Symptom-level network analysis distinguishes the unique associations of repetitive
negative thinking and experiential avoidance on depression and anxiety in a
transdiagnostic clinical sample

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Abstract

Repetitive negative thinking and experiential avoidance have been hypothesized to be related, transdiagnostic maintenance factors for depression and anxiety. Work to date has not examined these maintenance factors in a comorbid clinical sample using a symptom-level approach. Adults presenting for treatment to an intensive CBT program ($n = 492$) completed measures of depression and anxiety symptom severity, repetitive negative thinking, and experiential avoidance. Permutation testing indicates that repetitive negative thinking improved the predictability of excessive worrying and concentration, whereas experiential avoidance improved the predictability of feeling like a failure, difficulties relaxing, and being afraid something bad was going to happen. Applying network analysis helps to more precisely identify which symptoms of depression and anxiety are associated with transdiagnostic maintenance factors, thus providing insight into how these factors may contribute to the maintenance of co-occurring disorders.

Highlights

- Differences in network predictability for measured and synthetic (i.e., randomly shuffled) maintenance factors were examined for depression and anxiety symptoms.
- Permutation testing was used to test differences in network predictability.
- Experiential avoidance and repetitive negative thinking are associated with different anxiety and depression symptoms.
- Experiential avoidance is associated with predictability of the symptoms of trouble relaxing, failure, and being afraid only.
- Repetitive negative thinking is associated with predictability of the symptoms of poor concentration and excessive worry only.

Introduction

Depression and anxiety disorders are the two most common mental disorders in the world, as well as leading contributors to global disability (“WHO | Depression and Other Common Mental Disorders,” 2018). In addition, depression and anxiety disorders frequently co-occur (Kessler et al., 2005, 2008); this co-occurrence is associated with higher symptom severity and a longer duration of symptoms than presenting with just depression or an anxiety disorder (e.g., Lamers et al., 2011). Understanding how different maintenance factors may collectively and uniquely contribute to comorbid depression and anxiety may help with efforts to develop and refine treatment for this significant clinical challenge.

Repetitive negative thinking has received substantial attention as a cognitive maintenance factor for depression and anxiety (e.g., Drost, van der Does, van Hemert, Penninx, & Spinhoven, 2014; McEvoy, Watson, Watkins, & Nathan, 2013). Repetitive negative thinking, in the form of rumination and/or worry, has been found across the broad array of depression and anxiety disorders (for a review, see Ehrling & Watkins, 2008). Elevated repetitive negative thinking is associated with greater concurrent symptom severity (e.g., Spinhoven, Drost, van Hemert, & Penninx, 2015) and prospectively predicts depression and anxiety symptom severity (e.g., McLaughlin & Nolen-Hoeksema, 2011; Raes, 2012).

Repetitive negative thinking has also been theorized to relate to experiential avoidance (c.f., Cribb, Moulds, & Carter, 2006; Moulds, Kandris, Starr, & Wong, 2007). Experiential avoidance is another transdiagnostic maintenance factor for depression and anxiety (e.g., Hayes et al., 2004) and occurs when individuals attempt to avoid

aversive private experiences (e.g., emotions, thoughts, memories) by changing the form and frequency of these experiences and their associated contexts (Hayes, Wilson, Gifford, Follette, & Strosahl, 1996). Studies in clinical and non-clinical samples have found experiential avoidance to be positively associated with depression (e.g., Cribb et al., 2006), anxiety (e.g., Spinhoven, Drost, de Rooij, van Hemert, & Penninx, 2014), and repetitive negative thinking (e.g., Giorgio et al., 2010; Smith, 2008). Consequently, repetitive negative thinking and experiential avoidance appear to be interrelated transdiagnostic maintenance factors for depression and anxiety.

Although these two factors have been implicated in depression and anxiety, they are rarely studied at the same time, in part because past research often does not explicitly emphasize comorbidity (c.f., Eisma, 2015; Giorgio et al., 2010; Krieger, Altenstein, Baettig, Doerig, & Holtforth, 2013; Spinhoven, Drost, de Rooij, van Hemert, & Penninx, 2016). Further, studies that have examined these cognitive maintenance processes in relation to depression and anxiety have often relied upon samples that express a limited range of individual symptom severity (i.e., non-clinical populations; e.g., Bird, Mansell, Dickens, & Tai, 2013; Cernvall et al., 2016). However, discerning how repetitive negative thinking and experiential avoidance contribute to the maintenance of psychiatric comorbidity requires studying their relationship with psychopathology in a sample experiencing a larger range of severity for individual depression and anxiety symptoms (e.g., a clinical sample).

Moving beyond disorder-level analyses

Our understanding of how repetitive negative thinking and experiential avoidance maintain depression and anxiety may be further enhanced by adopting a more nuanced approach to studying psychopathology. Traditional approaches to conceptualizing and studying mental disorders assume underlying common causes or homogenous disease states (e.g., “Major Depressive Disorder” or “Generalized Anxiety Disorder”) that give rise to, and maintain, the symptoms observed in these disorders. These diagnostic categories can be helpful for clinicians who wish to communicate the general symptom patterns of patients with others. However, the continuing inability to identify common causes (e.g., Abi-Dargham & Horga, 2016; Dinga et al., 2019), heterogeneity within diagnostic categories (e.g., Fried & Nesse, 2015), and patterns of comorbidity across diagnostic categories (e.g., Adams, Balbuena, Meng, & Asmundson, 2016; McElroy, Fearon, Belsky, Fonagy, & Patalay, 2018) all call into question the validity of these diagnostic categories. The network approach to psychopathology (Borsboom, 2017; Borsboom & Cramer, 2013; Fried et al., 2017) provides an alternative conceptual framework for understanding the maintenance of psychiatric disorders and comorbidity between them.

