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# Examining Rumination, Devaluation of Positivity, and Depressive Symptoms via Community-Based Network Analysis

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## Abstract

**Objectives**

Rumination and devaluation of positivity are processes that contribute to the development and maintenance of depressive symptoms. We aimed to examine how these processes interrelate with depression via network analysis.

**Methods**

This study used network analysis to identify rumination communities, or closely-related items, in one network and then examine the interrelationships between rumination, devaluation of positivity, and depression in a second network.

**Results**

Three rumination communities emerged, replicating findings of Bernstein et al. (2019). The node representing negative self-views had strong relationships with nodes representing devaluation of positivity and brooding. Nodes representing brooding, ruminative reflection, and difficulty trusting positive feelings evidenced higher node strengths, suggesting that these may be more influential in the network.

**Conclusion**

Negative self-views may influence the extent to which depressed individuals process positivity and engage in brooding. In addition, brooding, ruminative reflection, and difficulty trusting positive feelings may be important therapeutic targets for depressed individuals.


*Keywords:* network analysis, rumination, fear of happiness, depression, reward devaluation

Rumination may be defined as a way of coping with distress that involves repeatedly focusing one's attention on feelings of distress, causes of distress, and consequences of distress (Nolen-Hoeksema, 1991). Rumination concurrently and longitudinally predicts depression (Nolen-Hoeksema et al., 2008; Treynor et al., 2003). Moreover, rumination interacts with negative affect dynamically, such that the experience of stress and negative affect can lead one to ruminate and vice versa (Fang et al., 2019). Rumination is a heterogeneous construct and previous research has suggested that there may be several components of rumination (Bernstein et al., 2019; Treynor et al., 2003).

Given the heterogeneity of rumination, a novel way to investigate this construct is with network analysis. This is a statistical method that may be used to examine the complex relationships among variables (Borsboom & Cramer, 2013; Jordan et al., 2020). More specifically, network analysis provides a set of novel statistical tools that seek to examine the interrelationships among distinct facets that make up a construct. In doing so, network analysis details specific relationships (termed *edges*, often statistically estimated with partial correlations) between variables (termed *nodes*). The associations in network models provide an estimate of the unique shared variance that each node has with every other node in the model. Furthermore, network analysis allows the researcher or clinician to determine the influence of specific nodes in the network by examining the number of or magnitude of connections a node has with other nodes (termed *centrality*), which may provide crucial information for symptoms to target for treatment. A focus on these interrelationships or influence of specific nodes may not otherwise be accounted for with the use of traditional analyses, such as latent variable modeling or regression-based approaches.

As such, network analysis may be particularly useful for examining rumination given its current conceptualization. Community analysis is a specific statistical method for network analysis that allows for the identification of nodes that are closely related and cluster together. In community analyses, each community in a network represents a cluster of nodes that are highly correlated with one another and distinct from nodes in other communities in the network (Jones, 2018). Rumination has previously been examined with network analysis using items from the Ruminative Responses Scale (RRS; Nolen-Hoeksema & Morrow, 1991) to examine the heterogeneity of rumination as a construct (Bernstein et al., 2019). Using community analysis, Bernstein et al. (2019) found that the items on the RRS fell within three distinct communities, suggesting shared commonalities among items in each of the communities. Their three communities were similar to prior factor analyses as their communities largely represented the reflection, brooding, and depression-related subscales of the RRS, supporting prior work (Treynor et al., 2003); however, it should be noted that their findings did not perfectly reflect the RRS subscales as there was some overlap in communities (i.e., some depression-related items fell within the resulting community that largely represented brooding). Their findings suggest that including rumination as a sum score in network analysis may not fully capture the heterogeneous nature of this construct (Bernstein et al., 2019), so assessing for resulting communities would allow for one to best examine how to investigate rumination in networks containing other constructs.

