Using Network Analysis to Compare Caregiver and Youth Reports of Youths' Depressive Symptoms

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Abstract

Objective: Multi-informant assessment is the gold standard for youth depressive symptoms, and discrepancies in symptom reports across caregivers and youths can predict important clinical outcomes. However, discrepancies are typically only evaluated by comparing the means of sum scores across informants. We took a broader approach that involved: 1) evaluating discrepancies at the symptom level and 2) using mean-level and network structure comparisons.

Method: Participants were clinically referred youths and their primary caregiver ($N = 298$ youth-caregiver pairings) ages 7-14. The sample was racially (52.68% Non-Caucasian) and socioeconomically (54.02% family income < \$40,000 per year) diverse. We compared whether youths and caregivers differed significantly on their means for each depressive symptom. We then conducted a Network Comparison Test to gauge the extent to which youths and caregivers differed in the associations between pairs of symptoms.

Results: Youths and their caregivers differed at the mean level on 12/21 symptoms, with caregivers reporting higher levels on all 12. However, youth-caregiver differences were found on only 3 of the 119 associations between pairs of symptoms (i.e., “edges”). *Perfectionism – feels unloved* was more strongly associated in the youth network, while *won’t talk – secretive* and *rather be alone – uninvolved* were more strongly associated in the caregiver network.

Conclusions: A symptom-level, multi-method approach to caregiver and youth discrepancies revealed that our understanding of discrepancies might depend on the type of analysis we use (mean-level vs. network structure). Integrating the mean-level and network approaches may produce a richer, more clinically useful understanding of symptom-level cross-informant discrepancies.

Keywords: adolescent, depression, network analysis, symptom level

Using Network Analysis to Compare Caregiver and Youth Reports of Youths' Depressive Symptoms

Major depressive disorder (MDD) has been identified as the leading cause of disability in children and adolescents (henceforth youths), predicting interpersonal problems, substance abuse, and elevated risk of suicide attempts (Hammen, Brennan, & Keenan-Miller, 2008; Whiteford et al., 2013; Wilson, Hicks, Foster, McGue, & Iacono, 2015). Even subclinical symptoms of depression can cause functional impairment in youths (Balázs et al., 2013). Accurate clinical assessment is critical to addressing the needs of youths with depressive symptoms and disorders, guiding case conceptualization, and informing intervention planning. Best practices in the assessment of depression in youths involves a multi-informant approach (Klein, Dougherty, & Olino, 2005) wherein clinicians obtain information about a clinical concern from multiple sources—most commonly, from youths and caregivers (Achenbach, 2006).

However, multi-informant assessment can also complicate diagnostic decision-making. Agreement across youths' and caregivers' reports of youths mental health problems is moderate at best (Birmaher, Brent, & Issues, 2007; De Los Reyes & Kazdin, 2005) and agreement is especially low for youths' depression compared to anxiety and externalizing problems (Angold et al., 1987; Cantwell, Lewinsohn, Rohde, & Seeley, 1997; De Los Reyes & Kazdin, 2005; Youngstrom, Loeber, & Stouthamer-Loeber, 2000). Cross-informant discrepancies between a youth and caregiver predict poor outcomes (Ferdinand, van der Ende, & Verhulst, 2004; Goolsby et al., 2018; Guion, Mrug, & Windle, 2009). However, the exact reason for these discrepancies remains unclear. Advancing understandings of these discrepancies may improve their interpretability, optimizing their potential to inform targeted treatment and mitigate the burdens of depression in youths.

While previous informant discrepancy research has focused on youth, caregiver, and family level factors (e.g., youth age, sex, and race/ethnicity, caregiver depression, and family stress; for a review, see De Los Reyes & Kazdin, 2005; see also Briggs-Gowan, Carter, & Schwab-Stone, 1996; Kim, Chan, McCauley, & Vander Stoep, 2016), a major barrier to addressing these questions may involve how youths' depression is measured. To date, research on caregiver-youth discrepancies in reports of

depression have relied on *depression symptom counts* or *mean severity scores* by informant, operationalizing cross-informant discrepancies via correlations between or differences in raters' scores. However, emerging research suggests the need to consider depression symptoms as individual entities, rather than as indicators of a latent disease construct (see Fried, 2015 for a symptom level perspective and Insel, 2014 for a latent perspective).

First, MDD is highly heterogeneous: diagnostic criteria place individuals with 5 of 9 diverse symptoms (such as excessive guilt, fatigue, and hopelessness) into a single category including >1000 possible symptom combinations (Fried & Nesse, 2015). As a result, youths and caregivers may score equivalently on a given measure of youths' depressive symptom severity—but they may receive those scores by endorsing very different symptoms.

Second, some depressive symptoms are more likely to reflect functional impairment than others. In one study of adults with MDD, hypersomnia accounted for less than 1% of functional impairment, while sad mood accounted for over 20% of impairment (Fried & Nesse, 2014). Similarly, youths reporting certain MDD symptoms, such as sad mood, are more likely to experience comorbid behavioral problems than youths endorsing somatic symptoms (Maasalo, Wessman, & Aronen, 2017). Thus, relying on sum scores may mask the nature and functional consequences of an individual's depressive symptomatology (Fried & Nesse, 2015).