Network models of psychopathology may provide a more fine-grained, symptom-level understanding of how repetitive negative thinking and experiential avoidance contribute to the maintenance of depression and anxiety. Network approaches to psychopathology adopt a causal systems perspective (Borsboom, 2008), whereby symptom co-occurrence is a product of one symptom causing another, rather than a product of a common cause (e.g., depression). Based on this conceptualization, mental disorders develop and persist based on the causal interaction of symptoms in a system

(Borsboom, 2017). For instance, in depression feelings of guilt and worthlessness may lead to sad mood and subsequent difficulties falling asleep, resulting in consequent fatigue that drives difficulties in concentration.

The continued interaction and reinforcement of symptoms in these networks thus leads to disorder maintenance. This network approach to understanding psychopathology provides a more detailed understanding of how individual symptoms may (or may not) differentially contribute to disorder maintenance. For example, symptoms that are more strongly associated with the presence and severity of other symptoms (i.e., central symptoms) may be stronger predictors of disorder maintenance than more weakly associated symptoms (i.e., peripheral symptoms; McNally, 2016). Given recent work documenting how symptoms within the same disorder differentially relate to risk factors (Fried, Nesse, Zivin, Guille, & Sen, 2014), underlying biology (c.f., Bowie, Milanovic, & Tran, 2019; Der-Avakian & Markou, 2012; Redlich et al., 2018), and functional impairment (Fried & Nesse, 2014), taking a symptom-level (rather than syndrome-level) approach appears particularly warranted.

Symptom-level approaches can also be applied beyond a single disorder, as comorbidity can be conceptualized as the transdiagnostic interaction of symptoms. Consider the example of depression again: if repetitive negative thinking leads to guilt, followed by sad mood and consequent difficulties falling asleep resulting in fatigue, that fatigue could lead to increased irritability followed by muscle tension and then feelings of being on edge (i.e., symptoms of Generalized Anxiety Disorder). Based on this symptom-level approach to psychopathology, if two disorders share similar or overlapping symptoms, they may be more likely to be comorbid.

One study that examined this specific hypothesis found that across the DSM, the shorter the distance (i.e., average number of connections from symptoms of one disorder to another) between the symptoms of two disorders, the higher the rate of comorbidity between those disorders (Borsboom, Cramer, Schmittmann, Epskamp, & Waldorp, 2011). However, even in studies that have examined the interconnected network structure of commonly co-occurring disorders (e.g., depression and anxiety disorders), not all symptoms are closely connected (c.f., Beard et al., 2016; McElroy et al., 2018; McElroy & Patalay, 2019). Considering symptoms and maintenance factors that likely bridge disorders (versus symptoms that associate with a single disorder) may provide particular insight into potential relationships that influence comorbidity. In summary, network models of psychopathology can provide a strong theoretical framework for understanding the maintenance and comorbidity of psychiatric disorder.

Incorporating non-symptom nodes into network models of psychopathology

Network models primarily focus on symptom interaction as maintenance factors of psychopathology. To date, our understanding of how previously-theorized maintenance processes (e.g., repetitive negative thinking, experiential avoidance) influence transdiagnostic symptom networks is limited. Most network studies of psychopathology that incorporate nodes measuring theorized maintenance factors generally focus on a single disorder (c.f., Galderisi et al., 2018; Heeren & McNally, 2016; Mullarkey, Dobias, & Bluth, 2018). The network studies that have examined maintenance factors of psychopathology with symptoms beyond a single disorder have included measures of personality (c.f., Pereira-Morales, Adan, & Forero, 2019; Yun et al., 2017), social connectivity/neighborhood environment (McElroy et al., 2019), and

neuropsychological functioning (Yun et al., 2017). Surprisingly, to our knowledge no study has examined the contributions of transdiagnostic maintenance factors drawn from cognitive models of psychopathology, such as repetitive negative thinking or experiential avoidance, to transdiagnostic symptom networks.

In fact, very few network studies of psychopathology have examined repetitive negative thinking. Faelens and colleagues (2019) found that rumination was positively associated with stress and depression and negatively associated with self-esteem in their network model. Bernstein et al. (2017) suggested that increasing levels of rumination predicted weaker executive control and greater self-criticism in their network analysis. Bernstein and colleagues (2019) also examined how rumination might be conceptualized from a network perspective, finding that passive, self-critical processes were more central in this rumination network. Although these studies examined repetitive negative thinking in the framework of network analysis, these studies did not examine a transdiagnostic array of symptoms¹ and recruited samples unselected for psychopathology. Moreover, no study to our knowledge has included experiential avoidance in network models of psychopathology or examined how it relates to repetitive negative thinking in such models.

The current study

Thus, we examined the contribution of repetitive negative thinking and experiential avoidance to the maintenance of depression and anxiety using network

¹ Faelens et al., 2019 included depression, anxiety and stress as nodes in their networks but these were sum scores from subscales of the Depression, Anxiety, and Stress Scales (see manuscript for further detail) and not specific symptoms associated with depression and anxiety.

analysis, examining whether including these factors (together and in isolation) made the symptom networks more predictable. To operationalize the impact of adding cognitive (i.e., non-symptom) maintenance factors to the symptom network, we examined their effects on the predictability of the overall network and individual symptoms within it. Predictability is the amount of absolute variance explained in a node by all other nodes included in the network (Haslbeck & Waldorp, 2018). Theoretically, adding important maintenance factors to a network should increase the predictability of the network overall, as more variance per node should be explained. However, previous research indicates risk and maintenance factors may be differentially associated with different symptoms (e.g., Fried et al., 2014), so there is also utility in examining predictability on a node by node basis.

