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Unpacking Rumination and Executive Control: A Network Perspective

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Abstract
Rumination is a common and problematic feature of depression and related disorders. It may reflect impairments in executive control. In this project, we used network analysis to explore the conceptualization of rumination in terms of impoverished top-down executive control. A total of 91 participants completed laboratory tasks of executive control, underwent a stressor, and reported on their level of rumination. We computed a regularized partial correlation network, relative importance network, and directed acyclic graph to estimate the functional relations among aspects of rumination and executive control. Results highlighted the centrality of self-criticism in the network. Perseverative thinking (e.g., brooding) predicted poor executive control, which in turn related to greater self-criticism. These complementary network perspectives suggest that multinode loops could be at play. This new approach to visualizing rumination may offer a more informative view of the interplay between problematic cognitive and affective processes, as well as ways of integrating self-report and behavioral variables.

Keywords
network analysis, relative importance, rumination, executive control, emotion regulation, directed acyclic graph

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Cognitive-affective response styles broadly describe how people think about and react to their own emotional experiences. Habitual use of generally adaptive strategies in the face of negative experiences moderates the impact of stressful life events on depression and related outcomes (Joormann & Vanderlind, 2014). Overuse of strategies that maintain or exacerbate negative emotions are particularly risky. Rumination is perhaps the prime example. Rumination describes perseverative, passive, self-focused thinking about the content, causes, and consequences of one's affective state, without taking any problem-solving action (Nolen-Hoeksema & Morrow, 1991). Though traditionally linked to depression, rumination appears best conceptualized as a transdiagnostic vulnerability and maintenance factor for affective dysregulation and related emotional disorders (McLaughlin & Nolen-Hoeksema, 2011; Wolkenstein, Zwick, Hautzinger, & Joormann, 2014).

Some forms of positive rumination can be beneficial (e.g., savoring positive experiences; Bryant, 2003; Wood, Heimpel, & Michela, 2003), and many people also believe that rumination in response to negative experiences is a productive strategy for insightful introspection (Papageorgiou & Wells, 2001). Yet, such repetitive negative thinking prolongs negative experiences and delays recovery; rumination maintains the salience of the stressor, promotes a negative attentional bias, and impairs solution generation (Donaldson, Lam, & Mathews, 2007; Joormann & Gotlib, 2010; Nolen-Hoeksema, Wisco, & Lyubomirsky, 2008). Rumination is further associated with other risk factors for emotion dysregulation including emotional inflexibility, greater reactivity and sustained response in the amygdala, and executive functioning deficits (Ray et al., 2005; Siegle, Steinhauer, Thase, Stenger, & Carter, 2002). Thus, despite its highly analytical bent, negative rumination appears emotionally counterproductive.

Given the prevalence and risk of ruminative response styles in emotional disorders, there is great theoretical

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and clinical interest in understanding the mechanisms of rumination and its therapeutic reduction. One hypothesis holds that rumination reflects impairments in executive control (De Lissnyder et al., 2012; Koster, De Lissnyder, Derakshan, & De Raedt, 2011; Whitmer & Banich, 2007). Broadly, reduced top-down executive control—processes that allow for adaptive, goal-dependent shifts in information processing, attention, and behavior (Diamond, 2013)—shows links to mood symptoms, anxiety, stress, and poor emotional response and regulation (Takeuchi et al., 2014). And more specifically, it appears that chronic ruminators struggle to disengage from their perseverative, emotionally charged thoughts in an effort to alter their ongoing internal narrative or redirect their thoughts to other topics. Therefore, impairments in executive control seemingly drive rumination. Furthermore, deficits in such control could impede a person's ability to process emotional information such that the requisite extra effort heightens the salience of the negative information, thereby perpetuating a cycle of perseveration and its emotional consequences (Chuen Yee Lo, Lau, Cheung, & Allen, 2012; Hester & Garavan, 2005).