Existing research on network estimation recommends that there be more observations than possible edges to estimate a stable network (Epskamp & Fried, 2018). Following these recommendations, a network investigating the RRS with all 22 items should have a sample size with at least 231 observations (e.g., participants) to reliably estimate a stable network. Therefore, including all items representing rumination in a network with other constructs may have more possible edges than pairwise interactions, resulting in a less stable network if the corresponding sample size is smaller. An alternative way to examine rumination in a network is to examine how the sum score of the RRS interacts with other constructs; however, the findings discussed above from Bernstein et al. (2019) suggest that doing so may oversimplify findings and that rumination is best examined as a multifaceted construct. Thus, one possible solution to examine rumination in a network with a smaller sample size is to (a) examine communities that emerge within an individual RRS network and then (b) include the resulting communities as nodes to examine the dynamic relationships between rumination and other constructs.

Less work has examined how rumination relates to positivity in a network. This is an important gap in the literature, given that for some depressed individuals, positive experiences or emotions may be distressing or devalued (Lass & Winer, 2020; Winer & Salem, 2016). Indeed, depressed individuals seem not only to *not* approach positivity, as do non-depressed populations (Pool et al., 2016; Winer et al., 2011), but they also evidence a reverse pattern by which they avoid positive information. Reward Devaluation Theory (RDT; Winer & Salem, 2016) posits that depressed individuals devalue and avoid positivity due to it being repeatedly associated with negative outcomes or emotions. For example, a depressed individual may have been excited about prospective happiness or positive experiences in the past; however, their excitement may have ultimately been met with disappointment. Individuals who have come to associate positive experiences with negative outcomes may believe that happiness is only temporary or that bad things happen whenever one is happy (Gilbert, McEwan, Catarino, & Baiao, 2014; Gilbert, McEwan, Catarino, Baiao, et al., 2014; Gilbert et al., 2012; Joshanloo, 2013; Joshanloo et al., 2015). They may have developed automatic thoughts that positive emotions (e.g., happiness, excitement, joy) do not last and are eventually followed with negative emotions (e.g., sadness, disappointment, anger). For example, they may think that good feelings never last or that something bad may happen if they feel happy (Gilbert et al., 2012). Over time, they may come to devalue positivity after repeated disappointments or negative outcomes and engage in maladaptive behaviors to decrease or avoid the experience of positivity.

In sum, not everyone views positivity in the same way, and some may actually exhibit *negative* views toward positivity. Understandably, if the experience of positivity has come to be associated with negative outcomes, individuals may cope with positive emotions using coping strategies that are traditionally associated with negative emotions. One example of a maladaptive behavior in response to positivity is dampening. This emotion regulation strategy is used to reduce the experience of positive emotions and has a similar cognitive process as rumination (Feldman et al., 2008; Raes et al., 2012; Werner-Seidler et al., 2013; Wood et al., 2003). Depressed individuals who devalue positivity may engage in dampening in response to prospective positivity or when they are unable to avoid positive situations or emotions entirely. For example, they may think (or ruminate) about things that could go wrong when they feel happy, excited, or enthused (Feldman et al., 2008). Indeed, both dampening and rumination have been found to be positively related to both devaluation of positivity and depressive symptoms (Joshanloo et al., 2014; Raes et al., 2012; Werner-Seidler et al., 2013). Thus, it seems that, for some individuals, the experience of positivity may lead to depressogenic processes, such as rumination and devaluation of positivity, which in turn contribute to the maintenance of depressive symptoms via a feedback loop.

Existing literature has examined the extent to which rumination and devaluation of positivity contribute to the development and maintenance of depressive symptoms; however, no known study has examined how individual elements within these processes relate to specific depressive symptoms. We thus wished to examine the relationship between rumination, devaluation of positivity, and depressive symptoms via network analysis to uncover how each of the main components interrelate as part of an overarching system. As noted previously, network analysis allows for a more fine-grained investigation as to how facets of a specific construct relate to one another, providing insight into possible dynamic or causal associations. Naturally, causal associations cannot be estimated with only cross-sectional data (Winer et al., 2016), and network models are best seen as exploratory or hypothesis-generating structures (Epskamp et al., 2018). However, we chose to investigate these relationships via network analysis as this methodology best represents our beliefs regarding the underlying data-generating mechanism (van Bork et al., 2019). That is, we assume depression is maintained via the interplay between its specific symptoms and the features that comprise rumination and devaluation of positivity. If, for example, we assumed that the various symptoms of depression are explained by a common cause (e.g., trait rumination), then fitting a unidimensional factor model would best represent this possible data-generating mechanism.

