (Y-BOCS) by trained raters, resulting in a total sample of 334 patients. Although this sample size is smaller than that utilized in many network analyses (e.g. Lee et al., 2024), it represents a well-characterized group of individuals receiving standardized treatment under rigorously controlled conditions yielding an ideal arena for conducting a network analysis of symptom change (as measured by the Y-BOCS) during EX/RP treatment. We quantified these relationships using network measures, including global efficiency, modularity, and weighted degree centrality. This analysis was conducted for the entire sample and across different EX/RP treatment progress classes (dramatic, moderate, little-to-no progress), which were identified in a previous study using growth mixture modeling (GMM) (Kim et al., 2023). In this initial test of this topic, we hypothesized that there would be observable differences in network structure and change depending on individuals' treatment progress patterns, as indicated by differential changes in global efficiency, modularity, and weighted degree centrality over time.

Methods

Participants

The data for this paper were derived from four clinical trials originally supported by National Institute of Mental Health and that were conducted at two specialized outpatient clinics in New York City, New York, and Philadelphia, Pennsylvania. Detailed explanations of these trials are available in other publications (Pagliaccio et al., 2019; Simpson et al., 2008; Simpson, Foa et al., 2013; Simpson, Foa et al., 2021). Institutional review board (IRB) approval was obtained for each study at their respective sites, and patients involved in the trials provided written informed consent. The final sample consisted of 334 OCD patients (Table 1), and this sample is described in detail in a study by Kim et al. (2023). Across the four trials included in our analysis, 46 participants (13.8%) from one trial (Pagliaccio et al., 2019) were unmedicated at baseline and during EX/RP treatment. The remaining participants (n = 288; 86.2%) from three trials (Simpson et al., 2008; Simpson, Foa et al., 2013; Simpson, Foa et al., 2021) were taking a serotonin reuptake inhibitor (SRI) at a maximally tolerated dose for at least 12 weeks at baseline but remained at least moderately symptomatic (Y-BOCS ≥18). Across these three samples, the mean duration of the SRI treatment at baseline ranged from

Table 1. Baseline demographic and clinical characteristics of the final sample (*N* = 334)

Variables	Total sample
Demographic variables	
Age (in years), mean (SD)	32.89 (11.58)
Female, *n* (%)	155 (46.4)
Years of education, mean (SD)	15.68 (2.42)
Married-partnered, *n* (%)	88 (26.3)
Non-Hispanic White, *n* (%)	312 (93.4)
Medication/treatment-related variables	
Currently on medication, *n* (%)	288 (86.2)
Previous CBT, *n* (%)	78 (30)
OCD features and baseline symptom severity	
OCD onset age, mean (SD)	16.13 (8.61)
YBOCS-Insight, mean (SD)	0.64 (0.85)
YBOCS-Avoidance, mean (SD)	1.77 (1.12)
Current comorbid psychopathology and baseline functioning	
Current comorbid anxiety disorder number, mean (SD)	1.32 (0.61)
HDRS scores, mean (SD)	7.76 (5.43)
Quality of life, mean (SD)	57.1 (16.15)

Note: OCD = Obsessive-compulsive disorder; CBT = Cognitive behavioral therapy; Y-BOCS = Yale–Brown Obsessive Compulsive Scale; HDRS = Hamilton depression rating scale.

https://doi.org/10.1017/S0033291725101906

65.7 weeks (SD = 101.6) to 79.4 weeks (SD = 156.1). For all medicated participants, SRI doses were maintained at stable levels throughout EX/RP.

Treatment

All participants underwent the same structured EX/RP format, comprising a total of 17 biweekly 90-minute sessions over an 8-week period. The treatment regimen included two introductory sessions, 15 exposure sessions, daily homework assignments, and between-session telephone check-ins. Adhering to an OCD treatment manual initially developed by Kozak and Foa (1997) and later updated by Foa et al. (2012), the EX/RP was administered by doctoral-level therapists (Ph.D. or Psy.D) with expertise in EX/RP. Active cases were discussed during group supervision in weekly conference calls.

Assessments

In all studies, independent evaluators (IEs), who were unaware of treatment randomization, assessed patients at baseline (week 0), midway through treatment (after session 8/week 4; midpoint assessment), and after completing EX/RP (after session 17/week 8; post-treatment assessment). Trained raters used the Structured Clinical Interview (SCID) for DSM-IV (First & Gibbon, 2004) and SCID-5 (First, 2014) following publication of the DSM-5 to evaluate patients' current and lifetime psychiatric disorders, as well as the onset age. IEs assessed the severity of patients' symptoms using the Y-BOCS (Goodman et al., 1989) for OCD. Additionally, demographic data, prior medication use, and history of CBT were collected.

Data analysis

Network analysis

Network analysis comprises a set of techniques used to examine the structures of interconnected entities. We used network analysis to examine how the interrelatedness of individual OCD symptoms, as assessed by the 10 items of the Y-BOCS symptom severity scale, evolved over the course of EX/RP treatment. We employed correlation-based network analysis (Batushansky et al., 2016), in which Pearson's correlation coefficients between all pairs of Y-BOCS symptom severity scale item scores were used to construct networks. We selected Pearson's correlation because our aim was to estimate *marginal* (rather than partial) associations between symptoms. Partial correlations, while useful for identifying unique associations, can remove meaningful shared variance and are more sensitive to measurement error and sampling variability (Forbes et al., 2019).

Correlation coefficients were transformed into z-scores using Fisher's z-transformation (Bond & Richardson, 2004; Fisher, 1915). To ensure network robustness, we applied a confidence interval–based thresholding method in which only z-scores with a lower bound of the 95% confidence interval greater than zero were retained. This approach helps filter out spurious correlations and enhance the interpretability and reliability of the network structure and is commonly used in psychological network research (Mareva et al., 2019; Williams & Rast, 2020). The retained z-scores from this process were then used to construct a network graph using the spring layout algorithm, a widely used method in network analysis research (Jacomy et al., 2014).