We examine three measurable, empirically validated executive control processes in this domain: inhibition (the ability to disregard interference of irrelevant information in working memory), set shifting (the ability to flexibly move attention to the relevant task), and updating working memory (the ability to manipulate information being maintained in working memory; e.g., Miyake et al., 2000). All three tasks have demonstrated preliminary negative associations with rumination. Specifically, individuals highly prone to rumination show weaker inhibitory control (Joormann & Gotlib, 2008; Whitmer & Banich, 2007), more difficulty manipulating information in working memory (Joormann & Gotlib, 2008; Joormann, Levens, & Gotlib, 2011), and larger task-switching impairments (Davis & Nolen-Hoeksema, 2000; De Lissnyder et al., 2012; Whitmer & Banich, 2007), particularly in the context of emotional, personally relevant stimuli (Beckwé, Deroost, Koster, De Lissnyder, & De Raedt, 2014; Koster, De Lissnyder, & De Raedt, 2013).

Despite these findings, there are important limitations of this line of work. Sufficient evidence of causality is lacking, perhaps because this research is in its early stages. But, it may be attributable to the conceptualization of rumination as a unitary construct measured by a sum score from a self-report measure. It has been arguably most succinctly described as self-critical "moody pondering" (Iqbal & Dar, 2015; Treynor, Gonzalez, & Nolen-Hoeksema, 2003). So it is curious that rumination is represented as a single index when you reconsider its definition, which includes these multiple components such as perseverative thinking, negativity, and self-focus. Hence, cognitive measures may be causally related to some, but not all, of these components. Deficits in executive control and rumination have demonstrated negative effects for everyday mood and wellbeing. Thus it is important to clarify how these processes causally interact and to develop methods of improving them. Even understanding how different facets of rumination itself interrelate may ultimately allow for more targeted and effective interventions.

In this project, we used network analytic methods to characterize the functional relations among self-reported features of rumination and integrated them with laboratory-based executive control measures. Network analyses were initiated in clinical psychology by Borsboom and colleagues (e.g., Borsboom, Cramer, Schmittmann, Epskamp, & Waldorp, 2011; Schmittmann et al., 2013) and have been increasingly applied to questions of psychopathology (e.g., Heeren & McNally, 2016; McNally, 2016; Robinaugh, LeBlanc, Vuletich, & McNally, 2014). Most network analyses have elucidated associations (edges) between nodes (psychiatric symptoms), endeavoring to characterize mental disorders as emergent phenomena arising from the causal interactions occurring among their constitutive symptoms (Borsboom & Cramer, 2013). Studying social anxiety disorder, Heeren and McNally (2016) expanded network approaches beyond symptoms to include laboratory measures of cognition and behavior. We extended this line of work by examining the functional relations among subjective, self-reported aspects of rumination and objective, behavioral measures of executive control within the same networks.

The network approach aims to identify *plausible* causal connections among directly observable and measurable variables that might be masked by traditional statistical approaches or when interpreted in terms of broad, unobserved latent variables (Costantini et al., 2015). In this way, formative variables, such as executive functioning or, as we propose, rumination, are broken up into their distinct component processes. Intuitively, it seems clear that such components interact with each other; for example, heightened self-criticism intensifies negativity. Thus, the axiom of local independence requisite for such variables to reflect a single, underlying entity, such as rumination, is violated. The network approach instead considers each variable as its own entity and explores interrelationships between them. Although terms like executive functioning and rumination may summarize a person's general ability or response style, they are less useful than their components when one endeavors to explore potential causal relations. Accordingly, we used several network analyses to begin visualizing the connections between variables and to compute complementary, informative metrics such as node centrality. In this way, we aim to identify new directions for research to explore the interplay between facets of rumination and laboratory measures of executive control.

Method

Participants

A total of 91 participants (52 women, 39 men, M_{age} = 23.48 years, SD = 4.59, age range = 18–39) completed the tasks and measures described later during 2015 and 2016. The racial and ethnic composition of this sample was 61.54% Caucasian, 7.69% African American, 19.78% Asian, and 10.99% multiracial or other, and 7.69% of participants identified as Hispanic or Latino. Data on socioeconomic status were not collected. Participants with a history of major head trauma, neurologic disorder, cognitive impairment, or a physical health problem indicated on the Physical Activity Readiness Questionnaire (Adams, 1999; Thomas, Reading, & Shephard, 1992) were excluded to avoid potential confounds in performance on cognitive tasks and for participant safety. The Institutional Review Board approved the study protocol, and participants provided informed consent prior to initiation of any study procedure. Participants were tested individually and in the same quiet laboratory room. At the start of each visit, participants performed one of three randomly assigned activities: resting, stretching, or moderate aerobic cycling for 25 min. For the analyses reported here, we used the data from the control (resting) visit of the larger study (Bernstein & McNally, 2017).