By extension, comparing sum scores obtained by caregivers and offspring may obscure meaningful information about the nature of discrepancies in their reports of youths' depression, regardless of how discrepancies are computed (e.g., through correlations, standardized difference scores, or regression-based methods). These limitations to the sum score approach may help explain how questions of *why* caregiver-youth discrepancies emerge in reports of youths' depression, and *how* clinicians and researchers should interpret those discrepancies when they emerge remain largely unanswered.

Compared to a sum score-level approach, a symptom-level approach to examining informant discrepancies in youths' depression carries at least two advantages. First, it may reveal discrepancies within specific symptoms, regardless of whether discrepancies emerge in total severity scores. For

instance, in a symptom-level analysis of youths' anxiety symptoms, caregiver-youth agreement was higher for observable symptoms (e.g., behavioral avoidance) than more internal symptoms (e.g. worry) (Comer & Kendall, 2004). Likewise, it has been suggested that less observable depressive symptoms, such as feelings of guilt or sadness, may be under-reported by caregivers relative to youths (Angold et al., 1987; Edelbrock, Costello, Dulcan, Conover, & Kala, 1986). Because these less observable depression symptoms (e.g., sadness, self-hatred) have shown stronger links to overall severity and comorbid psychopathology than more observable symptoms (e.g., sleep and appetite changes; Maasalo et al., 2017), formally characterizing symptom-level discrepancies between youths and caregiver reports may carry clinical value.

Second, a symptom-level approach may reveal informant differences in *patterns of associations* among youths' depressive symptoms. That is, certain symptoms might be more strongly associated with one another from youths' perspectives than caregivers' perspectives. For instance, as noted above, a caregiver might be more likely to identify behavioral symptoms of depression in her child (e.g., social withdrawal; hypersomnia) than the cognitive or emotional symptoms that might accompany them (e.g., feeling unloved). In contrast, youths might have greater awareness of any co-occurring observable and unobservable symptoms. In turn, the structure of depressive symptoms might differ by informant, with links among observable and unobservable depressive symptoms emerging as stronger per youth-report than caregiver-report. Such patterns might help account for and explain the nature of discrepancies across informants.

Theoretical and statistical advances in the network approach to psychopathology offer a framework for testing these possibilities. This approach states that individual symptoms interact with one another to create and maintain psychiatric disorders (Borsboom & Cramer, 2013; Bringmann et al., 2013; McNally, 2016). Network analysis is a leading approach to quantifying these symptom-symptom associations. This approach can identify *edges* (e.g., symptom-symptom associations), *central* symptoms, defined as symptoms that relate most strongly to other symptoms in a network, and *global strength*, the sum of all edge strengths in a network (van Borkulo & Millner, 2016). As one example, Mullarkey and

colleagues (2018) examined network structures of youth-reported depressive symptoms in a community sample of adolescents. Self-hatred, sadness, loneliness, and pessimism emerged as the most central depressive symptoms in adolescents' depressive symptom networks; additionally, several edges were identified as stronger than others (e.g., associations between sadness and crying; self-hatred and negative body image; and sadness and loneliness). Thus, examining symptom networks may help characterize the nature, structure, and driving features of youths' depression-related distress. Better understanding the structure of the disorder from caregiver and youths' perspectives, and any discrepancies between them, may help clinicians' identify those depressive symptoms most likely to yield discrepant reports. Such symptoms may be especially critical to assess and target during treatment.

Indeed, in addition to elucidating symptom-symptom links, network analysis also enables *comparison* of two networks containing the same set of symptoms. Such tests can quantify differences in symptom structures by specific variables of interest. Prior studies have examined network differences as a function of individual-level characteristics, such as youths' sex (Mullarkey, Marchetti, & Beevers, 2018). However, to our knowledge, only one study has examined differences in symptom networks by informant (e.g., comparing caregiver- versus youth-reported symptom network structures). This study compared the network structures of clinician report from patient interviews and patient report of PTSD symptoms among adults, and found that 2 edges out of 190 differed (Moshier et al., 2018). To our knowledge, no research has examined informant discrepancies between caregivers and youths from a network perspective. A network approach may help identify sources of informant discrepancies in a more precise, nuanced manner than is possible through severity scores alone; such a symptom-level examination might identify especially critical discrepancies to consider when planning and delivering treatment to youths.

To investigate the above possibilities, and to demonstrate a novel approach to characterizing cross-informant discrepancies in reports of youths' psychopathology, we used network analysis to evaluate the network structures of youths' depressive symptoms across caregiver and youth informants. Specifically, we examined whether caregiver- and youth-report networks differed in global strength (whether the overall strength of symptom-symptom connections differed by informant); network structure

(whether patterns of symptom-symptom connections showed global differences by informant); and specific network edges (whether specific symptom-symptom pairs showed stronger connections per caregiver versus youth reports). To provide clinically relevant evidence, we used a sample of youths whose emotional or behavioral problems were significant enough to have generated clinical referral, drawn from the baseline assessment in a clinical trial (Weisz et al., 2012).

