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Reexamining trait rumination as a system of repetitive negative thoughts: A network analysis

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ABSTRACT

Background and objectives: Rumination is strongly associated with risk, maintenance, and worsening of depressive and related symptoms, and it predicts poor treatment response and relapse. More work is needed to clarify the nature and malleability of rumination. We propose reexamining trait rumination as a system of interacting components ("nodes").

Methods: A regularized partial correlation network was first computed to estimate the functional relations among items from the Ruminative Responses Scale (RRS) (N = 403). We then tested whether items constitute multiple distinguishable sub-networks or communities, and if so, if particular items function as "bridges" connecting them.

Results: RRS items were not interchangeable, with network components varying widely in their centrality. We identified three communities of nodes and the nodes bridging these communities.

Limitations: Data were derived from a heterogeneous community sample and include items from a single measure. Thus, results should not be interpreted as definitive, but instead as hypothesis-generating and highlighting the utility of rethinking the conceptualization and measurement of rumination.

Conclusions: Of the larger set of cognitive patterns forming the rumination construct, the high centrality nodes were largely passive and self-critical processes. Community detection analyses identified a sub-network largely comprising items from the RRS that have traditionally been labeled reflective pondering and adaptive; however, strong bridge nodes were also from this community. This implies that in isolation or at low levels such processes may not be problematic, but that their persistence or intensification could be associated with the activation of more maladaptive processes.

1. Introduction

Everyone feels down sometimes. However, not everyone responds to such feelings in the same way. For example, some people tend to ruminate with repetitive, negative, and self-focused thoughts like "why am I so sad?" and "why can't I handle things better?" (Nolen-Hoeksema & Morrow, 1991). This cognitive-affective response style is strongly associated with risk, maintenance, and worsening of depressive symptoms (Nolen-Hoeksema, 2000, 1991; Nolen-Hoeksema, Wisco, & Lyubomirsky, 2008). Chronic rumination increases the salience of negative events and impairs problem-solving, thus exacerbating and prolonging negative mood states (Donaldson, Lam, & Mathews, 2007; Joormann & Gotlib, 2010; Nolen-Hoeksema et al., 2008). Longitudinal, prospective, and experimental data converge: getting stuck in this mental habit of "self-critical moody pondering", as it has been called, and getting stuck often, is a problem (Raes & Hermans, 2008; Watkins & Nolen-Hoeksema, 2014). And notably, frequent negative rumination and its consequences are not unique to depression, but are evident in anxiety disorders and related psychopathology as well (McLaughlin, Aldao, Wisco, & Hilt, 2014; McLaughlin & Nolen-Hoeksema, 2011).

Broadly considered as a core transdiagnostic feature of psychological disorders (e.g. Harvey, Watkins, Mansell, & Shafran, 2004; McLaughlin & Nolen-Hoeksema, 2011), rumination is a plausible target of treatment (Watkins, 2015). And there is preliminary evidence that rumination-focused therapies, such as mindfulness-based cognitive therapy (van Aalderen et al., 2012) and cognitive-behavioral approaches (Watkins et al., 2011), may improve treatment outcomes for depression. However, the results of such targeted interventions have been few and inconsistent, and in general, high rates of rumination predict slower treatment response, lower rates of recovery, and higher

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rates of relapse (Ciesla & Roberts, 2002; Schmaling, Dimidjian, Katon, & Sullivan, 2002). Given that rumination is so relevant for understanding emotional disorders and developing interventions, more work is needed to clarify the nature and malleability of rumination itself.

One limitation to extant efforts could be the conceptualization and subsequent measurement of rumination as a unitary construct. In reality, rumination is complex and multifaceted. For example, the typical definition includes components of perseveration, passivity, negativity, and self-focus. Furthermore, rumination about a negative experience can feel like a productive strategy for introspection and resolution (Papageorgiou & Wells, 2001). There have been important strides toward analyzing rumination to understand its function better. Factor analyses and other approaches have distinguished between adaptive versus maladaptive types of rumination or perseverative thinking, such as differentiating between abstract-evaluative and concrete repetitive thought (Watkins, 2008), or brooding and reflective pondering (Treynor, Gonzalez, & Nolen-Hoeksema, 2003). For example, abstract-evaluative thoughts (e.g. fixation on high-level, "why" aspects of one' situation) and brooding (e.g. "What am I doing to deserve this?") are more frequent and persistent in individuals with a history of major depression, those experiencing current symptoms, and those who eventually experience an episode than those without psychopathology. Such thinking patterns can increase the salience of negative thoughts and memories, delay problem solving or instrumental behaviors, and reduce cognitive and attentional flexibility (Nolen-Hoeksema et al., 2008; Watkins, 2008). In contrast, the links between mental health and more concrete thoughts (e.g. low-level, "how" details of one's situation) and reflection (e.g. analyzing one's thoughts) are less clear. Although there is evidence that such forms of self-reflection can be adaptive and benefit problem-solving, and that such thinking patterns are not elevated in individuals in remission from depressive episodes and are associated with *less* depression over time, they are associated with concurrent depressive symptoms and negative memory biases (Joormann, Dkane, & Gotlib, 2006; Nolen-Hoeksema et al., 2008). These models usefully categorize a person's general response style, the types of thoughts that are generally associated with mood symptoms, and the types of thoughts that typically have direct negative versus neutral or positive consequences.