Procedure and materials

Participants completed computerized tasks to assess basic working memory, inhibitory control, and task-shifting ability. They then underwent a two-part stressor, sat alone for 5 min, and concluded with questionnaires assessing rumination during that delay period. Cognitive tasks were administered through OpenSesame, an open-source graphical experimental platform (Mathôt, Schreij, & Theeuwes, 2012), on a 16-inch × 9-inch Dell monitor with a resolution of 1366 × 768 pixels and a refresh rate of 60 Hz. These activities required approximately 20 to 25 min to complete. Stimuli included neutral and negative words drawn from the Affective Norms for English Words list (Bradley, Lang, & Cuthbert, 1999), each of which had a valence rating on a 9-point scale. Words in the two groups significantly differed in mean valence ratings but did not differ in average length. Negative words were used to match the valence of the later stressor task and to measure executive control over valenced stimuli. In every task, participants were instructed to move as quickly as possible through the trials, while still being accurate.

N-back. Participants first completed an *n*-back task of working memory capacity, which included one practice block and two experimental blocks of 20 trials each. Participants were shown words one at time for 1,000 ms and instructed to click one button if the word on the screen was identical to one shown *n* (i.e., 2 or 3) trials before, and to click a different button if it was not. A fixation cross appeared between stimuli for between 1 and 5 s. The final score is the percentage of correct responses.

Emotional Flanker Task. Participants then completed the Emotional Flanker Task with Verbal Stimuli as a measure of inhibitory control. They began with two practice blocks of six items each. The first block included targets alone, and the second block included targets with flankers. During experimental blocks, sets of three words appear on screen simultaneously in a single column (minimum 500 ms, maximum 2,000 ms; 500 ms fixation cross before each set). Participants were instructed to identify the valence (negative/neutral) of the middle word (target). In congruent trials, the two identical flanker words and target word were the same valence, whereas in incongruent trials, the flanker words were different than the target word. A total of 28 target words (14 neutral, 14 negative) were presented twice, once with congruent and once with incongruent flankers, to yield a total of 56 trials. All trials were shown to participants in a randomized order. Performance was calculated from median (to avoid outliers) reaction time contrasts between trial types. Scoring was based on a combination of accuracy and reaction time. Reaction time contrasts were computed only for accurate trials. Conflict costs are reported for reaction time (e.g., difference in reaction times on congruent and incongruent trials). Higher congruence contrasts reflect reduced inhibitory ability.

Internal Shift Task. In the Internal Shift Task (IST; Beckwé et al., 2014), participants completed two versions of a test that reflects task-shifting abilities. In one version, participants kept a mental count of the respective number of negative words and neutral words they saw on the screen. During the other version, participants kept a mental count of whether words were nouns or adjectives. The same stimuli were used in both versions, and the order of the versions was counterbalanced across participants with a break in between. In each version, participants completed two practice blocks and nine experimental blocks. In one block, following a 500 ms fixation cross, 10 to 15 words would appear one at a time in a random order (exact number varied across blocks to ensure that individuals could not infer the number of words in the categories by means of subtraction). Participants were instructed to manually advance to the next word by pressing a designated key when they had mentally categorized the word and updated their count appropriately. At the end of each block, participants reported their counts. The reaction time for each word was recorded and coded. A switch sequence was a button press when the participant switched from one word category to the other (e.g., "angry" to "garden"). A nonswitch sequence was a button press when the participant saw same category twice in a row (e.g., "angry" to "anxious"). Switch costs can be calculated by subtracting median reaction times (to avoid outliers) of nonswitch sequences from switch sequences (Garavan, 1998; Monsell, 1996). Higher switch costs reflect reduced executive control, or more difficulty moving between categories compared to within categories.

Stressor. Participants then underwent a two-part stressor. The first part was embedded at the end of the cognitive tasks. Participants tried to solve as many verbal puzzles (e.g., anagrams, word completions) as possible. Participants were allowed a limited time per item and 30% of puzzles were not solvable, thereby ensuring the stressfulness of the task. Participants then completed a serial subtraction task for 2 min in front of the experimenter who indicated when a participant had made an error, but provided no other feedback. As intended with a stress induction, participants reported a significant decline in self-reported affect pre- to post-stressor, $t(90) = 5.08$, $p < .001$, $d_z = .53$. After the stressor task, participants sat alone quietly for 5 min. This delay was meant to enable, without compelling, rumination about the stressful experience. As there was no baseline assessment of state rumination, we assumed that reported rumination was, at least in part, stress-induced.