Our primary goal in this study was to ascertain whether a symptom-level approach to examining informant discrepancies might add value to existing approaches to informant discrepancy assessment. That is, if caregivers and youths report depressive symptoms as having inherently different structures or inter-relationships, these differences may help characterize and illuminate previously observed informant discrepancies in mean depressive symptom severity scores. Significant cross-informant differences in network global strength, network structure, or network edges would suggest the added value of a network approach, as opposed to the use of severity scores alone. Additionally, any differences between the nature of discrepancies observed at the mean-level and those observed at the network structure level could help broaden our understanding of informant discrepancies as a whole. We had only two a priori hypotheses due to the novelty of the research questions and approach. First, we hypothesized that associations among less observable, cognitive/emotional depressive symptoms would be stronger per youth-report than caregiver-report. Second, given evidence that caregivers may under-report youths' internalizing symptoms that are less observable (Comer & Kendall, 2004), we predicted that associations between *cognitive/emotional* depressive symptoms (e.g., hopelessness, guilt, or feeling unloved), which may be less observable, and *behavioral* depressive symptoms (e.g., social withdrawal; changes in eating; hypersomnia), which are more observable, would be stronger in youth-report networks than in caregiver-report networks.

Method

Participants

Participants provided data during assessment for eligibility for a treatment study, and the study was approved by the IRBs of all relevant institutions (Weisz et al., 2012). The youth sample (age $M = 10.25$ $SD = 1.75$ years old; range: 7 – 14 years) was racially diverse (47.32% Caucasian, 9.06% Black, 7.72% Latino(a), 3.02% Asian, 28.86% Multiethnic, 3.36% Other, 0.67% missing) with gender representation skewing slightly male (66.78% male, 32.89% female, 0.34% missing). Socioeconomic status of the sample as indexed by income was also diverse, with annual family incomes below \$40,000 per year for 54.02% of the sample, \$40,000-\$59,999 for 13.42% of the sample, \$60,000-\$79,999 for 11.41% of the sample, and > \$80,000 for 16.44% of the sample, per primary caregiver report (income was unreported by 4.70% of the sample).

A total of 298 pairs of youths and caregivers who completed the eligibility assessment for the study and had no missing item-level data on the symptom inventories of interest for present analyses (the Child Behavior Checklist and the Youth Self-Report Form; Achenbach & Rescorla, 2001). 35 participants (11.7% of original sample) were excluded for missing item-level data in this study, because missing item-level data can distort the relationships between symptoms and produce less replicable network analyses (Borsboom et al., 2017). The adult caregiver with primary responsibility for the youth's clinical care also reported on the youth's symptoms at this eligibility assessment. These caregivers (age $M = 41.17 \pm 9.71$ years old; range: 21 – 78 years) were 90.60% female. Specifically, 76.17% were biological parents, 7.38% were biological grandparents, 5.03% were adoptive parents, 3.36% were step-parents, and 4.03% were other adult caregivers (e.g., aunts, uncles). 4.03% of caregivers did not specify their relationship with the youth.

Measures

For the current analyses, the following two measures were utilized:

Youth Self-Report Form (YSR) and Child Behavior Checklist (CBCL)

Depressive symptoms were evaluated with the anxious-depressed/withdrawn-depressed narrowband scales from the Youth Self-Report Form (YSR; Achenbach, 1991) and Child Behavior Checklist (CBCL; Achenbach & Rescorla, 2001). The items on these scales are matched so that the youth (with the YSR) and caregiver (with the CBCL) report on the same symptoms of the youth's psychopathology. We chose to use both of these subscales because they include items representing the full range of depressive symptoms, including core symptoms of major depressive disorder (sad mood and anhedonia); physical symptoms (e.g. fatigue); behavioral withdrawal (e.g., preference for being alone), and cognitive distortions (e.g. feeling worthless or unloved). Combined, the anxious/depressed and withdrawn/depressed subscales of the YSR and CBCL contain 21 self-report items, and all items are measured on a 3-point Likert scale, ranging from 0 ("Not True") to 2 ("Very True or Often True") in response to statements about symptoms in the past six months (e.g., YSR - "*There is very little I enjoy*"; CBCL - "*There is very little he/she enjoys*"). The YSR and CBCL are both widely used to assess youth and caregiver report of youths' psychopathology, respectively (Achenbach & Ruffle, 2000; Polanczyk, Salum, Sugaya, Caye, & Rohde, 2015), and items are frequently combined across subscales to examine more general internalizing outcomes (Janssen et al., 2004; Vederhus et al., 2015).

Additional measures, unrelated to the current study's goal, were also administered. The trial registration includes all measures administered (NCT01178554: <https://clinicaltrials.gov/ct2/show/NCT01178554>).

Statistical Analysis

First, we compared the mean levels of each item as reported by the youths and caregivers. We used paired t-tests to compare each item, using Holm-Bonferroni corrections to account for multiple testing to match the correction for multiple tests employed in network comparison (van Borkulo & Millner, 2016).

In network analysis, each variable in the model is represented as a *node* (e.g. “sadness”), while the association between two nodes is shown as an *edge* (e.g. the relationship between “sadness” and “loneliness”). We first inspected mean, standard deviation, kurtosis, and skewness of all the YSR and CBCL items. The optimal way for estimating network models with trichotomous items is still unknown (Fried, Nesse, Guille, & Sen, 2015), so we estimated our networks using a graphical lasso procedure based on Spearman correlations. A graphical lasso network model can be conceived as a series of pairwise associations among variables after controlling for all the other associations. Further, a lasso with an l_1 -penalty is applied to shrink regression coefficients, reducing very small edges to 0 to create a more parsimonious model. . We chose to use the Extended Bayesian Information Criterion as a hyperparameter (EBIC; Ravikumar, Wainwright, & Lafferty, 2010) as this procedure has a very low false positive rate and approximates the true network as sample size increases (Barber & Drton, 2015). This type of network estimation prevents the relationship between two nodes being spurious due to a third node, and results in higher sparsity, or fewer estimated edges.