We constructed OCD symptom networks based on Y-BOCS items assessed at baseline, midpoint, and post-treatment for (a) the entire sample and (b) each of the three EX/RP treatment progress trajectory classes previously identified using GMM in a study by Kim et al. (2023). No new GMM analyses were conducted for the present study. In these networks, each node corresponds to a Y-BOCS item, with the size of the node indicating its weighted degree centrality, which reflects the extent to which the node interacts with other nodes. Consequently, a larger node size indicates more extensive interactions between that Y-BOCS element and other Y-BOCS elements in the network. The width of the edges represents the strength of the relationship between two nodes, and the spring layout algorithm positioned nodes with stronger connections closer together. We focused on examining positive edges, as the majority of negative edges estimated in our analysis did not meet the thresholding criteria.

Missing data analysis and imputation

To address missing data in Y-BOCS item scores across time points (baseline, mid-, and post-treatment), we used the expectation–maximization (EM) algorithm (Dempster et al., 1977) implemented in SPSS. Preliminary analysis showed that 10.2% of participants (n = 34) had at least one missing value, accounting for 5.6% of all data points across the 30 items (10 Y-BOCS symptom severity items × 3 assessment points). Little's MCAR test indicated that data were missing completely at random ($\chi^2 = 77.41$, $df = 79$, $p = .530$), supporting the use of EM. This method has shown comparable or superior performance to full information maximum likelihood (FIML) and multiple imputation in both accuracy and standard error estimation (Dong & Peng, 2013; Musil et al., 2002).

Computation of network measures and tests of significance

We computed network measures, including global efficiency, modularity, and weighted degree centrality to quantify network properties. *Global efficiency* is a measure of functional integration and is calculated as the average inverse shortest path length (Rubinov & Sporns, 2010). *Modularity* is the degree to which the network is divided into non-overlapping groups or modules (Newman, 2006). We describe the structure of the OCD symptom network in a hierarchical manner, referring to the top structure as the 'network' and subnetworks as 'modules', as is customary. We estimated modularity using an optimization algorithm that maximizes the number of edges within groups and minimizes the number of edges between groups (Newman & Girvan, 2004). *Weighted degree centrality* reflects the extent to which a given symptom is connected to all other symptoms in the network and is defined as the sum of the edge weights connected to a node (Candeloro et al., 2016; Opsahl et al., 2010). We computed two types of weighted degree centrality: (a) *average* weighted degree centrality, calculated as the mean of all node-level centrality values across Y-BOCS symptom severity scale items within the full sample and each treatment trajectory class, to capture overall network connectivity and (b) *node-level* weighted degree centrality computed separately for each Y-BOCS item within each trajectory class, to evaluate how strongly individual OCD symptoms are connected to others. This approach allows us to assess both general network density and the relative centrality of specific symptoms across distinct treatment trajectories.

To assess changes in network measures across assessment points within each treatment trajectory class (i.e. baseline versus midpoint, midpoint versus post-treatment, and baseline versus post-treatment), we conducted a non-parametric bootstrapping procedure (i.e. resampling with replacement) with 5,000 resamples (Carpenter & Bithell, 2000) within each treatment progress group.

https://doi.org/10.1017/S0033291725101906

This approach enables robust estimation of confidence intervals and statistical testing of network metrics (Epskamp et al., 2018). Using the bootstrapped samples, we computed correlation coefficients between Y-BOCS items, applied the thresholding method, and calculated network measures. This process yielded a distribution of 5,000 values per metric, from which we derived sampling distributions and conducted significance tests.

To mitigate concerns about inflated Type I errors due to multiple significance tests, we used false discovery rate (FDR) correction (Benjamini & Yekutieli, 2001). Specifically, we applied the Benjamini–Hochberg procedure, which controls the FDR by ranking the *P*-values and determining critical values to identify significant hypotheses (Benjamini & Hochberg, 1995). This approach was implemented in the context of bootstrapped z-tests to ensure the robustness of our findings. All network analyses were performed in MATLAB (version R2023a).

Results

Sample description

Table 1 shows the demographic and clinical characteristics of the 334 participants. The mean age of study participants was 32.89 years (*SD* = 11.58), and 46.4% were female. Most participants were White (93.4%). Patients had severe OCD symptoms at baseline with a mean score of 26.10 (*SD* = 3.97), which decreased to moderate symptoms by the midpoint assessment (*M* = 19.58, *SD* = 5.91) and further decreased to mild to moderate symptoms after treatment (*M* = 15.56, *SD* = 7.67). The three EX/RP treatment progress trajectories identified using GMM – previously reported by Kim et al. (2023) – were as follows: dramatic progress (n = 75), moderate progress (n = 174), and little-to-no progress (n = 85) classes.

Changes in OCD symptom network patterns during treatment (full sample)

In the *full sample* (n = 334), at baseline, the network of all Y-BOCS items was divided into the following two modules (Figure 1): (a) one module related to resistance/control over obsessions and compulsions (items 4, 5, 9, and 10) and (b) the other module related to interference/distress due to obsessions and compulsions (items 1, 2, 3, 6, 7, and 8). As shown in Figure 1, across treatment, the two previously separate modules became more integrated and interconnected. This was quantified by significantly (a) increased global efficiency across all assessment points; (b) decreased modularity across all assessment points; and (c) increased average weighted degree centrality across all assessment points. Significant changes in these network measures are visualized in Figure 2, and detailed results of the significance tests using the FDR correction are shown in Online Supplementary Table 1. In summary, at post-treatment, the network shifted towards a spherical shape (i.e. fully connected network), and the strength of associations between nodes increased over time, as indicated by edges that became thicker relative to the baseline (Figure 1).