We had two goals for the current study. Our first goal was to examine if the communities outlined by Bernstein et al. (2019) replicated in our study. Due to the similarities between their communities and prior factor analyses (Treynor et al., 2003), we anticipated that our communities would replicate and largely represent the suggested subscales of reflection, brooding, and depression-related rumination in the literature.

Our second goal was to then examine how rumination interrelated with elements of devaluation of positivity and depression to investigate potential therapeutic targets for depression. To ensure that the number of possible edges did not exceed the number of observations (Epskamp & Fried, 2018), we aimed to represent rumination in the second network with each resulting community of the RRS from the first network as individual nodes. In line with existing theories of depression (Beck, 1967; Winer & Salem, 2016), we predicted that all three constructs would be positively related; however, we did not make hypotheses about the extent to which particular edges and nodes would emerge as the strongest; so, our overarching investigation was guided by theory but the individual relations examined in our network analyses were exploratory in nature, with the exception of the community analyses of the RRS.

## Method

### Participants

Two-hundred and fifty-five participants ($N$ = 255, 157 females, $M_{age}$ = 19.20) were recruited from the psychology subject pool at a large southern university as part of their course credit. Given that we recruited students on campus, 50.2% of participants endorsed completing some college while 41.8% reported high school as their highest level of education completed. The study was approved by the university's Institutional Review Board (IRB #18-370).

### Procedure

Upon arriving to the laboratory, participants first completed an informed consent procedure with a graduate student. Next, participants engaged in several computer tasks that are described elsewhere and not relevant to the current analyses (see Collins et al., under review). Lastly, participants completed the Fear of Happiness Scale, Ruminative Responses Scale, and the Quick Inventory of Depressive Symptomatology Self-Report, among other measures that were not relevant to the current analyses.

### Self-Report Measures

#### *Ruminative Responses Scale (RRS)*

To examine rumination, participants completed the Ruminative Responses Scale (RRS). The RRS is a 22-item self-report measure that assesses rumination (Treynor et al., 2003). Items on the RRS range from 1 (“almost never”) to 4 (“almost always”) and can be summed for a total scaled score or for three subscale scores: reflection, brooding, and depression-related. Higher scores indicate greater levels of rumination ($M$ = 42.50, $SD$ = 13.86). The RRS demonstrated good internal consistency in this study with a Cronbach’s alpha of .94.

***Fear of Happiness (FHS)***

To examine devaluation of positivity, participants completed the Fear of Happiness Scale (FHS). The FHS is a nine-item self-report measure that assesses the respondent’s negative feelings about happiness and positive feelings in general (Gilbert et al., 2012). Items on the FHS range from 0 (“not at all like me”) to 4 (“extremely like me”) and are summed for a total scaled score. Nodes were made to individually include all nine items of the FHS scale to examine how different statements representing fear, avoidance, and dampening interact with constructs of depression and rumination in the network. Higher scores indicate greater levels of fearing happiness ($M$ = 7.80, $SD$ = 6.44). The FHS in this study demonstrated good internal consistency with a Cronbach’s alpha of .85.