However, in real life, people rarely fall into just one pattern of negative repetitive thinking. Instead, people exhibit different combinations of reflective, brooding, abstract, and concrete thoughts, for instance. Indeed, existing models fail to clarify why one person's pattern or combination of adaptive and maladaptive thoughts leaves them vulnerable to frequent, problematic rumination and associated mood symptoms, whereas another person's pattern of thinking does not. Although categorizing individual thoughts alone can be beneficial (e.g. adaptive or maladaptive, reflective or brooding, and abstract or concrete), such labels may become blurry once we consider how they all interact as a system.

We therefore propose reconsidering trait rumination from a network perspective. Currently, rumination and its sub-types are measured as single sum scores from self-report scales. As a result, component processes (e.g. items) or entire scales are treated as interchangeable and reflective of an underlying, latent response style. In some ways, this is perplexing as it is easy to generate examples of how component processes might interact (e.g., the more one criticizes oneself for failures, the more likely one is to brood about how sad one feels) and how these processes might be more or less influential on one's mood and circular thinking. Furthermore, some ostensibly neutral or even adaptive thinking styles from one factor, like reflection, may become problematic in relation to others. A network approach to reconceptualizing rumination and its components allows for these possibilities. The feature distinguishing this computational approach from factor analyses is that it characterizes rumination as a system of interacting components that do not have to have a common, underlying cause (Schmittmann et al., 2013). Accordingly, we can look for clues as to why some people get stuck in a pattern of ruminative responses and to what specific targets are ripe for intervention.

To do so, we used the items of the Ruminative Responses Scale (RRS; Nolen-Hoeksema & Morrow, 1991), the most common instrument for measuring trait rumination. There are important limitations to this approach. First, this is only one measure and thus results may vary with another scale. Second, some items do share conceptual overlap (e.g., going away to think about one's feelings and thinking about *why* one is feeling that way) as is typical of indices intended to reflect a conjectured latent, common cause. However, this intention notwithstanding such items need not measure the same process. Thus, although we take data-driven steps (described below) to reduce items that do appear to be measuring single processes, we still do not argue that the resulting network models completely capture the trait rumination construct. Nor do we argue that each item necessarily reflects a completely unique aspect of rumination. In fact, achieving these aims would likely require a rigorous, iterative process of including various self-report, behavioral, and other variables to devise a parsimonious and comprehensive measure for this purpose. We do argue that there is value in examining all items simultaneously as conceptual overlap is not synonymous with fungibility and simple sum scores likely occlude meaningful differences and interactions between components. The network approach is a fresh, data-driven way to gain new perspectives on how component processes or items cluster and relate to one another (individually and as sub-networks). Results can drive new hypotheses to be experimentally tested regarding different components of the rumination construct that might be most influential initiating or maintaining problematic response styles. The goal is to explore whether past approaches to quantifying rumination could be missing informative elements.

We have three primary aims: (1) explore whether and how RRS items interrelate in different ways, (2) test whether within this larger network RRS items constitute distinguishable communities (sub-networks) of processes, and (3) if so, are there particular items that function as "bridges," i.e. processes that connect or are shared by communities. These analyses can help to highlight especially potent component processes that may foster broader vulnerability for problematic emotional and cognitive responses. Additionally, community detection and bridge analyses could highlight thought patterns that make a person more likely to tip from adaptive reflection and introspection to maladaptive brooding. Overall, this new lens on rumination is exploratory. Each analysis has its strengths and limitations and is intended to provide new hypotheses about plausible causal connections between components of rumination.