First, to determine if the networks were stable and accurate enough to interpret, we performed a case-dropping bootstrap test to assess centrality stability and bootstrapped confidence intervals of edge-weights to assess the accuracy of network edges (Epskamp, Borsboom, & Fried, 2017). As we are primarily interested in comparing the strength of associations across networks, we assessed whether strength centrality, or the sum of the absolute values of all edges connected to a given node, was stable in this network. Other types of network centrality (betweenness and closeness) are not relevant for network comparison tests and therefore were not assessed (Valente, 2012). Centrality stability, operationalized with the correlation stability coefficient (i.e., *CS-coefficient*), represents the maximum proportion of cases that can be dropped and obtain a 95% probability that the correlation of the ranking between the centrality indicator in the original network and the network with the cases dropped from it will amount to 0.7 or larger (very large effect; Cohen, 1977). The *CS-coefficient* therefore tells us what percentage of our sample we would have to drop from our analyses before the strongest symptoms in the original, estimated network are no longer among the strongest symptoms. Epskamp and colleagues (2017) recommend

interpreting centrality indices with a CS-coefficient of at least 0.25, but above 0.5 is the preferred threshold based on simulations of known networks. We will evaluate which nodes are most central to both networks (i.e. stronger than 50% or more of other nodes within the network) and correlate the centrality of nodes across networks. This correlation of strength across networks will help us compare whether symptoms that are more central in the caregiver report network also tend to be more central in the youth report network.

After we gauged network *stability*, edge-weights *accuracy* was estimated with 95% bootstrap CIs. Larger CIs around individual edge-weights indicate reduced precision in the estimation of the edges, whereas narrower CIs around individual edge-weights imply a more trustworthy network. Significantly stronger edges were identified by examining the CIs of the difference between each pair of edges. If zero is included in CI, the difference between the two nodes should not be interpreted. All stability and accuracy analyses described above were performed using the *R*-package bootnet 1.0 (Epskamp et al., 2017).

Our primary analysis tested for differences between the networks of youth and caregiver report of youths' internalizing symptoms. The networks were visualized using *R*-package qgraph 1.4.3 (Epskamp et al., 2012) after applying the Procrustes rotation procedure within multidimensional scaling to allow for more visual interpretation of network differences (Jones, Mair, & McNally, 2018). We then tested whether the network global strength, or the sum of all absolute non-zero edges in the network, differed between youth and caregiver report (i.e. invariant global strength hypothesis). We then tested whether the structure of the two networks as a whole differed statistically (i.e. invariant network structure hypothesis) and, conditional to the previous test, tested whether any single edges were significantly different, after the Holm-Bonferroni correction for multiple comparisons (i.e., invariant edge strength hypothesis). We conducted all of these tests using the *R*-package NetworkComparisonTest 2.0.1 (van Borkulo & Millner, 2016). NetworkComparisonTest works by creating a "null model" for network comparison. It randomly shuffles whether participants are labeled as a youth or as a caregiver (e.g., datasets where youth and caregivers are mixed up), generates two networks, and compares the two. It repeats this procedure 1,000

times to generate a null distribution of comparisons. Then, this null distribution of comparisons is used to evaluate the original comparison between our two datasets. The p -values calculated represent the proportion of test-statistics belonging to the permuted datasets that are at least as extreme as the original estimated network (van Borkulo & Millner, 2016).

Regularization via LASSO directly impacts the sparsity of networks, causing some concern that interpretations about global strength might be influenced by the LASSO algorithm. Thus, we also performed sensitivity tests where the caregiver and youth report partial correlation networks without regularization were compared. As our sample is age-heterogeneous and the ability of youths to report on their symptoms may at least in part depend on age (De Los Reyes et al., 2015), we also conducted sensitivity tests to see whether the symptoms networks for children ages 7-10 and adolescents ages 11-14 differed by either youth or caregiver report. This sensitivity test allowed us to assess whether differential reporting by age is a potential confounding factor for our analyses.

Results

Descriptive statistics

Mean, standard deviation, skewness, kurtosis, and frequency of the YSR and CBCL item-level scores on the narrowband anxious/depressed and withdrawn/depressed subscales are reported in Table 1.

Table 1 Here

The overall mean and standard deviation of all symptoms combined, or a traditional raw mean score, was $M = 0.43$, $SD = 0.30$ for YSR items and $M = 0.61$, $SD = 0.36$ for CBCL items. The total mean scores of the YSR items and CBCL items were significantly, positively correlated with one another, albeit with small to medium effect size ($r = 0.17$, $p = .003$). This modest correlation is consistent with observed discrepancies in cross-informant reports of overall youth internalizing problems (De Los Reyes et al., 2015).

Mean level comparison of individual symptoms

As a first step, we compared the mean levels of each symptom reported by the youths and caregivers, respectively. We used Bonferroni-Holm corrected paired t-tests to estimate the differences in mean levels. We found that caregivers reported higher mean levels for most items, including *embarrassed, feels unloved, worthlessness, sadness, anxious, nervous, perfectionism, worry, won't talk, rather be alone, school fear, anhedonia, and suicidal ideation* (all $p < 0.01$ following Bonferroni-Holm correction, see Figure 1). The remainder of items were not significantly different between reporters based on corrected p-values ($p > 0.05$).