***Quick Inventory of Depressive Symptomatology Self-Report (QIDS-SR)***

To examine depressive symptoms, participants completed the Quick Inventory of Depressive Symptomatology Self-Report (QIDS-SR). The QIDS-SR is a widely used 16-item self-report measure of depressive symptoms (Rush et al., 2003). Items on the QIDS-SR are scored on a four-point Likert scale ranging from 0 to 4. In the present study, item 12 (suicidal ideation) was not included in the QIDS-SR on the basis that the researchers were not immediately available to respond to participants who were indicating clinically-significant distress as multiple participants were run simultaneously. Thus, a modified 15-item QIDS-SR was given to participants. Nodes were made to represent 8 symptoms of depression: sleep disturbance (maximum value of items 1-4, which examine difficulties falling asleep, staying asleep, early awakening, and excessive sleeping), sad mood (item 5), changes in appetite and weight (maximum value of items 6-9), concentration difficulties (item 10), self-criticism (item 11), loss of interest (item 13), energy/fatigue (item 14), and psychomotor functioning (maximum values of items 15-16). Higher scores indicate greater levels of depressive symptoms. Our sample represented a mild range of depressive symptoms ($M$ = 8.31, $SD$ = 4.49); however, sum scores varied from no depressive symptoms to the very severe range of depressive symptoms (i.e., 0-22.5). The QIDS-SR in this study demonstrated good internal consistency with a Cronbach's alpha of .78.

## Statistical Analyses

All analyses were carried out using the R software (Version 3.6.1). Missing data were removed with listwise deletion via the *na.omit* function prior to running the analyses, resulting in complete data for 241 participants.[1]

### *Rumination Replication Network*

**RRS Redundant Items.** Replicating previous methods (Bernstein et al., 2019), we used the *goldbricker* function from the R package *networktools* (Jones, 2018) and identified items that were highly intercorrelated ($r$ > .50) and had less than 25% of correlations that were significantly different within the pairs. We used the Hittner method to compare correlations (Hittner et al., 2003). Items meeting these criteria were then combined using the *reduce_net* function in

[1] Seven participants ($n$ = 7) were not administered the QIDS-SR during the study due to researcher error. Thus, listwise deletion was used to handle missing data in place of other methods (i.e., multiple imputation). Four participants ($n$ = 4) were not included due to non-compliance or experimental error. Three participants ($n$ = 3) did not have complete data.

*networktools*. This analysis identified redundancy in seven pairs of items which were subsequently combined. These pairs were treated as new variables and included in the following network comprised of 15 nodes representing rumination. See Table 1 for the list of the resulting nodes.

**Network Estimation.** The network of the resulting 15 RRS nodes after combining redundant pairs was estimated before using the R package *bootnet* (Epskamp et al., 2018). Following recommendations by Epskamp and Fried (2018), our final sample size of 241 is sufficient to estimate a reliable network as the number of observations is greater than the possible number of edges (i.e., 105). The network was estimated using a Gaussian Graphical Model (GGM) that examines the partial correlations between all variables. Each node represents a variable and the edges represent partial correlation coefficients between each node. We utilized the graphical least absolute shrinkage and selection operator (gLASSO), which is a regularization technique that can be employed to limit the number of spurious, or false positive, edges in a GGM network (Epskamp et al., 2018). Additionally, we utilized the extended Bayesian information criterion (EBIC) to set the tuning parameter (Chen & Chen, 2008). Node placement was visualized using the Fruchterman and Reingold algorithm, which places nodes that are more strongly connected closer together and nodes with stronger connections to other nodes are placed in the center (Fruchterman & Reingold, 1991).

We computed the centrality of the indices to identify node importance via strength centrality, as recent literature has suggested that closeness and betweenness should be interpreted with caution as they may be unsuitable for assessing node influence (Bringmann et al., 2019). Strength represents how much a node is directly connected to other nodes and is calculated by taking the sum of all of the absolute edge-weights that are connected to a given node. To investigate the stability of the strength centrality, the accuracy of the edge-weights of the network, and the differences between edge-weights and node strength for each node, we employed non-parametric bootstrapping methods with 2,500 samples using the *bootnet* package (Epskamp et al., 2018).

**RRS Community Detection.** Using the spinglass algorithm in the *igraph* package, we aimed to identify communities of nodes within this network with RRS items. This algorithm was run 1,000 times and the median number of communities to emerge was three, similar to findings from Bernstein and colleagues (2019). As noted above, one purpose of examining the items of the RRS redundancy and combining them into reduced nodes is to minimize the number of nodes included in our main network analysis while still investigating rumination as a heterogeneous construct. Thus, the items in each of the three communities were independently averaged together to create three new nodes to be included in the main network analysis, each representing a rumination community.