2. Methods

2.1. Participants

De-identified data came from adults (N = 403, 231 women) who enrolled in a research program concerning cognition, emotion, and exercise and who completed the RRS between 2014 and 2017 (Bernstein & McNally, 2016, 2017, 2018). Participants were between the ages of 18 and 58 (M_{age} = 24.59, SD = 7.27) and 102 identified as Hispanic or Latino (25.31%). The self-reported racial breakdown of the sample is as follows: 58.56% Caucasian or white, 10.67% African American or black, 18.11% Asian American or Asian, 0.50% Native American or American Indian, 8.19% multiracial, and 3.97% other or unreported. Participants ranged in years of education from less than high school to a graduate or professional degree; the majority (87.59%) of participants, however, reported completing at least some college courses, technical school, or an associate's degree. Participants also completed the Depression Anxiety Stress Scales, 21-item (DASS-21), which yields estimates of depression, anxiety, and stress severity (Lovibond & Lovibond, 1995). The depression subscale captures experiences like depressed mood, worthlessness, hopelessness, anhedonia, and psychomotor slowing. The anxiety subscale covers experiences like panic, general and situational anxiety, and somatic anxiety (e.g. trembling, racing heart). The stress subscale captures persistent, non-specific feelings such as hyperarousal, irritability, and tension. DASS-Depression scores ranged from 0 to 38 ($M = 6.11$, $SD = 6.72$), and 100 participants (24.81%) reported at least mild depression (DASS-Depression ≥ 10). DASS-Anxiety scores ranged from 0 to 40 ($M = 6.11$, $SD = 6.74$), and 138 participants (34.24%) reported at least mild anxiety (DASS-Anxiety ≥ 8). Finally, DASS-Stress scores ranged from 0 to 36, $M = 8.94$, $SD = 7.82$, and 89 participants (22.08%) reported at least mild stress.

2.2. Ruminative Responses Scale (RRS)

The 22-item RRS captures the tendency to ruminate in response to negative affect or mood. Participants rate a series of statements along a Likert-type scale ranging from 1 (almost never) to 4 (almost always) and responses are summed. Scores can range from 22 to 88. Higher scores indicate more habitual rumination. The measure has good internal consistency and is intended to measure trait rumination (Nolen-Hoeksema & Morrow, 1991). In the present study, participants' scores ranged from 22 to 88 ($M = 43.71$, $SD = 12.86$), Cronbach's alpha = .93.

2.3. Network analyses

2.3.1. Removing redundant items

Because the RRS was not designed for network analyses and there are items with apparent conceptual overlap, we first used a data-driven method for identifying items (i.e., nodes) potentially measuring the same process (i.e., aspect of rumination). First, we confirmed that the correlation matrix was positive definite (reflecting that items are not linear combinations of other items). Second, using the *goldbricker* function within the R package networktools (Jones, 2018; Levinson et al., 2018), we searched for pairs of items that were highly intercorrelated ($r > 0.50$) and that exhibited highly similar patterns with other items in the dataset (i.e., > 75% of correlations with other items did not significantly differ for a given pair). We used the Hittner method for comparing dependent correlations (Hittner, May, & Silver, 2003). Two pairs of nodes were identified and combined via the *reduce_net* function in networktools. The first principal component of the two variables in each pair were included in the reduced dataset as new variables. Twenty nodes are thus included in subsequent analyses.

2.3.2. Graphical LASSO network

To explore the relations among rumination components, we used the R package qgraph (Epskamp, Cramer, Waldorp, Schmittmann, & Borsboom, 2012) to compute a Graphical Gaussian Model (GGM). In this model we visualize conditional independence relations among RRS items and control for the effects of all other items (Epskamp, Borsboom, & Fried, 2018). The resulting network graph has several key features. Nodes represent variables (i.e., RRS items). Edges connect nodes and represent pairwise regularized partial correlations (described below). Edge color denotes the sign; green denotes positive associations and red negative associations. Edge thickness indicates the magnitude of the (regularized) partial correlation between two nodes. Nodes that are closer to the center of the graph are more strongly connected within the overall network (Fruchterman & Reingold, 1991). The GGM is regularized via the graphical LASSO (Least Absolute Shrinkage and Selection Operator) and uses polychoric correlations as input for variables is on an ordinal scale. This procedure excludes small edges likely to be false positives (Friedman, Hastie, & Tibshirani, 2011). An extended Bayesian Information Criterion (EBIC) model selection procedure (Foygel & Drton, 2011) within the qgraph package (Epskamp et al., 2012) further strengthens our confidence that edges in our model are “true” (assuming that the structure of the generating network is, indeed, sparse). One hundred models varying in sparseness are estimated and the model with the lowest EBIC value (given a certain hyperparameter γ) is selected. Here, γ was set to 0.5, which promotes a more conservative or sparse graph.