We consequently conducted the present study with the following goals: 1) test how repetitive negative thinking and experiential avoidance collectively impact the predictability of depression and anxiety symptoms in a network model based on a transdiagnostic psychiatric sample; 2) examine the unique associations between individual symptoms of depression and anxiety with repetitive negative thinking or experiential avoidance in this network; and 3) compare the associations between repetitive negative thinking and experiential avoidance with individual symptoms of depression, as well as with individual symptoms of anxiety, in this symptom network.

To test how repetitive negative thinking and experiential avoidance collectively impact the predictability of depression and anxiety symptoms in a network model, we compare the predictability of a symptom network with repetitive negative thinking and experiential avoidance against a null hypothesis model. The models were identical

except that the null model replaced the observed values for repetitive negative thinking and experiential avoidance with synthetic values created by randomly sampling from the distributions of these scores. By permuting the repetitive negative thinking and experiential avoidance scores, the null model examines randomly generated associations between these maintenance factors and depression/anxiety symptoms. If the null and measured models do not differ, this suggests that the maintenance factors are not important for the prediction of depression/anxiety symptoms. We also explored how predictability in the network including both repetitive negative thinking and experiential avoidance compared to a network where only one of the cognitive maintenance factors was permuted.

As most theories of repetitive negative thinking and experiential avoidance center on their association with cognitive and affective symptoms of depression and anxiety (e.g., rumination, worry, aversive emotions and thoughts), we hypothesized that cognitive and affective symptoms (e.g., depressed mood) would show higher predictability in the measured maintaining factor network compared to the synthetic maintaining factor networks. As theoretical accounts of repetitive negative thinking and experiential avoidance do not specify a relationship between these cognitive processes and more somatic/vegetative symptoms of depression and anxiety, we did not predict any differences in predictability for more somatic/vegetative symptoms (e.g., appetite problems) of depression and anxiety. These hypotheses were pre-registered on the Open Science Framework (<https://osf.io/4rf5e>) before we began data analyses. Together, these analyses examine what role, if any, repetitive negative thinking and

experiential avoidance play in the maintenance of depression and/or anxiety based on a symptom-level approach to these disorders.

Methods

Participants

The sample ($N = 492$) of adults (M age = 33.29 ± 13.16 years; range: 18 – 69 years) was primarily female (51.42% female, 48.58% male), and White (1.02% American Indian or Alaskan Native, 5.08% Asian, 3.46% Black or African American, 90.45% White, 0.61% Native Hawaiian or Pacific Islander, 0.20% Caribbean Islander, 1.63% choose not to answer, 1.42% do not know). All participants were patients within the Behavioral Health Partial Hospital Program at McLean Hospital between March and December 2015. The program consisted of evidence-based, individual and group treatments (e.g. Cognitive Behavioral and Dialectical Behavior Therapies) for mood, anxiety, personality, and psychotic disorders (for additional details, see Forgeard, Beard, Kirakosian, & Björgvinsson, 2018). The present study utilized de-identified self-report data from patients' admissions questionnaires. Patients provided consent for their questionnaire responses to be used for research purposes. The IRB for McLean Hospital approved all study procedures. All data were collected and managed via Research Electronic Data Capture (REDCap; Harris et al., 2009).

Measures

Acceptance and Action Questionnaire - II (AAQ-II). The AAQ-II (Bond et al., 2011) is a 7-item self-report scale designed to assess individuals' psychological inflexibility and experiential avoidance. Responders are asked to rate how true each

statement is about themselves (e.g., “*I’m afraid of my feelings*”) on an 8-point Likert scale of 0 (“*never true*”) to 7 (“*always true*”). The AAQ-II has adequate to good internal reliability (e.g., Bond et al., 2011; Flynn, Berkout, & Bordieri, 2016) and is used in a variety of research and clinical contexts (e.g., Brem, Shorey, Anderson, & Stuart, 2017; Chou, Yen, & Liu, 2018). The AAQ-II also demonstrates unidimensionality and measurement invariance (Bond et al., 2011). Internal reliability for the sum score of all items in this sample was good ($\alpha = .88$).

Perseverative Thinking Thinking Questionnaire (PTQ). The PTQ (Ehring et al., 2011) is a 15-item self-report questionnaire designed to assess repetitive negative thinking (e.g., rumination or worry). Responders are asked to rate how often each statement applies to themselves (e.g., “*Thoughts intrude into my mind*”) on a 5-point Likert scale of 0 (“*never*”) to 4 (“*almost always*”). The PTQ has good internal reliability in unselected and clinical samples (Černis et al., 2016; Ehring, Raes, Weidacker, & Emmelkamp, 2012). Recent work has suggested the PTQ is unidimensional (McEvoy et al., 2018) and demonstrates at least partial measurement invariance (Ehring et al., 2011). Internal reliability within the present sample for the sum score of all items was excellent ($\alpha = .96$).

Patient Health Questionnaire (PHQ-9). The PHQ-9 (Kroenke, Spitzer, & Williams, 2001) is a 9-item self-report scale designed to assess symptoms of depression over the past two weeks. Questions on the PHQ-9 cover a range of potential symptoms, including experiencing “*little pleasure or interest in doing things*” to “*poor appetite, or overeating*”. Responders rate how often they have experienced each symptom in the past two weeks on a 4-point Likert scale, ranging from 0 (“*not at all*”) to

3 (“*nearly every day*”). The PHQ-9 has good internal reliability (e.g., Cameron, Crawford, Lawton, & Reid, 2008) and is used to assess depressive symptoms for both research and clinical purposes (e.g., Cameron et al., 2008; Zatzick et al., 2018). Internal reliability for the sum score of all items was good within the present sample ($\alpha = .88$).