Changes in OCD symptom network patterns during treatment (three trajectory classes)

For all three trajectory classes, the pre-treatment network of Y-BOCS items consisted of the same two distinct modules observed

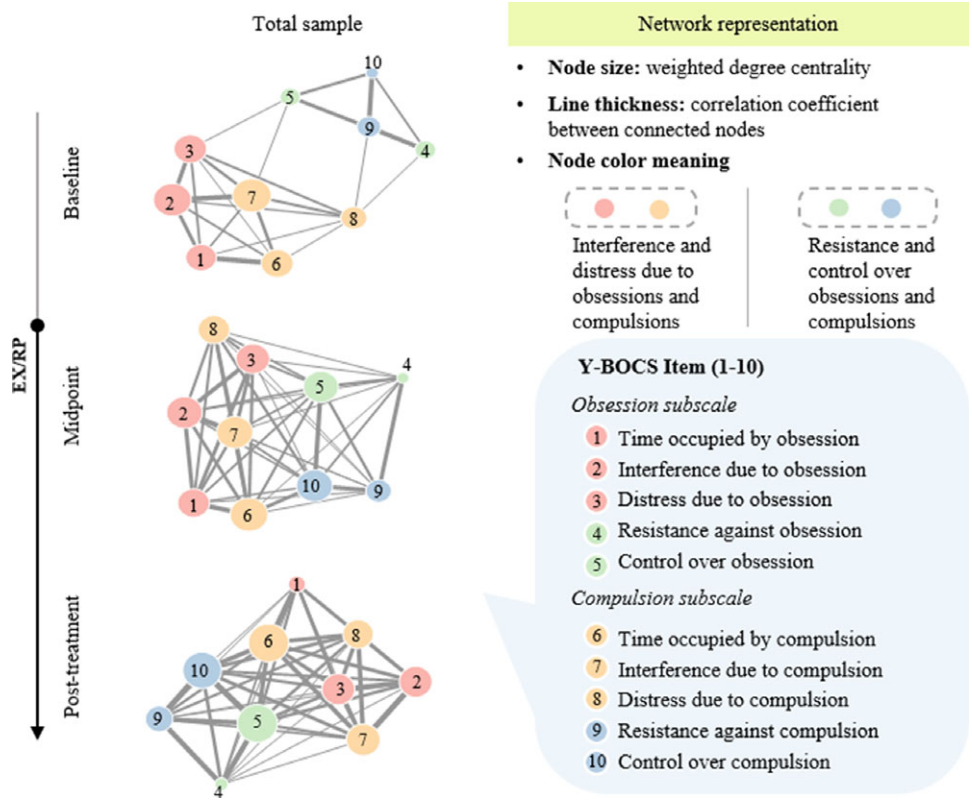

Figure 1. Changes in obsessive compulsive disorder symptom networks over time for the full sample in response to exposure and response prevention. *Note*: EX/RP = Exposure and response prevention.

https://doi.org/10.1017/S0033291725101906

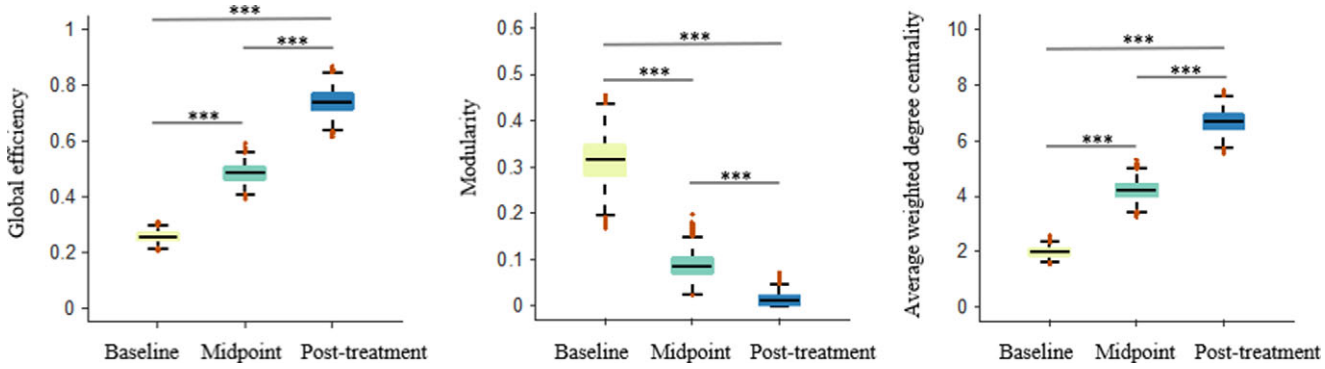

Figure 2. Changes in global efficiency, modularity, and average weighted degree centrality over time of the full sample. *Note.* *p < .05, **p < .01, p*** < .001.