We then computed expected influence indices for the graphical LASSO network (Robinaugh, Millner, & McNally, 2016). These centrality metrics quantify the cumulative importance of nodes within a network and take the presence of positive and negative edges into account. Nodes with high expected influence are hypothesized to drive the instigation, maintenance, and slowing of the network (Robinaugh et al., 2016). However, this network is undirected, and therefore the direction of influence cannot be specified or confirmed. *One-step expected influence* assesses the influence of a node in relation to its direct connections (i.e., nodes sharing an edge); it is the sum of edge weights attached to a given node. Calculations of *two-step expected influence* include both direct influences and secondary influences, or pathways from the node passing through its direct neighbors. Higher expected influence values indicate greater influence or importance in the network. Plots depict the normalized (z-scored) values for each node.

2.3.3. Community detection

To test whether the items cohere as one or multiple communities or subnetworks, we used the R package igraph (Csárdi & Nepusz, 2006) to examine community structure with the spin glass algorithm, $\gamma = 0.5$, start temperature = 1, stop temperature = .01, cooling factor = 0.99, spins = 20 (Reichardt & Bornholdt, 2006). This modularity-based community detection algorithm reveals whether nodes cluster into distinct, though interacting, subnetworks or communities (Heeren & McNally, 2018; Robinaugh, LeBlanc, Vuletich, & McNally, 2014). Nodes within a community are more strongly interconnected than they are with nodes in another community.

2.3.4. Bridge nodes

To identify important nodes that serve as bridges between communities (Heeren, Jones, & McNally, 2018; Jones, Mair, Riemann, Mugno, & McNally, 2018) we used the *bridge* function from the R package networktools (Jones, 2018). *One-step bridge expected influence* is the sum of edge weights connecting a given node to all nodes in the other community or communities. *Two-step bridge expected influence* is calculated similarly, but also captures the secondary influence of a given node on other communities. Plots depict the normalized (z-scored) values for ease of comparison and interpretation. These indices identify nodes that, when activated themselves, are most likely to activate nearby communities or subnetworks.

3. Results

RRS items and the abbreviated names to be used in figures are included in Table 1.

3.1. Graphical LASSO network

Fig. 1A includes the graphical LASSO network depicting regularized partial correlations among the 20 RRS nodes. A few pairwise connections stand out: thinking “I won't be able to do my job if I don't snap out of this” (*job*) with thinking “I won't be able to concentrate if I keep feeling this way” (*fut*), $r = .46$; thinking about how passive and unmotivated you feel (*passive*) with thinking about how you don't feel up to doing anything (*feel*), $r = 0.45$; thinking “What am I doing to deserve this?” (*deserve*) and thinking “Why do I have problems other people don't have?” (*problem*), $r = 0.40$; thinking about how alone you feel (*lonely*) and thinking about how sad you feel (*sad*), $r = 0.40$; analyzing recent events (*analyze*) with analyzing your personality to try to understand why you are depressed (*person*), $r = 0.35$. Additionally, a few small clusters of strongly interconnected nodes emerge. There is a cluster of concerns about functioning: thinking “I won't be able to do

Table 1
Items from the Ruminative Responses Scale (RRS).

Node label	Item
alone (combined)	go someplace alone to think about your feelings go away by yourself and think about why you feel this way
analyze	analyze recent events to try to understand why you are depressed
angry (combined)	think about how angry you are with yourself think "Why do I always react this way?"
concen	think about how hard it is to concentrate
deserve	think "What am I doing to deserve this?"
fault	think about all your shortcomings, failings, faults, mistakes
feel	think about how you don't feel up to doing anything
fut	think "I won't be able to concentrate if I keep feeling this way"
going	think "Why can't I get going?"
handle	think "Why can't I handle things better?"
job	think "I won't be able to do my job if I don't snap out of this"
lonely	think about how alone you feel
numb	think about how you don't seem to feel anything anymore
passive	think about how passive and unmotivated you feel
person	analyze your personality to try to understand why you are depressed
phys	think about your feelings of fatigue and achiness
problem	think "Why do I have problems other people don't have?"
sad	think about how sad you feel
wish	think about a recent situation, wishing it had gone better
write	write down what you are thinking about and analyze it

Note. "alone" and "angry" are combinations of the two items listed; values are the first principal component of the two initial RRS items.

my job if I don't snap out of this" (*job*), thinking "I won't be able to concentrate if I keep feeling this way" (*fut*), and thinking about how hard it is to concentrate (*concen*). There is a cluster of self-criticism: thinking about all your shortcomings, failings, faults, mistakes (*fault*), thinking about how angry you are with yourself (*angry*), thinking about a recent situation wishing it had gone better (*wish*), and thinking "Why can't I handle things better?" (*handle*). There is a cluster of passivity or lack of motivation: thinking about how you don't feel up to doing anything (*feel*), thinking about how passive and unmotivated you feel (*passive*), and thinking "Why can't I get going?" (*going*). And there is an analytical cluster: writing down thoughts in order to analyze them (*write*), being alone to analyze one's feelings and their causes (*alone*), analyzing one's personality (*person*), and analyzing recent events (*analyze*). To estimate the stability of edges, we bootstrapped the confidence regions of the edge weights (see Fig. S1 in Supplemental Materials) and used a bootstrapped difference test (see Fig. S2 in Supplemental Materials). Results suggest that edges are fairly stable and that the strongest edges are significantly larger than most others.