### *Rumination, Devaluation of Positivity, and Depressive Symptoms Network*

**Network Estimation.** The main network was comprised of all nine items of the FHS, the eight items of the QIDS-SR, and the three previously estimated community variables of the RRS (see Table 2 for the list of items and their corresponding node names). Following recommendations by Epskamp and Fried (2018), our final sample size of 241 is sufficient to estimate a reliable network as the number of observations is greater than the possible number of edges (i.e., 190). We estimated this network using the R package *bootnet* and followed the same procedure for centrality and bootstrapping as in the rumination network above.

## Results

### Descriptive Statistics

All data were assessed for normality and were within normal limits with skewness values < 3 and kurtosis values < 10 (Kline, 2015). Means, standard deviations, and skewness and kurtosis values for all of the nodes included in the full network are reported in Table S1.

**Rumination Network**

Figure 1 depicts the bootstrapped network with each of the 15 nodes in our network representing a single item from the RRS after combining redundant items[2]. Blue edges represent positive associations and red edges represent negative associations. The thickness of the edges indicates the magnitude of the associations between each node, with thicker edges representing stronger associations. Overall, the network evidenced a dense connectivity with 66 out of all possible 105 edges (62.9%) being above zero. The nodes *alone* and *sad* evidenced the highest strength centrality in the network (both nodes' strength centrality = 1.20). The correlation stability coefficient (*CS*-coefficient) was calculated to determine the maximum number of cases that may be dropped from the data to return a correlation of at least 0.7 between statistics. The *CS*-coefficient for strength was 0.59, which exceeds the preferred 0.50 cutoff for meaningful node interpretation (Epskamp et al., 2018). The bootstrapped edge-weight accuracy test suggests that the edges between *alone* and *think*, *unmotiv* and *feel*, and *handle* and *why* were among the strongest and most reliable connections within the network.

**Communities of the RRS**

Three communities emerged from our community detection analysis. The three communities largely resemble the subscales of the RRS (Treynor et al., 2003), and we have thus named the communities *reflection, brooding,* and *depressive symptoms*; however, it should be noted that some items from the depressive symptoms subscale of the RRS could be found in all

[2] Relevant figures from the bootstrapping analyses for the RRS network, including differences between edge-weights and node strengths and strength centrality, are located in Figures S1-S5.

three communities. As noted above, the Fruchterman and Reingold algorithm was used to determine node placement in our network. The algorithm places nodes that are more strongly connected with the overall network in the center of the network, so, although nodes in each community share commonalities with one another, they may not be visually placed next to each other in the network (Fruchterman & Reingold, 1991).

The reflection community consisted of the following nodes (see Table 1 for node names): *write*, *sad*, *alone*, *think*, and *sad_why*. The brooding community consisted of the nodes *deserve*, *fault*, *regret*, *handle*, and *why*. The depressive symptoms community consisted of the nodes *fut_job*, *concen*, *unmotiv*, *feel*, and *phys*. The resulting communities of the RRS in the estimated network are color-coded and included in Figure 1.

**Full Network**

In network analysis, the number of observations should exceed the number of estimated parameters in order to estimate a reliable network (Epskamp et al., 2018). Thus, given that the communities replicated the pattern seen by Bernstein and colleagues (2019), representing communities as nodes not only made theoretical sense, but also helped reduce the number of parameters in the model.