Generalized Anxiety Disorder 7-item Scale (GAD-7). The GAD-7 (Spitzer, Kroenke, Williams, & Löwe, 2006) is a 7-item self-report scale designed to assess symptoms of anxiety over the past two weeks. Questions on the GAD-7 cover a range of potential symptoms, including experiencing “*feeling nervous, anxious, or on edge*” to “*trouble relaxing*”. Responders rate how often they have experienced each symptom in the past two weeks on a 4-point Likert scale, ranging from 0 (“*not at all*”) to 3 (“*nearly every day*”). The GAD-7 has good internal reliability (e.g., Löwe et al., 2008) and is used to measure anxiety symptoms across many research and clinical contexts (e.g., Beard & Björgvinsson, 2014; Washington et al., 2018). Within this sample, internal reliability for the sum score of all items was good ($\alpha = .88$).

Statistical Analysis

Pre-registered analyses. We assessed descriptive data for each AAQ-II, PTQ, PHQ-9, and GAD-7 item (mean, standard deviation, kurtosis, and skew). We then used ordinal PHQ-9 items, ordinal GAD-7 items, continuous PTQ total scores, and continuous AAQ-II total scores to estimate multiple networks using Mixed Graphical Models (Haslbeck & Waldorp, 2015b). We utilized a Mixed Graphical Model (MGM) approach because, unlike more traditional Gaussian Graphical Models or Ising Models (Epskamp, Borsboom, & Fried, 2018; van Borkulo et al., 2014), MGMs allow for analyzing relationships between variables of different data types (e.g., ordinal and

continuous) simultaneously, rather than being restricted to analyzing data of one type (Haslbeck & Waldorp, 2015b).

These network models include each variable as a “node” that is connected to other variables, or nodes, in the network via “edges”. Each network “edge” represents a unique partial association between two variables that accounts for all other nodes included in the network. To avoid the inclusion of spurious relationships in our model, we utilized the LASSO regularization technique (Tibshirani, 1996) to shrink all edge-weights based on a set parameter. Under this penalty, smaller, potentially spurious edge-weights shrink to a value of 0. The present network was fitted using the *R*-package *mgm* version 1.2-4 (Haslbeck & Waldorp, 2015a) and was visualized using the *qgraph* version 1.5 *R*-package (Epskamp, Cramer, Waldorp, Schmittmann, & Borsboom, 2012).

Beyond network structure, node predictability analysis differs from indices of network structure (e.g. node centrality) in that it quantifies, on an absolute scale, how well specific nodes can be predicted by connected nodes in the network (Haslbeck & Fried, 2017; Haslbeck & Waldorp, 2018; von Stockert, Fried, Armour, & Pietrzak, 2018). In an MGM network, predictability for continuous and ordinal nodes is a measure of the variance explained by neighboring nodes, or R^2 (Haslbeck & Fried, 2017; Haslbeck & Waldorp, 2018). We anticipated adding maintenance factors (repetitive negative thinking and experiential avoidance) to the network would increase network predictability, whereas adding permuted maintenance factors would not significantly alter network predictability.

As per our pre-registration (<https://osf.io/4rf5e>), we first compared the results of node predictability analyses in two estimated MGM network models: a network with symptoms plus two synthetic nodes drawn at random from the same distributions as experiential avoidance and repetitive negative thinking, and a network with symptoms plus the original measured values of experiential avoidance and repetitive negative thinking. Creating synthetic versions of these variables allows us to examine descriptively whether adding maintenance factors to the network increases node by node predictability above and beyond adding random noise.

Exploratory analyses. Our pre-registered analyses did not propose to directly evaluate whether the two maintenance factors (repetitive negative thinking and experiential avoidance) significantly increase predictability of the transdiagnostic symptom network over the synthetic maintenance factors. We did not propose direct evaluation at time of pre-registration as no method had been developed to conduct this test. We have since developed a permutation test framework to formally test this hypothesis. Similar to the pre-registered analyses, we randomly sampled from the maintenance factors' distributions to create synthetic maintenance factor nodes and re-estimated the network with these permuted, synthetic maintenance nodes. However, in the exploratory analyses we repeated this procedure 30,000 times to generate a sampling distribution of network predictability under the null hypothesis and examine how extreme the original network's predictability was compared to the generated null distribution.

Empirical p values were then calculated as the fraction of random permutations that resulted in a network predictability due to chance that was equal to or greater than

the predictability in the original network. For example, by permuting repetitive negative thinking and re-estimating the network with a synthetic repetitive negative thinking node, we can see how many times this synthetic predictability value is greater than or equal to the original predictability value, divide by the number of permutations (e.g., 1,000) and arrive at the p value. So, if none of the 1,000 synthetic networks had a predictability higher than the original network's predictability, the p value would be $< .001$ (less than one in 1,000), but if 700 synthetic networks had a higher predictability than the original network the p value would be 0.70. Using this same process, we can also obtain an estimate of the change in predictability and associated 95% confidence interval for each node by taking the difference between the predictability of each node in the true measured network and the predictability of the same node in each synthetic network. Taking the mean of the difference across 30,000 networks serves as our estimate of change in R^2 , while taking the 2.5th and 97.5th percentile difference scores yields the 95% confidence interval for this estimated change in R^2 .