Fig. 1B includes estimates of one-step (EI1) and two-step (EI2) expected influence. Nodes with the highest expected influence include lack of motivation, or thinking about how you do not feel up to doing anything (*feel*; *EI1* = 1.25; *EI2* = 2.32), thinking about not being able to concentrate in the future (*fut*; *EI1* = 1.24; *EI2* = 2.26), analyzing your personality (*person*; *EI1* = 1.1.23; *EI2* = 2.29), and wondering why you cannot handle things better (*handle*; *EI1* = 1.13; *EI2* = 2.11). A person-dropping bootstrap procedure indicated that one-step expected influence estimates are highly stable (see Fig. S3 in the Supplemental Materials).

3.2. Community detection

The spin glass algorithm detected three communities of nodes, depicted in Fig. 2A. Community 1 included 6 items: analyzing recent events (*analyze*), separating oneself to think about what one feels (*alone*), writing down one's thoughts and analyzing them (*write*), and analyzing one's personality (*person*), thinking about feeling sad (*sad*), and thinking about feeling alone (*lonely*). Community 2 included 8 items: worrying about not being able to do one's job (*job*), thinking about how hard it is to concentrate (*concen*), worrying about not being able to concentrate in the future (*fut*), thinking about feelings of fatigue and achiness (*phys*), thinking about feeling passive and unmotivated (*passive*), thinking about not feeling anything (*numb*), wondering why one cannot get going (*going*), and brooding about not feeling up to doing anything (*feel*). Community 3 included 6 items: wondering what one did to deserve negative feelings (*deserve*), criticizing oneself for always reacting poorly and being angry with oneself (*angry*), wishing a