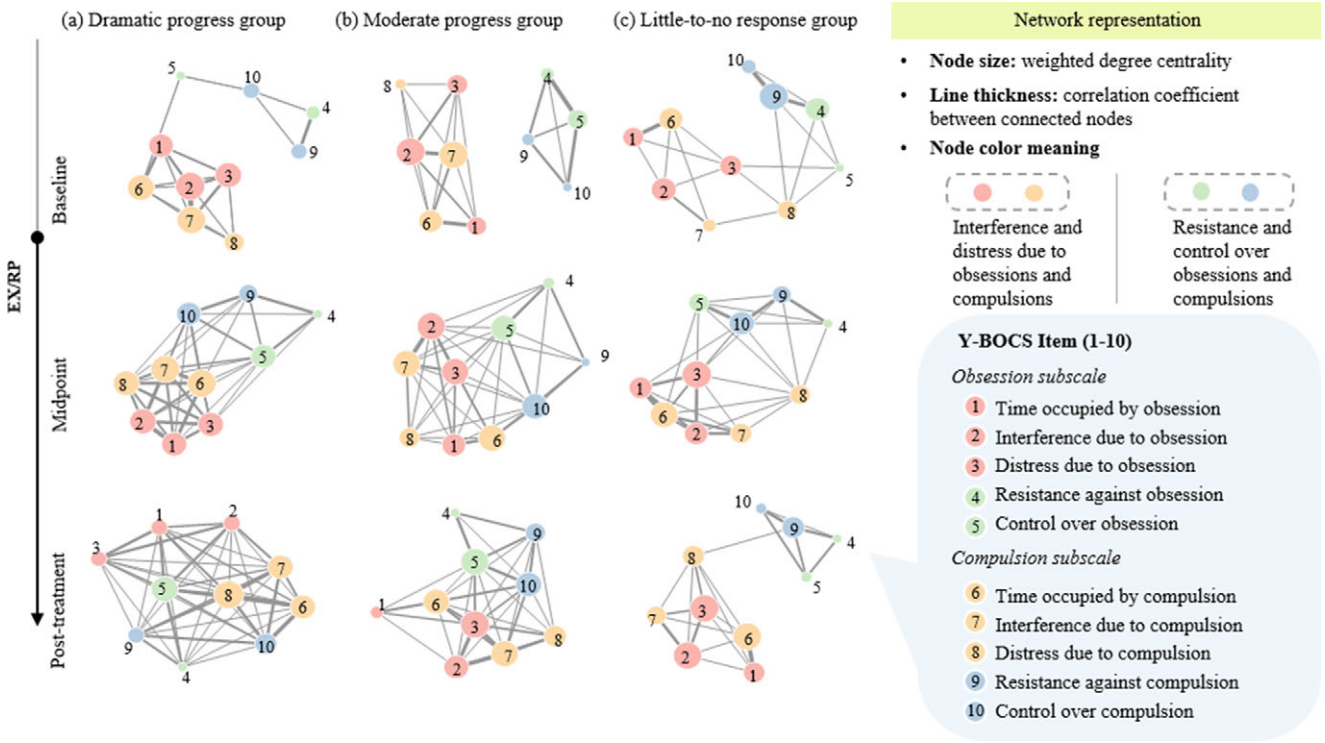

Figure 3. Changes in obsessive compulsive disorder symptom networks over time across three treatment progress trajectory classes in response to exposure and response prevention. *Note*: EX/RP = Exposure and response prevention.

in the full sample: (a) one module related to resistance/control over obsessions and compulsions and (b) the other module related to interference/distress due to obsessions and compulsions (Figure 3). However, how these two modules (Figure 3) and the three network measures (Figure 4) changed during treatment *differed by trajectory*, as described below. Detailed results of the significance tests for the change in the three network measures of the three trajectories using the FDR correction are shown in Online Supplementary Table 1.

Dramatic and moderate progress classes

As shown in Figure 3a and 3b, the two modules at baseline became more integrated and interconnected across treatment in both of these classes. This was quantified by significantly (a) increased global efficiency from baseline to midpoint and from baseline to post-treatment (Figure 4a); (b) decreased modularity from baseline to post-treatment (Figure 4b); and (c) increased average weighted degree centrality from baseline to midpoint and from baseline to post-treatment (Figure 4c).

At the same time, some differences were observed, as seen in Figures 3 and 4 and on inspection of the significance tests (Online Supplementary Table 1), particularly *from midpoint to post-treatment*. Specifically, in the dramatic progress group, there was a marginally significant increase in global efficiency (z = 2.020, p = .043, FDR critical value = .033), marginally significant decrease in modularity (z = −1.933, p = .053, FDR critical value = .036), and a significant increase in average weighted degree centrality (z = 2.230, p = .026, FDR critical value = .032), all of which indicated *progress* from midpoint to post-treatment; while in the moderate progress class, there was a marginally significant decrease (regression) in global efficiency (z = −1.950, p = .051, FDR critical value = .034)

https://doi.org/10.1017/S0033291725101906

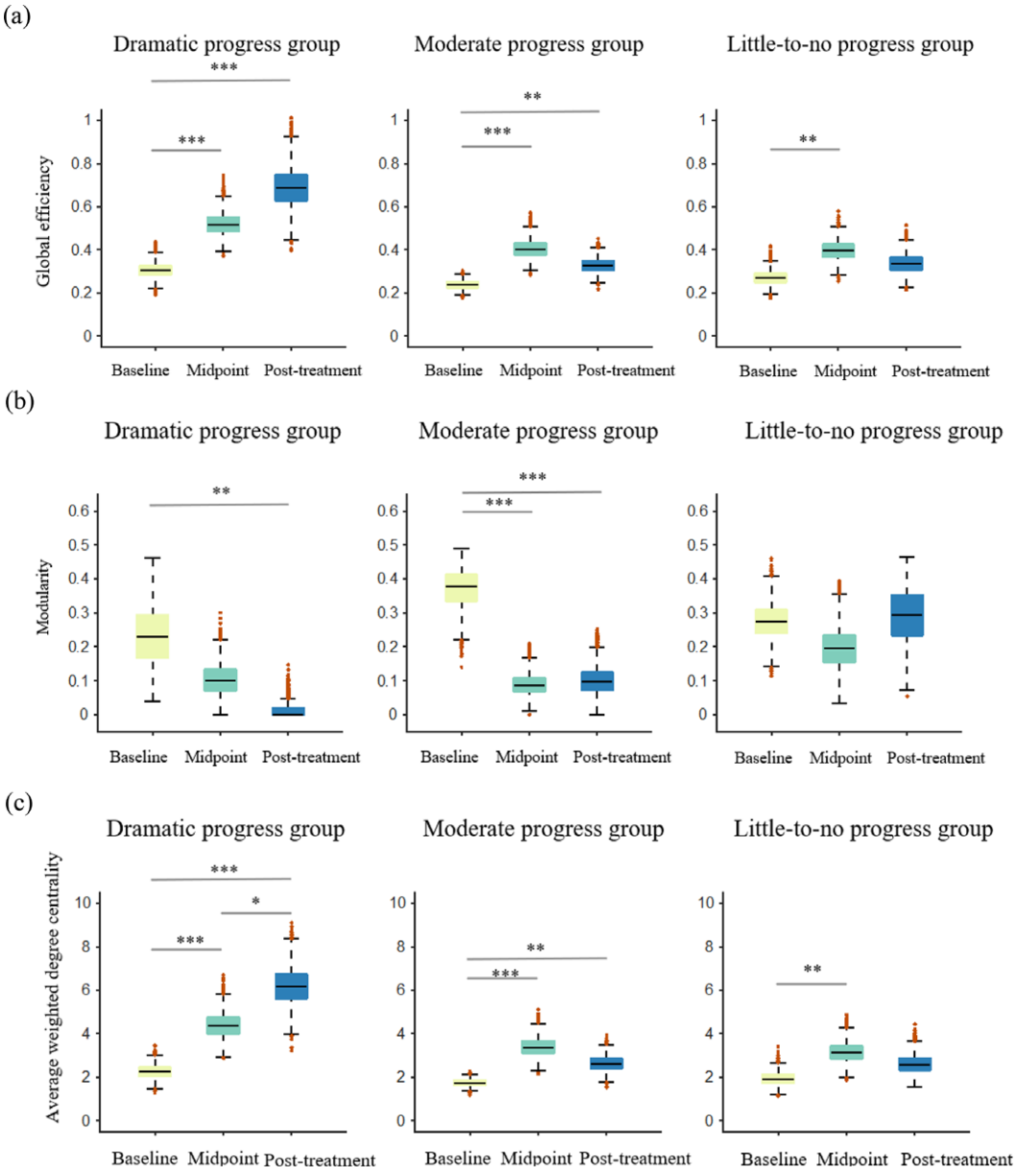

Figure 4. Changes in global efficiency, modularity, and average weighted degree centrality over time across three treatment progress trajectory classes. *Note.* *$p < .05$, **$p < .01$, $p^{***} < .001$.