Figure 1 Here

Stability and accuracy tests

For the youth-reported network node strength, or the sum of all absolute non-zero edge-weights in the network connected to each node, showed an excellent level of stability (i.e., *CS-coefficient* = 0.58). In other words, 58% of youths could be dropped before strength no longer had at least a 95% chance of being correlated 0.7 with the original rank order of symptoms. For the caregiver-reported network, strength (i.e., *CS-coefficient* = 0.62) also showed an excellent level of stability. No symptoms in the youth-report network were stronger than 50% or more of the other symptoms (Figure S1), but *sadness* and *anxiety* were stronger than 50% or more of the other symptoms in the caregiver report network (Figure S2). The strength of symptoms across informant networks were highly correlated (*Spearman's r* = 0.50; 95% CI 0.09, 0.77) as displayed in Figure S3, indicating that the centrality of symptoms was similar across networks.

Both the caregiver (Figure S4) and youth (Figure S5) report networks appear to be estimated with reasonable accuracy, given that some of the observed edges in both networks were significantly stronger than other estimated edges.

Network comparison tests

Figure 2 shows the networks of youth-reported youths' symptoms and caregiver-reported youths' symptoms. The test for global network strength differences, or the sum of all absolute non-zero edge-weights in the networks, showed a statistical difference with the caregiver-report network being more strongly connected than the youth-report network (global strength difference = 1.20; caregiver-report global strength = 9.07, youth-report global strength = 7.87; $p = 0.02$). The two networks also differed in terms of network structure, as a test of whether any edges differed between the two networks was statistically significant (maximum difference = 0.36; $p < .001$). After applying a Bonferroni-Holm correction, the only differences in edge strength across networks that remained statistically significant were *perfectionism-feels unloved* (youth-report: 0.15; caregiver-report 0.00; $p < 0.001$), *won't talk – secretive* (youth-report: 0.00; caregiver-report 0.36; $p < 0.001$), and *rather be alone – uninvolved* (youth-report: 0.06; caregiver-report 0.39; $p < 0.001$). That is, *perfectionism-feels unloved* was more strongly associated in the youth-report network compared to the caregiver-report network, while *won't talk – secretive* and *rather be alone – uninvolved* were more strongly associated in the caregiver-report network compared to the youth-report network.

Figure 2 Here

Sensitivity tests for network comparison tests

The edges in our estimated networks were overwhelmingly positive, as expected, but a few negative edges did emerge. Thus, we first conducted a sensitivity test by treating negative edges as negatives, rather than taking absolute values of edges, or the global *expected influence* (Robinaugh, Millner, & McNally, 2016). This metric can be interpreting the total *positive* connectivity in the network, rather than simply the degree of connections, which is highly influenced by the GLASSO procedure. The test for global network expected influence using GLASSO estimation was non-significant (global expected influence difference = 0.63; caregiver-report global expected influence = 8.50, youth-report global strength = 7.87; $p = 0.12$), indicating that negative edges were driving the significant global

strength difference observed between the reporter networks. That is, the nodes in the caregiver network were more *predictable* based on other nodes, compared to the youth network, but they did not *cohere* more (i.e., correlate more positively) compared to the youth network. We also conducted sensitivity analyses using partial correlation networks, and found the same pattern of results (See Section S1).

Symptom strength also did not strongly relate with symptom standard deviation in the youth ($r_s = -0.36$,; 95% CI: -0.69, 0.08), the caregiver network ($r_s = 0.34$,; 95% CI: -0.11, 0.67), or when symptom strength and standard deviation from both networks are combined ($r_s = -0.03$,; 95% CI: -0.46, 0.41), indicating that differences in symptom variance between networks did not drive centrality values (Terluin, Boer, & Vet, 2016).

We also considered whether symptom networks differed by either youth or caregiver report when separating children (ages 7-10) and adolescents (ages 11-14). The test for global network strength differences did not show a statistical difference between child and adolescent networks per youth (global strength difference = 0.70; child global strength = 7.28, adolescent global strength = 7.98; $p = 0.56$) or caregiver report (global strength difference = 0.65; child global strength = 7.92, adolescent global strength = 8.57; $p = 0.41$). The child and adolescent networks also did not differ in terms of network structure per youth (maximum difference = 0.24; $p = .60$) or caregiver report (maximum difference = 0.20; $p = .87$). Therefore, no evidence emerged for differences in network structure as a function of youths' developmental stage.

Discussion

We took a novel, network analysis approach to examining cross-informant discrepancies in youths' depression. Some evidence supported our first hypothesis: that less visible cognitive/emotional symptoms would show stronger associations with each other in the youth report depression network compared to the caregiver report depression network. Specifically, the association between *perfectionism-feels unloved* was stronger in the youth report network than the caregiver report network. Still, there are other edges that might have supported our prediction that did not significantly differ between networks in this sample. Contrary to our second hypothesis, there were no observed differences between the youth and

caregiver networks for associations between more observable *behavioral* symptoms and less observable *cognitive/emotional* symptoms. We instead found some evidence that at least certain more observable, behavioral symptoms associated with withdrawal were more strongly associated in the caregiver report network (*won't talk – secretive* and *rather be alone – uninvolved*). Overall, youths and caregivers reported significantly discrepant mean levels for a majority of the symptoms (12/21) while youth and caregiver network structures of symptoms were broadly similar. That is, only 3 edges differed out of 119 estimated edges, and symptom centrality was strongly correlated across youth and caregiver networks, *Spearman's* $r = 0.50$. Thus, the mean-level approach and the network approach painted markedly different pictures of cross-informant agreement/discrepancy: At the mean-level, discrepancies were the rule, whereas at the network level, they were the exception.