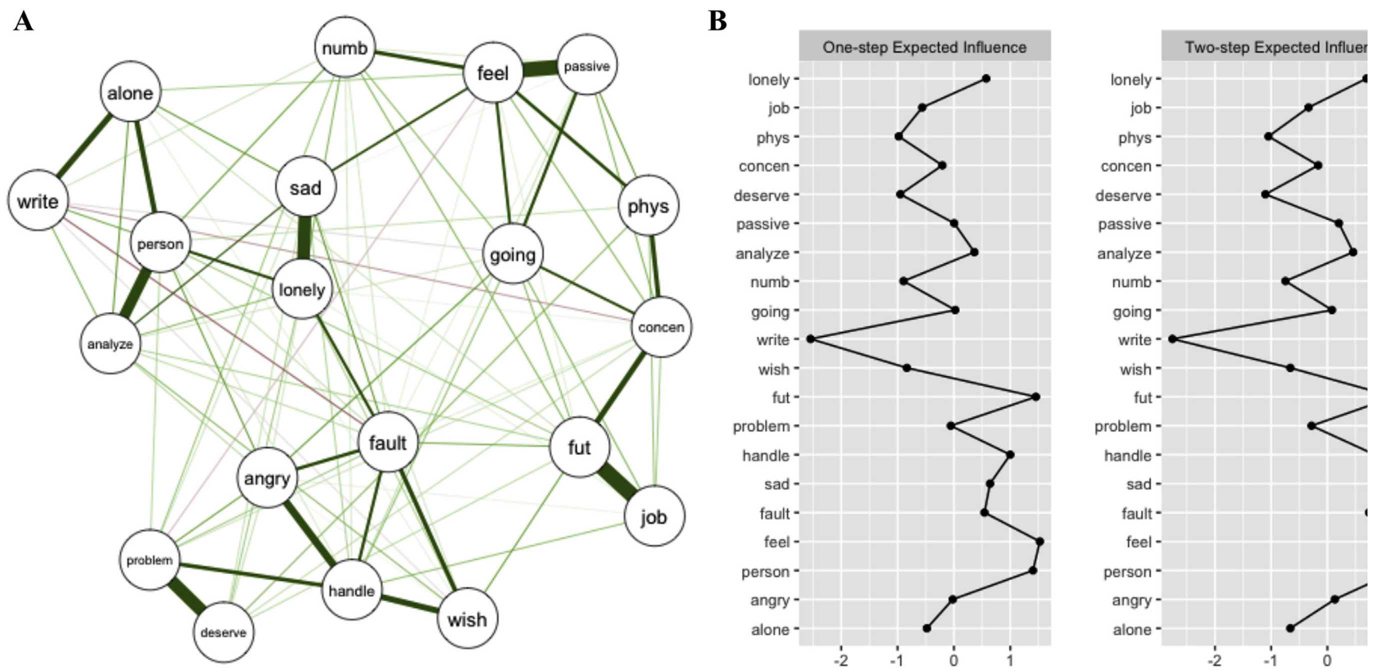

Fig. 1. Graphical LASSO using polychoric correlation and expected influence metrics. *Note.* Items are detailed in Table 1 (A) Edge thickness reflects magnitude of association (thickest edge, *r* = 0.46). Green lines reflect positive correlations and red lines reflect negative associations. (B) Expected influence centrality plot. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

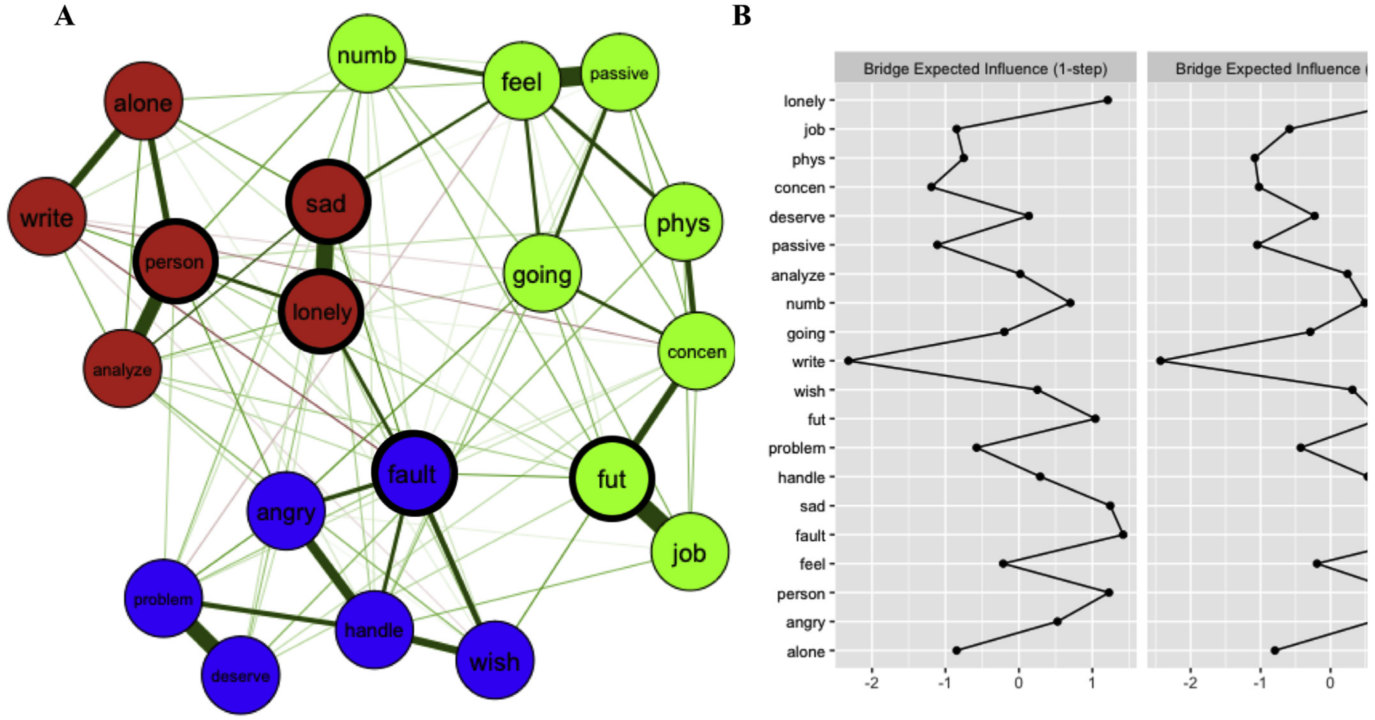

Fig. 2. Graphical LASSO network highlighting community structure and most influential bridge nodes. *Note.* Items are detailed in Table 1 (A) Community 1 is represented in red, Community 2 in green, and Community 3 in blue. Nodes with the highest bridge expected influence are denoted with thick outlines. (B) Bridge expected influence metrics. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

recent situation had gone better (*wish*), wondering why others do not have these problems (*problem*), brooding on why one does not handle things better (*handle*), perseverating on one's faults and mistakes (*fault*).