and average weighted degree centrality ($z = -1.804$, p = .071, FDR critical value = .038), all of which indicated marginally significant *regression*. These differences also align with the differential changes in the *node-level* weighted degree centrality of each Y-BOCS item between the two classes: in the dramatic progress group, all 10 items significantly increased from baseline to post-treatment, whereas only 4 items (items 3, 5, 6, and 10) increased in the moderate progress class (Online Supplementary Table 2 and Online Supplementary Figures 1 & 2).

Overall, these observations suggest that the dramatic progress class experienced more consistent and continued improvements across multiple assessments compared to the moderate progress class. As a result, at post-treatment, the network of the dramatic progress class shifted to a more spherical shape (i.e. a fully connected network), as indicated by consistent and uniform distances between nodes. Moreover, the strength of the associations between nodes increased over time, as indicated by thicker edges compared to the baseline (Figure 3a).

Little-to-no progress class

As shown in Figure 3c, the two modules became somewhat more integrated and interconnected in the first half of treatment as indicated by significantly increased (a) global efficiency (Figure 4a) and (b) average weighted degree centrality (Figure 4c) from baseline to midpoint. However, there was no significant change in modularity from baseline to midpoint (Figure 4b). Moreover, there were no further significant changes in any of the three network measures from midpoint to post-treatment. Ultimately, there were no significant changes in any of the three network measures from baseline to post-treatment. Similarly, *node-level*

https://doi.org/10.1017/S0033291725101906

weighted degree centrality increased from baseline to post-treatment for only one item (item 3) (Online Supplementary Table 2 and Online Supplementary Figures 1 & 2).

Discussion

This study is the first to use network analysis to examine (a) how associations among Y-BOCS symptom severity items change during EX/RP treatment and (b) whether these associations differ across distinct treatment response trajectories previously established using GMM (Kim et al., 2023). Prior to treatment, we found two distinct modules of OCD symptoms: one related to *resistance/control* over obsessions and compulsions and another related to *interference/distress* due to obsessions and compulsions. These two modules were apparent in both the full sample (n = 334) and each of the treatment progress trajectory classes. We also found that these two modules integrated over the course of EX/RP treatment, as indicated by significant longitudinal changes: (a) increases in global efficiency, (b) decreases in modularity, and (c) increases in average weighted degree centrality. This integration was most pronounced in those who responded best to EX/RP.

Our finding of two distinct modules of OCD symptoms before treatment is consistent with a prior study that used factor analytic approaches. Specifically, conducting factor analyses of the Y-BOCS symptom severity scale items in 100 adults with OCD, Deacon and Abramowitz (2005) found two clusters of symptoms, which they termed 'resistance/control' and 'severity' subscales; these two clusters were composed of the same Y-BOCS items as our two modules. These two modules are also consistent with neurobiological models of OCD. For example, Van den Heuvel et al. (2016) proposed a neurobiological model for OCD that highlights altered interactions and reduced functional connectivity between (a) cortico-striatal circuits subserving behavioral control of motor and cognitive processes and (b) limbic circuits associated with negative affect (e.g. anxiety and distress). The identification of these two distinct OCD symptom modules across two studies suggests a re-evaluation of OCD symptom structure beyond the traditional obsession-compulsion dichotomy and a different way to explore how OCD symptoms might associate with brain circuit alterations (e.g. by focusing on these two modules and their relevant circuits).

We also found that these modules – and the relationship between individual OCD symptoms – changed during EX/RP treatment, with patterns differing by treatment trajectory. In particular, for the groups that showed a dramatic and moderate response to EX/RP, there was greater integration and interconnection among the OCD symptoms over time, as indicated by significant increases in global efficiency, decreases in modularity, and increases in average weighted degree centrality. These changes were most pronounced in the dramatic progress class. Increased average weighted degree centrality suggests that symptoms became more interconnected, and this pattern was observed across the majority of Y-BOCS items, but only among treatment responders. This finding aligns with the 'positive spirals' hypothesis proposed by McElroy et al. (2019), which suggests that as overall symptom severity decreases, inter-symptom connectivity may increase in those responding to treatment. Consistent with this, previous studies have reported increased connectivity among depressive symptoms following pharmacological treatment (Bos et al., 2018), psychological interventions (Fried et al., 2016; McElroy et al., 2019), and intensive treatment in partial hospital programs (Beard et al., 2016).

Moreover, the finding that two modules (i.e. interference/distress and resistance/control) became increasingly integrated over time *only* in treatment responders suggests the possible formation of a clinically beneficial feedback cycle. This group was more likely to have engaged with EX/RP principles, which are explicitly designed to foster a self-reinforcing positive feedback cycle – for example, patients learn to resist obsessions and compulsions, which in turn reduces distress or anxiety and facilitates further improvement. Indeed, a substantial body of research has shown that patient adherence to EX/RP skills not only predicts but also forecasts treatment improvement (Simpson et al., 2011, 2012; Wheaton et al., 2016). Taken together, these findings suggest that changes in network connectivity may offer clinically meaningful insights into prognosis and treatment response (McElroy et al., 2019).

In contrast, the little-to-no progress class exhibited a different pattern; although global efficiency and average weighted degree centrality increased significantly in the first half of treatment (but not modularity), there was no further progression in the second half. Moreover, none of these network metrics showed significant change post-treatment relative to baseline. One possible interpretation is that the absence of continued integration reflects a stalled network reorganization process at the group level, consistent with a lack of sustained OCD symptom improvement in this group. Additionally, the lack of change in modularity may suggest that the symptom network in poor responders remained *compartmentalized*, possibly due to sustained avoidance, under-engagement with EX/RP, or a weak therapeutic alliance. In this context, limited integration may reflect entrenched symptom configurations that resist change and hinder treatment response.