Figure 2 depicts the bootstrapped network with each node in our network representing a single item, with the exception of the rumination communities representing their own nodes.[3] These items are color-coded to indicate which self-report measure they belong to. Overall, the network evidenced a dense connectivity with 92 out of all possible 190 edges (48.4%) being above zero. The nodes *trust*, *brooding*, and *reflection* evidenced the highest node strengths in the network. It should be noted that the three communities of RRS items were densely connected to

[3] Relevant figures from the bootstrapping analyses for the RRS network, including differences between edge-weights and node strengths and strength centrality, are located in Figures S6-S10.

one another, however, which may thus contribute to why *reflection* and *brooding* evidenced high node strength. The *CS*-coefficient for strength was 0.44, which is below the preferred cutoff of 0.5, but above the acceptable cutoff of 0.25 (Epskamp et al., 2018). The bootstrapped edge-weight accuracy test suggests that the edges between *brooding* and *reflection*, *depressive* and *brooding*, and *worry* and *blue* were among the strongest and most reliable in this network. When examining the edges between nodes of different measures, the edges between *reflection* (RRS community) and *concentrate* (QIDS-SR item), between *deserve* (FHS item) and *view* (QIDS-SR item), and between *brooding* (RRS community) and *view* (QIDS-SR item) exhibited the strongest edge-weights.

## Discussion

The results of the Ruminative Responses Scale (RRS; Nolen-Hoeksema & Morrow, 1991) community analysis replicated those found by Bernstein et al. (2019). Not only did three communities emerge in both studies, but each individual item in the RRS ended up in the same three communities in our study as it did in Bernstein and colleagues' study. The only minor difference between the two studies is that our analysis resulted in more items being considered redundant. We found seven pairs of items that were redundant to each other, in comparison to two pairs of items by Bernstein et al. (2019). The nodes in each of our three rumination communities closely resembled the factor structure of the RRS, as also noted by Bernstein et al. (2019) in their analyses. Specifically, items representing reflection, brooding, and depressive symptoms were each classified together in communities. Thus, our replication provides further evidence that it is especially important that future examination of rumination via network analysis utilize methods beyond simple sum scores. Investigating rumination as a sum score may simplify the heterogeneity of the construct and exclude crucial information of how the three communities interact with each other and other nodes in distinct ways. Overall, these results provide support for Bernstein and colleagues' (2019) conclusions that rumination is a multifaceted construct, and thus measurements of rumination using only a sum score may be inadequate.

Results of the second network incorporating the rumination communities, devaluation of positivity, and depressive symptoms indicate that all three constructs are positively related to each other, in line with previous research (Giorgio et al., 2010; Joshanloo et al., 2014; Raes et al., 2012; Werner-Seidler et al., 2013). Items that belong to the same measure exhibited strong connections to one another, which is likely due to the shared similarities among items measuring the same construct. The node representing the brooding community of rumination shared strong connections with both the reflection and depressive communities. Moreover, the brooding node evidenced greater strength centrality than both of the other rumination nodes. This supports previous findings that suggest brooding may be more detrimental than reflective pondering in regard to its impact on symptoms of psychopathology (for a review, see Nolen-Hoeksema et al., 2008).

When examining edge-weights between nodes of different constructs, a strong relationship emerged between the reflection community of rumination and the QIDS-SR item representing difficulties concentrating. This is consistent with cognitive theories of rumination, such as the impaired disengagement hypothesis, which posit that rumination may be the result of poor cognitive control in the face of distress and/or negative affective states (Koster et al., 2011). Whereas healthy individuals also tend to ruminate on stressful events or negative affect states, the impaired disengagement hypothesis suggests that some individuals have difficulty disengaging and redirecting their attention away from negativity. Depressed individuals who engage in reflective pondering may indeed be more likely to have difficulties disengaging from negativity. Reflective pondering is often viewed as less detrimental than brooding, as it does not include the aspects of self-criticism present in brooding; however, reflective pondering—at least as measured as a facet of rumination—is still often predictive of depressive symptoms (Nolen-Hoeksema et al., 2008). Thus, individuals who engage in reflective pondering may experience more depressive symptoms concurrently (e.g., difficulties with concentration).