Integrating these differing analytic perspectives may enrich our understanding of informant discrepancies and their impact on important, depression related outcomes. It is possible, for example, that youths and caregivers might disagree as to the mean level of symptoms while showing strong agreement as to how those symptoms relate to each other. Our mean-level findings fit with previous findings by Comer and Kendall (2004), with similar numbers of youth/caregiver discrepancies found in both studies, despite differences in the populations sampled (youths referred for clinical depression, anxiety, and conduct vs. youths referred for anxiety specifically) and the adjustments for multiple testing employed (Holm-Bonferroni vs. none). However, the picture changed markedly when we shifted from mean level comparison to comparison of edge weights across reporter networks. Future analyses could examine how caregiver and youth reporters experience different types of discrepancies (mean-level vs. network structure). For example, both reporters might experience mean-level discrepancies as disagreement about specific behaviors, while they might experience network-level discrepancies as disagreement about which behaviors feed into one another. This second type of disagreement may be less commonly observed and discussed, but can be clinically important as interrupting the negative spiral of symptoms is often a focus of treatment. Indeed, it could be argued that youth-caregiver agreement on the *dynamics* of depression—i.e., how symptoms relate to one another and link together in episodes of depression—may be at least as

important to prevention and treatment as agreement on mean levels of symptoms. Network analysis may provide a lens through which youth and caregiver understanding of the dynamics may be viewed, and a method for studying whether level of youth-caregiver agreement relates to important outcomes, including outcomes of intervention.

There was a single stronger association between less visible depression symptoms in the youth network compared to the caregiver network (*perfectionism – feels unloved*). Thus, youths might report these particular symptoms as more tightly linked than their caregivers do. The tighter link between youth-perceived perfectionism and feeling unloved may warrant increased attention in clinical assessment, as caregivers—who tend to refer youths for treatment (Warnick, Gonzalez, Weersing, Scahill, & Woolston, 2011)—may be unlikely to identify these symptoms’ co-occurrence. Importantly, this type of discrepancy would also not be well detected by mean-level analysis, as both *perfectionism* and *feels unloved* were actually reported at significantly higher mean-levels by caregivers than by youths. Still, we only observed this tighter link between less visible symptoms in one symptom pair; results do not suggest that youths reported *all* less visible symptoms as more intertwined than their caregivers did. Taking a symptom level approach, as in this network analysis, may allow us to better understand disorders by shifting us away from generalizations and toward specific empirical findings.

Contrary to our hypothesis, we did not observe stronger relationships between less visible symptoms and more visible symptoms in the youth network compared to the caregiver network. However, these null relationships may have resulted from features specific to the sample. First, in the present sample, referral to a clinical trial was based partly on a caregiver reporting high youth symptoms; second, caregivers in this study over-reported symptoms relative to youths far more often than the reverse. Prior theory suggests that the stronger links between less visible and more visible symptoms will only occur in the cases where caregivers under-report less visible symptoms relative to youths (Angold et al., 1987; De Los Reyes et al., 2013; Edelbrock et al., 1986). A replication of these analyses in a non-selected sample, where caregivers may be less likely to over-report symptoms, could help elucidate whether discrepancies in mean levels of individual symptoms across reporters (or the lack thereof) can

influence whether we observe different network structures across reporters. Regardless of the results of that replication, we echo recent calls for network analysis frameworks to more formally integrate the mean levels of individual symptoms with our analysis of associations between symptoms (Bringmann & Eronen, 2018). This integration may allow us to better predict structural differences at certain mean levels (e.g. when youths are over-reporting compared to caregivers) but not at others (e.g. when caregivers are over-reporting compared to youths). This approach would allow informant discrepancy researchers to more readily integrate knowledge about mean-level and network level discrepancies.

We also found some non-hypothesized structural differences between the youth and caregiver networks, specifically that associations between two sets of more visible symptoms (*won't talk – secretive* and *rather be alone – uninvolved*) were stronger in the caregiver network compared to the youth network. As these differences were not hypothesized, interpretations are exploratory. Previous research indicates that caregivers and youths may focus more on different aspects of depression when reporting symptoms, with the least congruent reporting occurring on more visible behavioral symptoms (Cole, Hoffman, Tram, & Maxwell, 2000). Present results provide converging evidence for that phenomenon from the network perspective. Again, discrepancies of this nature would not be uncovered using mean-level analysis: while *won't talk* and *rather be alone* both are reported at a higher mean-level among caregivers, the symptoms they relate more strongly to (*secretive* and *uninvolved*) do not differ at the mean-level across informants.

The current study elucidates some group-level differences in network structures between averages of youth reports of symptoms and averages of caregiver reports of symptoms. In the future, using experience sampling methods to obtain many reports of youths' symptoms over time—both from individual youths and caregivers—would allow us to construct idiographic symptom networks for both youths and caregivers (Bringmann, Lemmens, Huibers, Borsboom, & Tuerlinckx, 2015; Fisher, Reeves, Lawyer, Medaglia, & Rubel, 2017). This individualized network construction could allow us to examine whether mean-level discrepancies being more common than network structure discrepancies across informants generalizes to the individual level (Fisher, Medaglia, & Jeronimus, 2018). It would also allow us to test whether having both types of discrepancies, network and mean-level, relate to even worse

outcomes than having only one type of discrepancy. Discrepancies across informants at the sum score level predict less favorable emotional, functional, and behavioral youth outcomes (Ferdinand et al., 2004; Guion et al., 2009) and poorer response to mental health treatment (Ferdinand, van der Ende, & Verhulst, 2006; Goolsby et al., 2018). Present results suggest another type of discrepancy (i.e. differential associations between symptoms across informant) that may further elucidate differential youth outcomes.