We carried out this process of creating synthetic nodes via random sampling and re-estimating the networks 30,000 times separately for: 1) repetitive negative thinking alone 2) experiential avoidance alone, and 3) repetitive negative thinking and experiential avoidance simultaneously. We compared both the average predictability and node-by-node predictability of the measured network to the three synthetic networks. To correct for multiple comparisons, we applied a Holm-Bonferroni correction to the generated list of p -values (Holm, 1979).

In keeping with existing robustness techniques (Epskamp et al., 2018), we evaluated the accuracy of our edge-weights using bootstrapped 95% CIs. CIs were

calculated using the range of 1,000 bootstrapped samples for each edge-weight, with larger edge-weight CIs indicating more variable and less precise estimates for those edges (Fried & Haslbeck, 2018). The data and R code used for our analyses is posted on the Open Science Framework project for this study (<https://osf.io/23x8n/>).

Results

Descriptive statistics

The average sum scores for PHQ-9 and GAD-7 were $M (SD) = 14.94 (6.54)$, scores ranging from 0 - 27, and $M (SD) = 11.41 (5.56)$, scores ranging from 0 - 21, indicating, on average, moderate to high levels of depression and anxiety. Mean composites for experiential avoidance ($M = 32.66$; $SD = 8.31$; range = 7 - 49) and repetitive negative thinking ($M = 38.39$; $SD = 12.71$; range = 0 - 60) were comparable to previous studies of treatment-seeking samples (c.f., Bond et al., 2011; Topper, Emmelkamp, Watkins, & Ehling, 2017). Further descriptive statistics of all individual symptoms and maintenance factors are reported in Table 1.

Network estimation

Per our pre-registration plan, we assessed item informativeness, or the standard deviation of each depressive symptom, to evaluate whether each symptom had enough variation to be able to contribute to the network analysis (Mullarkey, Marchetti, & Beevers, 2019). PHQ-9 item 8, *psychomotor difficulties*, had the lowest standard deviation of each of the parameters ($SD = 0.96$). The informativeness of this item was within 2.5 standard deviations of the average informativeness for all parameters, therefore no parameters were excluded from the analyses.

The network for depressive symptoms, anxiety symptoms, repetitive negative thinking, and experiential avoidance was estimated using an MGM (mixed graphical model) with the hyperparameter set to 0.00 to maximize discovery. The hyperparameter and included nodes were specified in our pre-registered analysis plan (<https://osf.io/4rf5e>). In line with our pre-registered analyses, we also estimated a network with depressive symptoms, anxiety symptoms, and synthetic versions of both repetitive negative thinking and experiential avoidance created by randomly sampling from their distributions (see Figure 1 for a visual depiction of the two networks).

While visual inspection of the networks will not lead to correct inferences about the overall network structure (Jones, Mair, & McNally, 2018), we can evaluate which symptoms share direct connections with each maintenance factor (Mullarkey et al., 2018). In the measured network model, repetitive negative thinking is associated with *suicidality*, *worrying too much*, *restless*, *concentration*, and *failure* while experiential avoidance is associated with *failure* and *afraid something awful*. In the null network model, with synthetic repetitive negative thinking and synthetic experiential avoidance, neither synthetic maintenance factor was connected to any symptoms.

Edge weight accuracy

Edge weight accuracy was acceptable as indexed by width of non-parametric CIs for all 37 non-zero edges in the network. After creating a sampling distribution using 1000 bootstrapped samples for each edge, we tested how many edge weights (associations between symptoms) were significantly stronger than other edge-weights. As seen in Figure 2, the network is reasonably accurate with more than 25% of the edges being significantly stronger than at least 10% of other edges. 31 edge weights

were penalized to zero and therefore not included in the network. Therefore, a relatively sparse (54.4% of potential edges were estimated > 0) and accurate network was estimated in this sample.

Network characteristics

In this network, the two most central symptoms (i.e., the symptoms with the greatest strength) were “worrying too much” (from the GAD-7) followed by “fatigue” (from the PHQ-9). The three strongest edges were between “can’t stop worrying” and “worrying too much” among anxiety symptoms, between “repetitive negative thinking” and “experiential avoidance”, and between “anhedonia” and “depressed mood” among depression symptoms. The strongest edge across symptom dimensions was between “psychomotor” from the depression items and “restlessness” from the anxiety items. Symptom and edge centrality plots are displayed in Figures 2 and 3, respectively.

Pre-Registered Analyses: Descriptively Evaluating Predictability Across Networks

The differences in predictability across the measured and synthetic maintenance factor networks are displayed in Table 1. The largest difference across networks was the measured network predicting 2.8% more absolute variance in *irritability*. Seven symptoms did not differ in predictability across the networks at all (*anhedonia, fatigue, appetite, psychomotor, suicidality, anxious, restless*), six symptoms had higher predictability in the measured network (*failure, concentration, worrying too much, trouble relaxing, irritable, afraid something awful*), and three symptoms had higher predictability in the synthetic network (*depressed mood, sleep, can’t stop worrying*). However, as these pre-registered analyses rely on a single permutation for synthetic nodes, it is possible the symptoms exhibiting higher predictability in the synthetic

network are a result of random chance. We thus proceeded with exploratory analyses to more formally evaluate differences between the measured and synthetic networks.

Exploratory Analyses: Formally Evaluating Whether Maintenance Factors

Increase Predictability

Repetitive negative thinking.