Interestingly, the QIDS-SR item "view of myself," is strongly related to both the brooding community of rumination and the FHS item "I feel I don't deserve to be happy." This suggests that self-reference may be an important link between rumination and devaluation of positivity. This finding supports prior research that has suggested that depressed individuals hold negative self-schemas and devalue positivity as they are less likely to endorse positive words to describe themselves than non-depressed individuals (Beck, 1967; Dainer-Best et al., 2017; Gotlib et al., 2004; Shestyuk & Deldin, 2010; Vazquez et al., 2008). Moreover, depressed individuals who engage in brooding may have a tendency to dwell on previous experiences where they have failed or not achieved their desired goal. Thus, they may ruminate about negative self-views (e.g., low self-worth), which may result in feeling as if they do not deserve to experience positive emotions, or vice versa.

The FHS item "I find it difficult to trust positive feelings," which exhibited a high node strength in the network, did not exhibit strong relationships between nodes of other constructs (e.g., rumination and depressive symptoms). This may suggest that this node is highly influential within other nodes of the FHS; however, it is not directly influential for rumination and depressive symptoms when accounting for all other partial correlations in the network.

Moreover, other FHS items, including “I feel I don’t deserve to be happy” may be more interrelated with other constructs.

Though the network showed dense connectively overall, there were no strong edge-weights directly connecting FHS items and rumination communities. There may be two reasons this. First, network analysis examines the partial correlations among nodes. Thus, these constructs may appear less strongly connected to each other due to depressive symptoms being strongly connected to both constructs, or it may be that depressive symptoms serve as the mechanism in between these two processes. However, it would be difficult to make inferences about this mechanism due to the cross-sectional nature of our analyses. Second, our choice of utilizing the FHS may have limited our ability to make associations with rumination. Whereas several FHS items represent dampening, a similar process to rumination, the FHS also assesses fears and avoidance of positivity. Thus, other measures assessing devaluation of positivity, and more explicitly dampening, such as the Responses to Positive Affect Scale (RPA; Feldman et al., 2008), could be utilized to better examine how this construct relations to rumination; however, it should be noted that there may be similar conceptual overlap between some items of the FHS and the RPA. Future work may benefit from examining the dynamic relationships between dampening, rumination, and depressive symptoms in a network.

Taken together, these network findings suggest that rumination, devaluation of positivity, and depressive symptoms are all positively related. Individuals who experience depressive symptoms and hold negative self-views may be more likely to engage in rumination and have negative beliefs about happiness. Specifically, engaging in automatic cognitive processes, such as rumination or dampening, contribute to the maintenance of depressive symptoms and devaluation of positivity.

**Clinical Implications**

Understanding how factors including rumination and avoidance of positivity relate to the development and maintenance of depressive symptoms has the potential to meaningfully impact treatment. Engaging in rumination may lead to or maintain several symptoms of depression, so targeting rumination during treatment may in turn decrease one's overall level of depressive symptoms. However, whether symptoms of depression are inter-related to devaluation of positivity ("view of self" ↔ "I feel I don't deserve to be happy" in our second network) may alter ruminative content, and thus represents a non-traditional treatment target.

Traditional treatments for depression have frequently placed emphasis on reducing negative affect; however, some depressed individuals may not benefit from these treatments due to their reduced positive affect. Indeed, individuals who experience anhedonia or have difficulties experiencing positive affect are more likely to demonstrate poorer response to these treatments, including poorer long-term outcomes (Craske et al., 2016), as reducing negative affect may not target the underlying problem associated with positivity. Positive affect treatments may be better suited for individuals who have difficulties experiencing difficulties with positive affect. Moreover, these treatments may able to target both devaluation of positivity and rumination, given that those who have a tendency to dampen their positive affect also engage in more rumination of negative affect (Feldman et al., 2008). Recently developed positive affect treatments have shown promising results (Craske et al., 2019; Dunn, Widnall, Reed, Owens, et al., 2019; Dunn, Widnall, Reed, Taylor, et al., 2019; Geschwind et al., 2020; Taylor et al., 2017), including increases in positive affect and decreases in negative affect (for a review, see Winer et al., 2019). Although positive affect treatments do not specifically target rumination, they target negative cognitions that may interfere with their ability to experience and savor positive affect.