For example, a clinician attempting to treat the youths in this sample could examine Figure 1 and Figure 2 side by side and derive important, additive information from both visuals. Using Figure 1, the clinician might discover which symptoms caregivers report more often than youths, along with symptoms about which caregivers and youths broadly agree. Using Figure 2, the clinician might discern which symptoms tend to cluster together more according to youth report compared to caregiver report (e.g. *perfectionism – feels unloved*) and vice-versa (*rather be alone – uninvolved*). The mean level informant discrepancies offers the clinician important information about where the youth and caregiver might disagree on the *overall severity* of the disorder, while the network- or symptom-level informant discrepancies offer information about *where specifically* the youth and caregiver might disagree on the structure of the disorder. Informant discrepancies in perceived *severity* of the disorder and in the perceived *nature* of the disorder could lead to different types of disagreements over appropriate treatment plans and whether sufficient progress is being made in treatment. The results from this study provide a framework for elucidating both types of discrepancies. Future research could examine whether knowledge of those discrepancies can improve treatment outcomes.

This study has limitations that suggest avenues for future research. While our sample was large enough to construct stable symptom networks for both caregivers and youths, a larger sample would have greater power to detect more structural differences between youth and caregiver networks. Absence of evidence for structural differences across networks cannot be considered evidence of absence. However, given the high stability of strength and relatively high accuracy in both youth and caregiver networks, we can be more confident that the evidence for differences between the informant networks observed here were not spurious (Epskamp et al., 2017). Future research could examine and extend this multi-method

approach to informant discrepancies in larger samples. Also, we used a clinical youth sample, results carry most relevance for treatment-seeking youths with clinically significant psychopathology and may not generalize to a non-selected sample (De Los Reyes et al., 2011).

Still, the novel set of methods used here may be applied directly to non-selected samples. Further, multi-informant assessment is the gold standard approach in assessing improvements among clinical samples of youths (Klein et al., 2005), and these findings can further inform that practice. For example, if certain symptom pairs are consistently more strongly associated in the youth report compared to caregiver report, researchers could compare sum scores weighted by the strength of edge-weights (e.g. (Boschloo, Borkulo, Borsboom, & Schoevers, 2016) across informants rather than comparing raw sum scores. This could improve our ability to predict the future course of the depressive disorder. For example, weighting symptoms based on a network-parameter, strength centrality, better predicts whether adults will develop a major depressive episode over the following six years than raw symptom scores (Boschloo et al., 2016). Perhaps weighting symptoms by cross-informant discrepancies, especially given our finding that strength centrality is similar across informant networks, could improve our ability to forecast naturalistic or treatment outcomes for youths' depressive symptoms as well.

Applying a network analysis approach to discrepancies between youth and caregiver report of depression symptoms in this sample is only one framework for investigating informant discrepancies. Established descriptive methods and more advanced techniques like multilevel factor analysis can also be applied to help us better understand cross-informant discrepancies (Flake & Petway, 2018). A symptom level approach to understanding informant discrepancies does not require abandoning previous methods, but instead calls for us to focus on a different level of analysis. Previous studies have tended to focus on single explanatory factors for these discrepancies, but some studies have begun to examine multiple explanatory factors for discrepancies simultaneously (e.g., De Los Reyes et al., 2011). Examining multiple explanatory factors for informant discrepancies simultaneously while considering multiple levels of analysis (e.g. mean level and network structure) may help deepen our understanding of the structure of youths' depression. Applying novel methods like network analysis along with these more established

methods to individual and pairs of depressive symptoms, rather than sum scores, could produce important theoretical and clinical insights. In concert, these approaches could allow us to better understand the structure and implications of informant discrepancies in depression symptoms.

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Table 1. Mean, standard deviation, minimum, maximum, skewness, and kurtosis, and frequency of symptoms (n = 298)