3.3. Bridge nodes

Estimates of one-step and two-step bridge expected influence are plotted in Fig. 2B. Standardized one-step bridge expected influence (*bridge EI1*) and two-step bridge expected influence (*bridge EI2*) values are reported. From Community 1, analyzing your personality (*person*), thinking about how one feels sad (*sad*), and thinking about how one feels lonely (*lonely*) had the highest overall bridge expected influence: one-step (*bridge EI1* = 0.40; *EI1* = 0.40; *EI1* = 0.40) and two-step (*bridge EI2* = 0.96; *EI2* = 0.85; *EI2* = 0.90) influence. Anticipating difficulty concentrating in the future (*fut*), from Community 2 and perseverating on past mistakes (*fault*) were also highly influential for both one-step (*bridge EI1* = 0.37, *EI* = 0.43) and two-step (*bridge EI2* = 0.76; *EI2* = 0.98) estimates. The most influential bridge nodes are highlighted in Fig. 2A.

4. Discussion

We first examined the interplay between components of a trait rumination measure (RRS) by computing a graphical LASSO network. The pairs or clusters of nodes that emerged as most strongly interconnected in the graphical LASSO were clinically interpretable. Items that intuitively seem most related mechanistically emerged with the strongest edges, such as brooding about feelings of sadness as well as loneliness or repetitive self-criticism with self-directed anger and wishing recent situations had gone or been handled better. These pairs, however, did not in turn relate uniformly to other items in the network. This pattern yields two important implications. First, it highlights that overall, these components were not interchangeable; edge strength and expected influence varied widely across the network and even with communities (to be discussed below). Overall, these patterns support the notion that rumination is a multifaceted construct and should be measured and experimentally tested as such (Bernstein, Heeren, & McNally, 2017). Reducing it to a single sum score could be oversimplified or misleading as people can achieve equal scores with items being endorsed in significantly different patterns (Fried & Nesse, 2015).

Second, network models highlight the value of viewing nodes as processes that can interrelate. Other analytic approaches could find similar correlations between variables, but importantly diverge in their implicit assumption that such relationships reflect an underlying latent factor and thus logically preclude causal connections among the variables (van der Maas et al., 2006). Importantly, these data are cross-sectional and cannot speak to causal connections. The present analyses should encourage follow-up work that can. For instance, it is important to investigate to what extent these relationships are maintained at the individual level. Time series models would highlight dynamic influences between nodes and test whether nodes with high expected influence cross-sectionally (e.g., not feeling up for doing anything, analyzing one's personality) would also be nodes that might disproportionately activate other problematic thinking patterns, intensify the connectedness of the network, and prevent slowing or deactivation (Robinaugh et al., 2016). And subsequent targeted experimental work could begin to assess the impact of upregulating or downregulating single nodes on the overall network structure. Current results support the hypothesis that thoughts characterized as passive and self-critical (e.g., brooding on past mistakes) are especially problematic for the phenomenon of rumination. However, these may just be downstream consequences of other ruminative processes. More work is needed to test these predictions as well as the alternative possibility that nodes are highly central because they are most affected by other nodes. Finally, given the novelty of this approach, the current results require direct replication to test whether the same communities and central nodes emerge.

Findings could also have implications for the RRS and other measures of rumination. Currently, simple sum scores are used. If centrality estimates reflect importance to the network and thus ruminative response styles overall, perhaps weighting questionnaire items according to its centrality could yield improved indices. In related work, using standardized strength centrality values to weight individual depressive symptoms improved predictions of major depressive disorder onset (Boschloo, Van Borkulo, Borsboom, & Schoevers, 2016). Additionally, researchers developing shorter measures might use expected influence or strength centrality indices to focus on the most central items (Heeren, Bernstein, & McNally, 2018). Such items could identify those individuals most at risk for having or developing problematic patterns of negative, repetitive thinking as they are nodes that could be driving the broader rumination network.

Our hope is that research reconceptualizing rumination as the interplay of several processes could ultimately have clinical implications, such as identifying specific, measurable, and malleable targets for meaningful intervention through individual or idiographic network analyses (Fisher, Reeves, Lawyer, Medaglia, & Rubel, 2017). In line with network theory, targeting highly central nodes could be an efficient way of dampening the entire network through direct and indirect connections (Costantini & Perugini, 2016; Valente, 2012). This conjecture rests on two assumptions that merit investigation. The first is that we can deactivate nodes in a specific, isolated fashion. It is possible that such specific targeting may be very difficult to achieve in practice (i.e., several nodes are targeted at once, not just the node of interest). The second is that of activation and deactivation symmetry. Activating a node may, indeed, produce propagating effects whereby other nodes are turned on. But the process may not work both ways. Deactivation may prove difficult. Hence, once the network is fully activated, it may be self-sustaining in virtue of the activation propagating among nodes other than the original instigator or driver.