Thus, these treatments may be beneficial by helping individuals increase and maintain positive affect as they may in turn hold more positive self-views about themselves and engage in less rumination.

Relatedly, rumination-focused cognitive behavioral therapy (RFCBT) may also be modified to reduce rumination and improve positive affect concurrently. RFCBT was developed with the belief that individuals engage in rumination to avoid the possibility of being faced with a negative outcome or unpleasant event and utilizes components from both behavioral activation (BA) and cognitive-behavioral therapy (CBT; Hvenegaard et al., 2015; Watkins et al., 2011). This treatment has demonstrated a greater reduction in depressive symptoms compared to CBT (Hvenegaard et al., 2019). Modifying RFCBT to target negative thinking about positivity may be beneficial, as individuals would learn to challenge maladaptive thoughts that maintain avoidance of positivity and also engage in activity scheduling to combat any avoidance behaviors related to positivity.

**Limitations**

Although this is the first examination of a rumination network that includes both elements of fear of happiness and symptoms of depression, the novelty of the study's findings should be considered in the context of its limitations. We first wish to note that we do not have a pre-registration for the current study. We agree strongly that pre-registrations should be completed whenever possible. Our hypothesis related to the replication of Bernstein et al. (2019) is drawn from their findings, and thus the replication hypothesis is self-evident; moreover, we have noted explicitly that our second network examining rumination, devaluation of positivity, and depressive symptoms is exploratory in nature. However, the lack of a pre-registration is a limitation of this paper, and we encourage clinical researchers to pre-register their research to distinguish between hypothesis-testing (confirmatory) and exploratory research.

Our sample consisted of undergraduate students at a southern university, thus possibly limiting the generalizability of our findings. However, the fact that these results replicated the findings of Bernstein et al. (2019) provides compound evidence for both generalizability and replicability. In addition, the means for each of the measures in our study were lower than comparative clinical samples, and future research may benefit from examining these relationships with clinical samples. However, using a strictly clinical sample can introduce biased results due to Berkson's bias, and examining a network with high cutoff scores (e.g., severe range of depressive symptoms and higher) may result in network structures that don't represent the true structure (Berkson, 1946; De Ron et al., 2019).

Although network analysis allows for a more fine-grained examination of how these constructs interrelate, the cross-sectional nature of our data collection limits any conclusion regarding causality (Jordan et al., 2020; Winer et al., 2016). Future longitudinal studies may further uncover how these constructs influence each other and evolve over time. Finally, the sample size is relatively modest for cross-sectional network analysis. Although there are currently no firm guidelines as to an appropriate sample size to node (or edge-weight) ratio, we encourage further replication of the network presented in this study. In addition, one promising tool is the *netSimulator* function from the *bootnet* package, which allows one to approximate a power analysis based on varying simulations of different samples sizes (e.g., 100, 250, or 500), given an adjacency matrix from an already constructed network (Epskamp et al., 2018). Thus, future studies can use parameters detailed in this study and in Bernstein et al. (2019) to determine sample sizes that may further increase sensitivity and specificity of edge-weight detection.

## Conclusion

This study was the first to (a) replicate the Ruminative Responses Scale (RRS) community analysis findings from Bernstein and colleagues (2019) and (b) use network analysis to examine the relationships between rumination, devaluation of positivity, and depressive symptoms. The replication of the findings from Bernstein and colleagues (2019) supports the proposed factor structure of the RRS (Treynor et al., 2003), and reinforces the multifaceted nature of rumination as a construct. This finding can guide future network analyses examining rumination, in that these replicated findings suggest that rumination may be best represented using multiple nodes, rather than a single sum score. When examining the full network, the constructs of rumination, devaluation of positivity, and depressive symptoms were all positively related to each other, with notable edges between the three constructs being related to negative views of the self. Thus, individuals who experience depressive symptoms that organize around negative self-views and negative beliefs about happiness may be more likely to engage in rumination in a way that maintains negative affect. Further work can continue to elucidate the structures and processes by which individuals come to avoid positivity in their lives.

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