To more formally determine the impact of repetitive negative thinking and experiential avoidance on network predictability, we created a null distribution of “synthetic node” networks. We randomly sampled from the distribution of repetitive negative thinking, creating a permuted (“synthetic”) version of this variable, and re-estimated the network 30,000 times. The original network had an average predictability of 49.87% per node and the synthetic repetitive negative thinking networks had an average predictability of 49.65% per node. Compared to the null distribution generated by the 30,000 versions of the synthetic network, the original network’s predictability was higher than 29,981 values ($p < .001$), indicating the original network had significantly more predictability than the synthetic network.

The measured network was associated with increased predictability in two symptom nodes (one depression and one anxiety symptom) compared to the synthetic repetitive negative thinking network: concentration (mean R^2 change: 1.69%, 95% CI: 1.1% to 2.4%, Holms-Bonferroni corrected $p = .002$) and worrying too much (mean R^2 change: 0.80%, 95% CI: 0.8% to 0.8%, Holms-Bonferroni corrected $p < .001$). The measured network also indicated increased predictability in experiential avoidance (mean R^2 change: 10.93%, 95% CI: 10.9% to 11.4%, Holms-Bonferroni corrected $p < .001$).

Experiential avoidance.

We then created a synthetic node network for experiential avoidance using the same process described above. The original network had an average predictability of 49.87% per node for all symptom nodes. The synthetic network had an average predictability of 49.54% per node. Compared to the null distribution generated by the 30,000 versions of the synthetic network, the original network's predictability was higher than 29,999 values ($p < .001$), indicating the measured network had significantly more predictability than a network with synthetic experiential avoidance.

The measured network was associated with increased predictability in three symptom nodes (one depression and two anxiety symptoms) compared to the synthetic experiential avoidance network: trouble relaxing (mean R^2 change: 5.60%, 95% CI: 5.6% to 5.6%, Holms-Bonferroni corrected $p < .001$), feeling like a failure (mean R^2 change: 2.07%, 95% CI: 2.0% to 2.7%, Holms-Bonferroni corrected $p < .001$), and being afraid something awful would happen (mean R^2 change: 0.80%, 95% CI: 0.8% to 0.8%, Holms-Bonferroni corrected $p = .040$). The measured network also indicated increased predictability in repetitive negative thinking (mean R^2 change: 12.18%, 95% CI: 11.6% to 14.7%, Holms-Bonferroni corrected $p < .001$).

Repetitive negative thinking and experiential avoidance.

We finally examined a synthetic network with both repetitive negative thinking and experiential avoidance permuted simultaneously, using the same process described above. The original network had an average predictability of 49.87% per node for all symptom nodes. The synthetic change in peripheral symptoms network had an average predictability of 49.48% per node. Compared to the null distribution generated

by the 30,000 versions of the synthetic network, the original network's predictability was higher than 29,997 values ($p < .001$), indicating the original network had significantly more predictability than the synthetic network.

The measured network was associated with increased predictability in six symptom nodes² (two depression and four anxiety symptoms) compared to the synthetic repetitive negative thinking and experiential avoidance network: irritability (mean R^2 change: 2.83%, 95% CI: 2.8% to 3.1%, Holms-Bonferroni corrected $p = .043$), trouble relaxing (mean R^2 change: 0.70%, 95% CI: 0.7% to 0.7%, Holms-Bonferroni corrected $p < .001$), feeling like a failure (mean R^2 change: 2.62%, 95% CI: 2.1% to 3.4%, Holms-Bonferroni corrected $p < .001$), being afraid something awful would happen (mean R^2 change: 1.30%, 95% CI: 1.3% to 1.3%, Holms-Bonferroni corrected $p = .027$), concentration (mean R^2 change: 1.95%, 95% CI: 1.2% to 2.7%, Holms-Bonferroni corrected $p = .003$), and worrying too much (mean R^2 change: 0.60%, 95% CI: 0.6% to 0.6%, Holms-Bonferroni corrected $p = .001$). The measured network also, as expected, demonstrated greater predictability in both repetitive negative thinking (mean R^2 change: 54.25%, 95% CI: 53.0% to 54.3%, Holms-Bonferroni corrected $p < .001$) and experiential avoidance (mean R^2 change: 54.55%, 95% CI: 53.3% to 54.6%, Holms-Bonferroni corrected $p < .001$).

This formal approach to testing how these maintenance factors impact symptom predictability provides a helpful comparison for results from our less formal, pre-

² To attempt to contextualize the importance of repetitive negative thinking and experiential avoidance, we also permuted each individual symptom using a similar process to examine how overall network predictability and individual symptom predictability are impacted. As it is not possible to compare whether the increase in predictability across these different permuted networks significantly differ, these results are only included in the Supplemental Materials.

registered analyses. All six symptoms associated with an increase in predictability in the original, pre-registered analyses (i.e., failure, concentration, worrying too much, trouble relaxing, irritable, afraid something awful) were associated with significant increases in predictability in our more formal exploratory analyses. Of the three symptoms associated with decreased predictability in the measured network compared to the synthetic network, one symptom (i.e., sleep) did not appear to significantly decrease predictability (mean R^2 change: -0.40%, 95% CI: -0.5% to 0.2%). Surprisingly, depressed mood (mean R^2 change: -2.50%, 95% CI: -2.5% to -2.5%) and can't stop worrying (mean R^2 change: -1.29%, 95% CI: -1.3% to -1.1%) demonstrated lower predictability in the measured model compared to the synthetic models.