Community detection analyses revealed three distinct subnetworks. Clusters overlapped with past factor analyses in many ways. For example, Community 1 encompasses all items from the reflection factor identified by Treynor et al. (2003). However, results suggest that dwelling on feelings of sadness and loneliness were highly interrelated to these other nodes that are typically viewed as adaptive. Traditionally, brooding and dysphoria-related factors, described as passive, judgmental thinking, are associated with poor outcomes and considered maladaptive, whereas reflection is not (Raes & Hermans, 2008; Schoofs, Hermans, & Raes, 2010; Treynor et al., 2003). However, this factor structure does not hold in clinical samples (Whitmer & Gotlib, 2011). Subnetworks and bridge analyses can help us understand why the line between contemplative introspection and self-critical repetitive thinking may be neither distinct nor consistent. Within the subnetwork of Community 1, it seems that reflection and passively dwelling on negative emotions highly covary; whereas the former processes may not intrinsically be problematic, the tendency to engage in such behaviors may increase the likelihood that people passively and problematically perseverate in the event that they experience negative affect. Furthermore, although temporal, experimental, and individual-level work is needed to test these new hypotheses, highly influential bridge nodes are those that could plausibly have the greatest effect on nodes *outside* their own community. One typically “adaptive” item from the reflection community (Community 1)— analyzing one's personality—was a highly influential bridge node in the entire network. This implies that in isolation or at low levels such a process may not be problematic, but that its presence, persistence, or intensification (e.g., due to lack of success or clarity; Vine, Aldao, & Nolen-Hoeksema, 2014) may be associated with the activation of more maladaptive processes—such as self-criticism without taking problem-solving actions. Findings were surprising as reflection items have historically been considered to reflect more concrete, detail-oriented self-reflection; one might have expected only repetitive abstract-evaluative thinking items to be strongly related to less constructive outcomes and to be strong bridges (Watkins, 2008; Watkins, Moberly, & Moulds, 2008; Watkins & Moulds, 2005). This could signify people getting stuck in initially adaptive reflection or pondering, at the exclusion of problem solving action, and highlight the passive nature of ruminative thoughts as a more central or important component. Furthermore, the strongest bridge node was a self-critical one, or perseverating on past mistakes. Thus, it could be associated both with such excessive introspection and with the broader set of traditionally problematic, ruminative thoughts.

Importantly, our data are from a community sample. Although participants were distributed across the full range of RRS scores and more than a third reported at least mild symptoms of depression or anxiety, it is possible that the results might differ if we were to replicate the study in an explicitly clinical sample. Doing this work and comparing results to subclinical and control samples would be informative, particularly as rumination is a robust risk factor in the presence or absence of clinical symptoms. Additionally, to ultimately capture the causal nature and temporal dynamics of these processes, time-series and experimental methods are warranted. Within-person networks may also reveal specific bridge or high vulnerability nodes to be targeted for an individual that are not highly central at the population level (Epskamp et al., 2018). Future research should also manipulate the variables included in such analyses. In line with prior work, we chose to include all RRS items in this initial study (Heeren et al., 2018; Watters, Taylor, Quilty, & Bagby, 2016). It is possible, and in fact likely, that some items are unimportant or that other important variables are missing. For example, the present study is limited in that only one assessment of rumination was included. Despite its frequent usage, the RRS focuses largely on depressive rumination and results may not generalize to other forms of repetitive negative thought. Furthermore, nodes comprising measures other than self-report ones, such as performance on behavioral tasks (e.g., Heeren & McNally, 2016), can be added to explore causal mechanisms at different levels of analysis.

4.1. Conclusions

The present study is not definitive. Instead, it is intended to highlight the utility of rethinking the conceptualization and measurement of rumination. Specifically, results encourage us to consider sub-components of trait rumination as processes of interest in their own right and as interacting. Our findings reveal structural dynamics among these features of habitual depressive rumination and suggest tools for further examining component processes within the network framework and as they relate to clinical risk and outcomes. Without the assumption that these items necessarily reflect one or more latent constructs, we can perhaps develop more targeted, or at least different, conceptualizations and interventions. Given the large body of research demonstrating clinical consequences of a ruminative response style, the present findings could generate novel research questions to clarify the nature of rumination and develop more targeted and effective interventions.

Conflicts of interest

Authors have no conflicts of interest to disclose.

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Appendix A. Supplementary data

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