At first glance, these findings appear to contrast with a recent large-scale study on depression, which found that *poorer* treatment response was associated with *higher* baseline network connectivity, although this association was largely attributable to differences in baseline symptom variance (Lee et al., 2024). A key methodological distinction is that their study examined cross-sectional symptom networks, in which greater connectivity is typically associated with greater severity (Robinaugh et al., 2020). In contrast, our study focused on *group-level longitudinal* changes in connectivity over the course of treatment. This difference raises the possibility that the increased integration and connectivity observed in responders in our study reflect meaningful symptom restructuring over time, rather than statistical artifacts related to baseline variance. Supporting this interpretation, our additional analysis[1] found that changes in item-level variance were not significantly associated with changes in symptom centrality across time points. These findings underscore the importance of examining symptom networks through both longitudinal and cross-sectional lenses to clarify how connectivity relates to treatment response. In sum, our findings indicate that more integrated OCD symptom networks tend to be observed among those with better EX/RP outcomes, suggesting a potential association between network reorganization and treatment response in this population.

Although these results should be interpreted as an initial test in a well-characterized sample, the differences observed among the EX/RP treatment trajectory classes may have both neurobiological

[1]To assess whether network changes were influenced by changes in item-level variance, we correlated variance across time points with changes in weighted degree centrality for each Y-BOCS item. All correlations were non-significant (dramatic progress: $r = 0.009$, $p = .961$; moderate progress: $r = -0.044$, $p = .819$; little-to-no progress: $r = -0.085$, $p = .654$), suggesting that network changes were not attributable to variance shifts.

https://doi.org/10.1017/S0033291725101906

and treatment implications. With regards to neurobiology, we speculate that the integration of the two OCD symptom network modules in those who responded to EX/RP reflects underlying changes in interactions between cortico-striatal and limbic circuits, resulting in enhanced cognitive control and reduced anxiety and distress (Van den Heuvel et al., 2016). On the clinical front, that integration of the two modules was most evident in EX/RP responders, indicating that patients who learn to control obsessions and compulsions also experience less distress and interference, and vice versa. One possible explanation is that enhanced control of obsessions and compulsions due to EX/RP leads to reduced interference and distress. It is also possible that increased distress tolerance due to EX/RP leads to better control over obsessions and compulsions. Indeed, Cougle et al. (2011) found that poor distress tolerance predicted an increase in obsessional symptoms 1 month later, suggesting that interventions aimed at improving distress tolerance may be particularly beneficial in reducing obsessions. Regardless of the direction of change, identifying how to foster early links between these two symptom modules might allow for more individualized intervention and increase the likelihood of moderate to dramatic treatment progress. Perhaps this shift in network connectivity could also serve as an indicator for early identification of treatment responders and non-responders.

This study has several strengths: the use of manualized EX/RP treatment and evaluations of OCD symptom change by trained independent evaluators and the integration of network analysis with longitudinal trajectory analysis (GMM). There are also several limitations. First, given that the majority of participants were concurrently taking medication, some observed network changes theoretically could reflect pharmacological effects rather than, or in addition to, the effects of EX/RP. However, because (a) most patients entered EX/RP treatment with at least moderate OCD symptoms despite an adequate dose and duration of an SRI and (b) the trials were designed to evaluate how EX/RP augments outcomes beyond maintenance pharmacotherapy, it is more likely that the observed network changes are primarily attributable to EX/RP. Nonetheless, concurrent pharmacotherapy remains a relevant confound, and future research should assess whether similar changes occur in non-medicated samples to better isolate EX/RP effects. Second, while we observed the integration of two separate modules over time in responsive classes, the exact order and timing of these changes could not be fully elucidated. Future research is needed to explore the specific temporal dynamics of how successful control of obsessions and compulsions leads to reduced interference and distress, and vice versa, ultimately forming a mutually reinforcing positive cycle. Third, some Y-BOCS items are interrelated (e.g. the response to item 5 under some conditions may depend on the response to item 4), leading to possible clustering of these correlated items into the same resistance/control module. Fourth, our sample size—especially within the smaller trajectory subgroups ($N < 100$)—was modest for conducting network comparisons. As prior research suggests that detecting reliable differences in network structure may require substantially larger samples (e.g. $N \approx 750$; Lee et al., 2024), our findings should be regarded as an initial investigation in a heretofore unstudied area and yet interpreted with caution given that replication in larger samples is needed. Finally, our sample consisted primarily of non-Hispanic white individuals, which may affect the generalizability of our findings.

In conclusion, this study is the first to use network analysis to investigate how OCD symptom networks change over time during outpatient EX/RP treatment and across different trajectories of progress as previously identified through GMM. This analysis reveals two distinct modules of OCD symptoms (resistance/control versus interference/distress) in adults with OCD. These two modules became integrated across EX/RP treatment, particularly in moderate and dramatic responders. Future studies should examine whether this shift in network connectivity corresponds to changes in underlying brain circuitry and/or potentially serves as an indicator for early identification of treatment responders and non-responders.

Supplementary material. The supplementary material for this article can be found at http://doi.org/10.1017/S0033291725101906.

Acknowledgments. We thank everyone who participated in these studies.

Financial support. Our study used a de-identified dataset that included data from studies funded by the National Institute of Mental Health (NIMH) R01 MH-45436, R01 MH-45404, K23 MH-01907, and R01MH 104648. During this project, Dr. Hyunsik Kim was supported in part by the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea (NRF-2022S1A3A2A02089938; NRF-RS-2024-00466765).

Competing interests. In the last five years, Dr. Simpson has received royalties from Cambridge University Press and UpToDate, Inc, served on a Scientific Advisory Board December 12, 2024 for Otsuka Pharmaceuticals, and receives a stipend from the American Medical Association for serving as Associate Editor for JAMA-Psychiatry. None of these represent a conflict of interest. This content is solely the responsibility of the authors and does not necessarily represent the official views of the funding sources. All other authors reported no conflict of interest.

References

Batushansky, A., Toubiana, D., & Fait, A. (2016). Correlation-based network generation, visualization, and analysis as a powerful tool in biological studies: A case study in cancer cell metabolism. *BioMed Research International*, **2016**.