In summary, repetitive negative thinking adds an average of 0.22% predictability per node in this sample, while experiential avoidance adds an average of 0.33% predictability per node. When considered together, repetitive negative thinking and experiential avoidance has 0.39% more predictability per node than the null model. Based on exploratory analyses with 30,000 synthetic networks, repetitive negative thinking and experiential avoidance significantly increased predictability in the depression and anxiety symptom network: repetitive negative thinking was associated with increased predictability in concentration and worrying too much, while experiential avoidance was associated with increased predictability in trouble relaxing, feeling like a failure, and being afraid something awful would happen. Both maintenance factors were associated with increased predictability in symptoms of depression *and* symptoms of anxiety.

Discussion

Repetitive negative thinking and experiential avoidance have been posited to serve as interrelated transdiagnostic maintenance factors for depression and anxiety. However, previous studies that have attempted to examine how these cognitive processes overlap and contribute to psychiatric comorbidity have relied on non-psychiatric samples and have adopted approaches that assume depression and anxiety are monolithic constructs. This study instead applied a network approach to psychopathology that proposes that mental disorders, whether for single or comorbid disorders, are maintained by the interaction of individual symptoms rather than a latent common cause (e.g., depression). To our knowledge, no study has examined how these cognitive maintenance factors are associated with depression and anxiety using a symptom-level approach. This study sought to specifically test the impact of repetitive negative thinking and experiential avoidance on symptom predictability in a network of depression and anxiety symptoms in a naturalistic clinic sample.

In accordance with theoretical models of repetitive negative thinking and experiential avoidance, we hypothesized that including nodes for repetitive negative thinking and experiential avoidance would result in higher predictability of cognitive and affective symptoms in the network compared to a network with synthetic nodes generated by randomly sampling from the distributions of repetitive negative thinking and experience avoidance. We did not hypothesize any differences in predictability for vegetative symptoms (e.g., changes in appetite) between the network with the measured maintaining factors and the network with the synthetic factors.

Based on our pre-registered analytic plan, we identified hypothesized descriptive differences between the transdiagnostic symptom network with measured nodes

compared to the network with generated “synthetic” nodes on cognitive and affective symptoms. Specifically, the measured network was associated with higher predictability in a variety of cognitive and affect symptoms (e.g, failure, concentration, worrying too much, irritable, afraid something awful) while the generated synthetic network was associated with increased predictability in fewer cognitive/affective symptoms (i.e., sadness, can’t stop worrying). Vegetative symptoms either did not significantly differ between networks (i.e., fatigue, appetite, psychomotor) or exhibited higher predictability in the synthetic network (i.e., sleep). In our exploratory analyses, we were able to formally test these relationships and found that the measured network was associated with higher predictability in only cognitive and affective symptoms (i.e., irritability, trouble relaxing, feeling like a failure, being afraid something awful would happen, concentration, and worrying too much). In addition, although repetitive negative thinking was associated with higher predictability in experiential avoidance (and vice-versa), repetitive negative thinking and experiential avoidance were associated with increased predictability in distinct sets of symptoms of depression and anxiety.

Our findings suggest that repetitive negative thinking may be associated with the maintenance of depression and anxiety through its relationship with concentration and worry, respectively. These findings support previous research underscoring the overlap between repetitive negative thinking and worry (Ehring & Watkins, 2008). Surprisingly, repetitive negative thinking was associated only with one of the two worry items listed, “worrying too much” (i.e., it was not associated with “can’t stop worrying”). This divergent relationship may indicate that, in this clinical sample, repetitive negative thinking (as measured by the PTQ) better captures a respondent’s beliefs that they may

be worrying excessively, rather than the level of control they feel over whatever worries do arise. For example, if an individual has an important job interview coming up, repetitive negative thinking may not necessarily index the controllability of the worry (that might be appropriate given the circumstances, such as the day before the interview), but rather the excessive nature of the worry. These findings require replication and further study, though.

In addition, our results highlight the utility of further studying the potential interplay between repetitive negative thinking and processes associated with concentration, such as attentional control (Koster, De Lissnyder, Derakshan, & De Raedt, 2011). Indeed, previous studies that have experimentally manipulated concentration through cognitive training paradigms have found that improving attention or cognitive control reduces repetitive negative thinking, depression, and anxiety symptom severity (e.g., Sari, Koster, Pourtois, & Derakshan, 2016; Siegle, Ghinassi, & Thase, 2007). In short, our findings based on symptom-level network analyses converge with previous research examining repetitive negative thinking in a latent disorder framework and highlight the potential relevance of excessive worry and concentration difficulties to the study of repetitive negative thinking.

Our findings also suggest that experiential avoidance may maintain depression and anxiety through a separate set of relationships than repetitive negative thinking. Experience avoidance was found to increase the predictability of feeling like a failure, trouble relaxing, and being afraid something awful will happen. Previous research has suggested the impact of experiential avoidance on depression and anxiety may be accounted for by repetitive negative thinking (Spinhoven et al., 2016). In our study, we

found that experiential avoidance did not overlap with repetitive negative thinking with regard to the specific symptom nodes showing increased predictability when including repetitive negative thinking (i.e., concentration and worrying too much). Rather, experiential avoidance was associated with increased predictability in other symptom nodes for depression (indexing self-criticism) and anxiety (indexing persistent worry and catastrophic worrying). Although experiential avoidance has been associated with self-criticism in depression (e.g., Krieger et al., 2013; Moroz & Dunkley, 2015), the relationship between experiential avoidance and persistent or catastrophic worry has not been clearly studied. Consequently, our results may suggest a direction for further research into how experiential avoidance might contribute to catastrophic or persistent worry.