Symptoms	YSR/CBCL#	Mean YSR	SD YSR	Skewness YSR	Kurtosis YSR	Mean CBCL	SD CBCL	Skewness CBCL	Kurtosis CBCL
Anhedonia	5	0.44	0.69	1.27	0.22	0.57	0.68	0.78	-0.57
Crying	14	0.48	0.69	1.08	-0.14	0.57	0.68	0.80	-0.57
Afraid of Situations	29	0.61	0.74	0.76	-0.81	0.55	0.73	0.92	-0.56
Afraid of School	30	0.17	0.46	2.71	6.67	0.32	0.62	1.76	1.82
Afraid of Thoughts	31	0.41	0.64	1.31	0.50	0.35	0.62	1.59	1.29
Perfectionism	32	0.46	0.72	1.23	0.02	0.72	0.76	0.51	-1.12
Feels Unloved	33	0.25	0.54	2.05	3.19	0.68	0.76	0.60	-1.05
Worthless	35	0.26	0.54	1.94	2.81	0.68	0.71	0.55	-0.90
Rather Be Alone	42	0.37	0.60	1.37	1.37	0.56	0.70	0.86	-0.55
Nervous or Tense	45	0.57	0.70	0.81	-0.61	0.89	0.74	0.18	-1.18
Too Anxious	50	0.36	0.57	1.34	0.80	0.70	0.75	0.54	-1.05
Guilty	52	0.27	0.53	1.84	2.44	0.30	0.55	1.66	1.77
Refuse to Talk	65	0.34	0.55	1.37	0.91	0.54	0.67	0.86	-0.43
Secretive	69	0.63	0.72	0.67	-0.82	0.74	0.72	0.43	-1.01
Self-Conscious	71	0.48	0.69	1.09	-0.14	1.11	0.72	-0.16	-1.08
Too Shy/Timid	75	0.58	0.71	0.81	-0.63	0.63	0.70	0.65	-0.78
Suicidal Ideation	91	0.10	0.35	3.49	12.39	0.17	0.43	2.43	5.38
Fatigue	102	0.35	0.60	1.53	1.22	0.41	0.65	1.30	0.44
Sadness	103	0.51	0.66	0.92	-0.32	0.89	0.71	0.16	-1.00
Uninvolved	111	0.59	0.71	0.77	-0.68	0.43	0.63	1.18	0.26
Worry	112	0.84	0.80	0.30	-1.37	1.07	0.75	-0.12	-1.24

Captions for Figures in Cross Informant Network Analysis

Figure 1: Mean level discrepancies between youth and caregivers for individual depression symptoms. Point estimates above 0 on the y-axis indicate higher caregiver reporting of that symptom compared to youth report, while point estimates below 0 on the y-axis indicate higher youth reporting of that symptom compared to caregiver report. The point estimates have error bars around them representing the 95% CI for the estimate.

Figure 2: Depression symptom networks for youth as reported by both youth and caregivers. Symptoms are represented by circular nodes while relationships between them (edges) are represented by blue and red lines connecting the nodes. Blue edges denote positive associations between nodes, and red edges denote negative associations between nodes. Thicker edges denote stronger associations between nodes. Networks were plotted with multidimensional scaling and then brought into a comparable space using the Procrustes approach (Jones, Mair, & McNally, 2018). Nodes that appear closer together in the network are also more strongly associated in terms of edge weights, while nodes that are further away from each other are less strongly associated.

Caregiver

Stress= 0.31

Youth

Stress= 0.32

- 5: Anhedonia
- 14: Crying
- 29: Situational Fear
- 30: School Fear
- 31: Do Wrong
- 32: Perfectionism
- 33: Unloved
- 35: Worthlessness
- 42: Rather Alone
- 45: Nervous
- 50: Anxious
- 52: Guilt
- 65: Won't Talk
- 69: Secretive
- 71: Embarrassed
- 75: Shy
- 91: Suicidal Ideation
- 102: Fatigue
- 103: Sadness
- 111: Uninvolved
- 112: Worry

Greater Parent Reporting

Appendices

Figure S1. Nonparametric bootstrapped difference test for strength in the youth report network. Gray boxes indicate no difference between nodes, whereas black boxes indicate significant difference ($\alpha = 0.05$). Values reported in the diagonal represent the strength values of each node.

Figure S2. Nonparametric bootstrapped difference test for strength in the caregiver report network. Gray boxes indicate no difference between nodes, whereas black boxes indicate significant difference ($\alpha = 0.05$). Values reported in the diagonal represent the strength values of each node.

Figure S3. Visual comparison of strength centrality across caregiver and youth report networks

Figure S4. Accuracy of caregiver network. Lighter gray sections indicate 95% confidence intervals for the edge-weight, and non-overlapping edges indicate that one edge is stronger than another. The red points indicates the sample mean for the edge-weight point estimate, while the dark gray points indicate the bootstrapped means for the edge-weight point estimate.

Figure S5. Accuracy of youth network. Lighter gray sections indicate 95% confidence intervals for the edge-weight, and non-overlapping edges indicate that one edge is stronger than another. The red points indicates the sample mean for the edge-weight point estimate, while the dark gray points indicate the bootstrapped means for the edge-weight point estimate.

Section S1. Sensitivity Tests with Partial Correlations

We conducted a sensitivity analysis using partial correlation networks, rather than GLASSO. Because the regularization inherent in GLASSO directly affects the sparsity of the network, we wanted to test whether global differences were robust when GLASSO was not used. We continued to use global expected influence for this test. The test for global network expected influence differences using partial correlation networks did not show a statistical difference across reporter networks (global strength difference = -0.18; caregiver-report global strength = 8.63, youth-report global strength = 8.81; $p = 0.43$). So, the global difference observed when using a network comparison test with a LASSO penalty is not robust to a test when using a network comparison test with partial correlations.

Using partial correlation networks, the two networks did differ in terms of network structure, as a test of whether any edges differed between the two networks was statistically significant (maximum difference = 0.43; $p < .001$). After applying a Bonferroni-Holm correction, the only differences in edge strength across networks that remained statistically significant statistically different were *won't talk – secretive* (youth-report: -0.04; caregiver-report 0.40; $p < 0.001$) and *rather be alone – withdrawn* (youth-report: 0.10; caregiver-report 0.44; $p < 0.001$). So, *must be perfect-feels unloved* was no longer a statistically significantly different edge when comparing partial correlation networks, while *won't talk – secretive* and *rather be alone – withdrawn* were both still more strongly associated in the caregiver-report partial correlation network compared to the youth-report partial correlation network.