Beard, C., Millner, A. J., Forgeard, M. J., Fried, E. I., Hsu, K. J., Treadway, M. T., … Björgvinsson, T. (2016). Network analysis of depression and anxiety symptom relationships in a psychiatric sample. *Psychological Medicine*, **46** (16), 3359–3369.

Benjamini, Y., & Hochberg, Y. (1995). Controlling the false discovery rate: A practical and powerful approach to multiple testing. *Journal of the Royal statistical society: series B (Methodological)*, **57**(1), 289–300.

Benjamini, Y., & Yekutieli, D. (2001). The control of the false discovery rate in multiple testing under dependency. *Annals of Statistics*, 1165–1188.

Bond, C. F., & Richardson, K. (2004). Seeing the Fisher Z-transformation. *Psychometrika*, **69** (2), 291–303.

Borsboom, D. (2017). A network theory of mental disorders. *World Psychiatry*, **16**(1), 5–13.

Borsboom, D., & Cramer, A. O. (2013). Network analysis: An integrative approach to the structure of psychopathology. *Annual Review of Clinical Psychology*, **9**, 91–121.

Bos, F. M., Fried, E. I., Hollon, S. D., Bringmann, L. F., Dimidjian, S., DeRubeis, R. J., & Bockting, C. L. (2018). Cross-sectional networks of depressive symptoms before and after antidepressant medication treatment. *Social Psychiatry and Psychiatric Epidemiology*, **53**(6), 617–627.

Brandes, U. (2005). *Network analysis: Methodological foundations* (Vol. **3418**). Springer Science & Business Media.

Candeloro, L., Savini, L., & Conte, A. (2016). A new weighted degree centrality measure: The application in an animal disease epidemic. *PLoS One*, **11**(11), e0165781.

Carpenter, J., & Bithell, J. (2000). Bootstrap confidence intervals: When, which, what? A practical guide for medical statisticians. *Statistics in Medicine*, **19**(9), 1141–1164.

Cougle, J. R., Timpano, K. R., Fitch, K. E., & Hawkins, K. A. (2011). Distress tolerance and obsessions: An integrative analysis. *Depression and Anxiety*, **28**(10), 906–914.

De Boer, N. S., de Bruin, L. C., Geurts, J. J., & Glas, G. (2021). The network theory of psychiatric disorders: A critical assessment of the inclusion of environmental factors. *Frontiers in Psychology*, **12**, 623970.

Deacon, B. J., & Abramowitz, J. S. (2005). The Yale-Brown obsessive compulsive scale: Factor analysis, construct validity, and suggestions for refinement. *Journal of Anxiety Disorders*, **19**(5), 573–585.

Dempster, A. P., Laird, N. M., & Rubin, D. B. (1977). Maximum likelihood from incomplete data via the EM algorithm. *Journal of the Royal Statistical Society: Series B (Methodological)*, **39**(1), 1–22.

Dong, Y., & Peng, C.-Y. J. (2013). Principled missing data methods for researchers. *Springerplus*, **2**(1), 222.

Epskamp, S., Borsboom, D., & Fried, E. I. (2018). Estimating psychological networks and their accuracy: A tutorial paper. *Behavior Research Methods*, **50**, 195–212.

First, M. B. (2014). Structured clinical interview for the DSM (SCID). *The Encyclopedia of Clinical Psychology*, 1–6.

First, M. B., & Gibbon, M. (2004). The Structured Clinical Interview for DSM-IV Axis I Disorders (SCID-I) and the Structured Clinical Interview for DSM-IV Axis II Disorders (SCID-II).

Fisher, R. A. (1915). Frequency distribution of the values of the correlation coefficient in samples from an indefinitely large population. *Biometrika*, **10**(4), 507–521.

Foa, E. B., Huppert, J. D., Leiberg, S., Langner, R., Kichic, R., Hajcak, G., & Salkovskis, P. M. (2002). The obsessive-compulsive inventory: Development and validation of a short version. *Psychological Assessment*, **14**(4), 485.

Foa, E. B., Yadin, E., & Lichner, T. K. (2012). *Exposure and response (ritual) prevention for obsessive compulsive disorder: Therapist guide*. Oxford University Press.

Forbes, M. K., Wright, A. G., Markon, K. E., & Krueger, R. F. (2019). The network approach to psychopathology: Promise versus reality. *World Psychiatry*, **18**(3), 272.

Freeman, L. C. (2002). Centrality in social networks: Conceptual clarification. . Social network: critical concepts in sociology. Londres: Routledge, **1**, 238–263.

Fried, E. I., Epskamp, S., Nesse, R. M., Tuerlinckx, F., & Borsboom, D. (2016). What are'good'depression symptoms? Comparing the centrality of DSM and non-DSM symptoms of depression in a network analysis. *Journal of Affective Disorders*, **189**, 314–320.

Fried, E. I., van Borkulo, C. D., Cramer, A. O., Boschloo, L., Schoevers, R. A., & Borsboom, D. (2017). Mental disorders as networks of problems: A review of recent insights. *Social Psychiatry and Psychiatric Epidemiology*, **52**, 1–10.

Goodman, W. K., Price, L. H., Rasmussen, S. A., Mazure, C., Fleischmann, R. L., Hill, C. L., … Charney, D. S. (1989). The Yale-Brown obsessive compulsive scale: I. Development, use, and reliability. *Archives of General Psychiatry*, **46** (11), 1006–1011.

Jacomy, M., Venturini, T., Heymann, S., & Bastian, M. (2014). ForceAtlas2, a continuous graph layout algorithm for handy network visualization designed for the Gephi software. *PLoS One*, **9**(6), e98679.

Kim, H., Wheaton, M. G., Foa, E. B., & Simpson, H. B. (2023). Identifying trajectories of symptom change in adults with obsessive compulsive disorder receiving exposure and response prevention therapy. *Journal of Anxiety Disorders*, **96**, 102711.

Koran, L. M., & Simpson, H. B. (2013). Guideline Watch (March 2013): Practice Guideline for the Treatment of Patients with Obsessive-Compulsive Disorder. Arlington, VA: American Psychiatric Association.