These findings also suggest that transdiagnostic maintenance factors like repetitive negative thinking and experiential avoidance can improve upon our modeling of transdiagnostic symptom networks, significantly increasing the predictability of the overall network model. Both repetitive negative thinking and experiential avoidance were associated with increased predictability in symptoms of depression and anxiety. Moreover, these symptoms exhibiting increased predictability were not the same symptoms across both maintenance factors or the symptoms that bridged depression and anxiety most strongly in this sample (i.e., psychomotor symptoms with restlessness). These results suggest that repetitive negative thinking and experiential avoidance may serve as distinct, albeit associated, bridge factors in the persistence of depression and anxiety.

It is critical to note that although repetitive negative thinking and experiential avoidance likely increase overall network predictability more than some symptom nodes like appetite, psychomotor symptoms, or suicidality, the increase in predictability in the overall network is moderate in relation to the inclusion of other symptom nodes like depressed mood, anhedonia, or feeling anxious. Indeed, inclusion of these two transdiagnostic cognitive maintenance factors only reliably increased predictability in 7 out of the 16 symptom nodes in our network. In addition, experiential avoidance and repetitive negative thinking were not the most central nodes within the network (worrying too much and fatigue were). Consequently, repetitive negative thinking and experiential avoidance may not be the most important cognitive maintenance factors associated with depression and anxiety. These results continue to point to the hypothesis that risk and maintenance factors for depression and anxiety very likely contribute to the onset and persistence of *specific* symptoms. This work underscores the need for further research adopting a symptom-level approach as additional research is required to clarify processes that maintain other symptoms such as depressed mood or feeling anxious.

Network studies of psychopathology ought to more regularly incorporate theoretically-relevant maintenance factors to further our understanding of how these syndromes may be maintained, both within and across disorders. This suggestion rings especially true given the line between what is a symptom of a disorder and what is a maintenance factor is arbitrary, especially in network models of psychopathology, where disorder maintenance is predicated on node-to-node activity. Moreover, by including multiple maintenance factors, investigators can examine how these factors differentially

impact nodes in these networks and highlight how these individual factors may bridge disorders across common and unique pathways.

Clinically, our results suggest that therapeutic techniques specifically targeting repetitive negative thinking versus experiential avoidance may help reduce depression and anxiety symptom severity via unique pathways. Clinicians may want to consider the expression of symptoms of excessive worry versus feeling like a failure, trouble relaxing, or being afraid of something awful happening as suggestions to target repetitive negative thinking versus experiential avoidance using cognitive therapeutic skills. However, it is important to note that our between-subjects findings may not necessarily generalize to within-subject processes and further study is necessary to validate this pattern of results using a within-subjects study design.

Our findings highlight the utility of applying transdiagnostic network models of psychopathology to study theoretically-identified maintenance factors, both conceptually replicating previous research and suggesting new directions for investigation. We also demonstrate how one can empirically test these relationships through the use of permutation testing (see Supplemental Materials and OSF link, <https://osf.io/23x8n/>, for R code and further details). Study strengths include a relatively large sample of individuals presenting for treatment with minimal inclusion and exclusion criteria. It is worth noting that we did not select individuals based on clinical diagnosis or symptom cut-off scores for depression and anxiety for our sample; indeed, symptom severity sum scores in our sample ranged from 0-27 for depression (via the PHQ-9) and 0-21 for anxiety (via the GAD-7). Selecting participants for network analyses based on diagnostic category or a symptom severity cut-off can reduce the validity of analyses in

these networks when trying to generalize findings to other populations (e.g., sub-clinical samples; see de Ron, Fried, & Epskamp, 2019 for further discussion). However, as we are specifically interested in the maintenance of psychopathology in the symptom network examined here, we do not expect our findings to generalize to healthy samples.

Our study is also limited in our ability to generalize to more ethnically- and racially-diverse samples as our sample was mostly White. This limitation is more salient in the context of network analysis given potential differences in symptom expression between White and non-White participants (e.g., Anderson & Mayes, 2010; Kim & López, 2014). Studies that specifically recruit more diverse samples to examine differences in symptom network dynamics between various ethnic or racial groups are needed. Another limitation is the use of cross-sectional data; longitudinal and experimental study designs are necessary to test the findings drawn from the model in this study. Cross-sectional studies cannot depict the time course of disorder maintenance, only suggest potential components involved in disorder maintenance. Also, as noted previously, the relationships illustrated with this between-subjects design may not be representative of within-subject networks for clinical samples (Fisher, Medaglia, & Jeronimus, 2018). Within-subject, longitudinal study designs are necessary to validate our findings regarding how repetitive negative thinking and experiential avoidance may maintain depression and anxiety symptoms in a complex, transdiagnostic sample.

Despite these limitations, our study points to repetitive negative thinking and experiential avoidance as having distinct impacts on the predictability of a transdiagnostic network model of depression and anxiety maintenance. While the

addition of repetitive negative thinking significantly improved the predictability of nodes indexing worrying too much and concentration, experiential avoidance improved the predictability of a separate set of symptom nodes, including feeling like a failure, having trouble relaxing, and being afraid something bad was going to happen. As risk and maintenance factors of depression and anxiety likely contribute to the onset and maintenance of specific symptoms in these symptom networks, future research ought to more thoroughly incorporate these factors based on theoretical models of psychopathology.

Acknowledgments

Many thanks go to Jason Shumake for serving as a consultant regarding the development of formal testing of differences in predictability across the measured and synthetic networks. Thanks also go to Josie Lee for her dedicated efforts with data collection.

Contributions

K.J.H., M.M., and T.B. designed the study and wrote the protocol. K.J.H. and M.M. managed the literature searches. M.M. conducted the statistical analyses and M.D. reproduced the analyses. K.J.H. wrote the first draft of the manuscript. All authors contributed to and have approved the final manuscript.

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