Kozak, M. J., & Foa, E. B. (1997). *Mastery of obsessive-compulsive disorder: A cognitive-behavioral approach: Therapist guide*. Psychological Corporation.

Kuckertz, J. M., McNally, R. J., Riemann, B. C., Van Borkulo, C., Bellet, B. W., Krompinger, J. W., … Falkenstein, M. J. (2022). Does the network structure of obsessive-compulsive symptoms at treatment admission identify patients at risk for non-response? *Behaviour Research and Therapy*, **156**, 104151.

Latora, V., & Marchiori, M. (2001). Efficient behavior of small-world networks. *Physical Review Letters*, **87**(19), 198701.

Lee, C. T., Kelley, S. W., Palacios, J., Richards, D., & Gillan, C. M. (2024). Estimating the prognostic value of cross-sectional network connectivity for treatment response in depression. *Psychological Medicine*, **54**(2), 317–326.

Mareva, S., team, C., & Holmes, J. (2019). Transdiagnostic associations across communication, cognitive, and behavioural problems in a developmentally at-risk population: A network approach. *BMC Pediatrics*, **19**(1), 452.

McElroy, E., Napoleone, E., Wolpert, M., & Patalay, P. (2019). Structure and connectivity of depressive symptom networks corresponding to early treatment response. *EClinicalMedicine*, **8**, 29–36.

Musil, C. M., Warner, C. B., Yobas, P. K., & Jones, S. L. (2002). A comparison of imputation techniques for handling missing data. *Western Journal of Nursing Research*, **24**(7), 815–829.

National Collaborating Centre for Mental Health (UK). (2006). *Obsessive-compulsive disorder: Core interventions in the treatment of obsessive-compulsive disorder and body dysmorphic disorder*. Leicester (UK): British Psychological Society (UK) (NICE Clinical Guidelines, No. 31.).

Newman, M. E. (2006). Modularity and community structure in networks. *Proceedings of the National Academy of Sciences*, **103**(23), 8577–8582.

Newman, M. E., & Girvan, M. (2004). Finding and evaluating community structure in networks. *Physical Review E*, **69**(2), 026113.

Olatunji, B. O., Christian, C., Brosof, L., Tolin, D. F., & Levinson, C. A. (2019). What is at the core of OCD? A network analysis of selected obsessive-compulsive symptoms and beliefs. *Journal of Affective Disorders*, **257**, 45–54.

Opsahl, T., Agneessens, F., & Skvoretz, J. (2010). Node centrality in weighted networks: Generalizing degree and shortest paths. *Social Networks*, **32**(3), 245–251.

Pagliaccio, D., Middleton, R., Hezel, D., Steinman, S., Snorrason, I., Gershkovich, M., … Simpson, H. B. (2019). Task-based fMRI predicts response and remission to exposure therapy in obsessive-compulsive disorder. *Proceedings of the National Academy of Sciences*, **116** (41), 20346–20353.

Pósfai, M., & Barabási, A.-L. (2016). *Network science*. Citeseer.

Robinaugh, D. J., Hoekstra, R. H., Toner, E. R., & Borsboom, D. (2020). The network approach to psychopathology: A review of the literature 2008–2018 and an agenda for future research. *Psychological Medicine*, **50**(3), 353–366.

Robinaugh, D. J., Millner, A. J., & McNally, R. J. (2016). Identifying highly influential nodes in the complicated grief network. *Journal of Abnormal Psychology*, **125**(6), 747.

Rubinov, M., & Sporns, O. (2010). Complex network measures of brain connectivity: Uses and interpretations. *NeuroImage*, **52**(3), 1059–1069.

Simpson, H. B., Foa, E. B., Liebowitz, M. R., Huppert, J. D., Cahill, S., Maher, M. J., … Williams, M. T. (2013). Cognitive-behavioral therapy vs risperidone for augmenting serotonin reuptake inhibitors in obsessive-compulsive disorder: A randomized clinical trial. *JAMA Psychiatry*, **70**(11), 1190–1199.

Simpson, H. B., Foa, E. B., Liebowitz, M. R., Ledley, D. R., Huppert, J. D., Cahill, S., … Franklin, M. (2008). A randomized, controlled trial of cognitive-behavioral therapy for augmenting pharmacotherapy in obsessive-compulsive disorder. *American Journal of Psychiatry*, **165** (5), 621–630.

Simpson, H. B., Foa, E. B., Wheaton, M. G., Gallagher, T., Gershkovich, M., Schmidt, A. B., … Cahill, S. (2021). Maximizing remission from cognitive-Behavioral therapy in medicated adults with obsessive-compulsive disorder. *Behaviour Research and Therapy*, 103890.

Simpson, H. B., Huppert, J. D., Petkova, E., Foa, E. B., & Liebowitz, M. R. (2006). Response versus remission in obsessive-compulsive disorder. *Journal of Clinical Psychiatry*, **67**(2), 269–276.

Simpson, H. B., Maher, M. J., Wang, Y., Bao, Y., Foa, E. B., & Franklin, M. (2011). Patient adherence predicts outcome from cognitive behavioral therapy in obsessive-compulsive disorder. *Journal of Consulting and Clinical Psychology*, **79**(2), 247.

Simpson, H. B., Marcus, S. M., Zuckoff, A., Franklin, M., & Foa, E. B. (2012). Patient adherence to cognitive-behavioral therapy predicts long-term outcome in obsessive-compulsive disorder. *The Journal of Clinical Psychiatry*, **73**(9), 13941.

Van den Heuvel, O. A., van Wingen, G., Soriano-Mas, C., Alonso, P., Chamberlain, S. R., Nakamae, T., … Veltman, D. J. (2016). Brain circuitry of compulsivity. *European Neuropsychopharmacology*, **26** (5), 810–827.

Wheaton, M. G., Galfalvy, H., Steinman, S. A., Wall, M. M., Foa, E. B., & Simpson, H. B. (2016). Patient adherence and treatment outcome with exposure and response prevention for OCD: Which components of adherence matter and who becomes well? *Behaviour Research and Therapy*, **85**, 6–12.

Williams, D. R., & Rast, P. (2020). Back to the basics: Rethinking partial correlation network methodology. *British Journal of Mathematical and Statistical Psychology*, **73**(2), 187–212.