State rumination. Participants then answered a series of questions about their emotional response to the stressor. Five questions assessed negative perseverative thinking during the previous 5 min, based on those of LeMoult, Arditte, D'Avanzato, and Joormann (2013). Participants indicated how much they had been thinking about their performance ("perseveration"), how negative their thoughts were ("negativity"), how much they had been criticizing themselves ("self-criticism"), how much they thought about their negative emotional experience ("brooding"), and to what extent they replayed parts of what happened in their mind ("replaying"). These items demonstrated good internal consistency ($\alpha = .91$).

Network estimation and visualization

We used the R package qgraph to compute and visualize the networks (Epskamp, Cramer, Waldorp, Schmittmann, & Borsboom, 2012). In each network, nodes are positioned to visually represent the relative strength of their connections. Node placement was determined by Fruchterman and Reingold's (1991) algorithm; nodes that are depicted closer together are more strongly connected, and nodes that are nearer to the center of the graph have the strongest connections to other nodes. We computed three complementary types of networks. As 7 participants were missing at least one data point, rows with missing values were omitted on a pairwise basis when we computed correlations.

We used a graphical Gaussian model (GGM) to estimate the first network. In this network, edges represent conditional independence relationships between nodes when controlling for the effects of all other nodes (Epskamp & Fried, 2016). It is common to regularize GGMs via the graphical LASSO (Least Absolute Shrinkage and Selection Operator), which serves two primary functions (Friedman, Hastie, & Tibshirani, 2011). First, it computes regularized partial correlations between pairs of nodes, thereby eliminating spurious associations (edges) attributable to the influence of other nodes in the network. Second, it shrinks trivially small associations to zero, thereby removing potentially "false positive" edges from the graph and producing a sparse graph comprising only the strongest edges. We used the R package qgraph (Epskamp et al., 2012) that automatically implements the graphical LASSO regularization in combination with extended Bayesian information criterion (EBIC) model selection (Foygel & Drton, 2011). In this approach, 100 different network models are estimated with different degrees of sparsity. Then, the model with the lowest EBIC value is selected, given a certain value of the hyperparameter gamma (γ); this balances including false-positive edges and removing true edges. The hyperparameter γ is usually set between zero and 0.5 (Epskamp & Fried, 2016). As the value of γ nears 0.5, the EBIC will favor a simpler model that contains fewer edges. As the value of γ nears zero, the EBIC will favor a model with a greater number of edges. Following previous studies, we opted to set γ to 0.5 to be confident that our edges are genuine (Epskamp & Fried, 2016). Green lines represent positive partial correlations, whereas red lines represent negative partial correlations. A thicker edge denotes a larger association between two nodes.

To quantify the importance of each node in the graphical LASSO network, we computed centrality indices (Boccaletti, Latora, Moreno, Chavez, & Hwang, 2006; Freeman, 1978). Centrality indices reflect how connected and thus potentially clinically relevant a node is in a network. The *betweenness* centrality is the number of times that a given node lies on the shortest path length between any pair of other nodes. *Closeness* centrality captures the average distance of a node from all other nodes in the network, and is computed from the inverse of the weighted sum of shortest path lengths connecting a given node to all the other nodes in the network. Node *strength* is the sum of the edge weights attached to that node. Each index was calculated with the R package qgraph (Epskamp et al., 2012). For each index, higher values reflect greater centrality, and hence more importance in the network. We created a plot that depict the normalized (*z*-scored) centrality values.

We then computed a relative importance network (Heeren & McNally, 2016; McNally et al., 2015; Robinaugh et al., 2014). This model considers the contribution each predictor makes to R^2 after controlling for multicollinearity, thereby assigning a relative importance metric (*lmg*) between 0 and 1 to each edge (Grömping, 2006; Johnson & LeBreton, 2004). Edges in this network are weighted and also represent predictive directionality with arrows. We used the R package relaimpo (Grömping, 2006). Centrality indices were also computed for the relative importance network. The strength parameter here can be broken up into *in-strength* and *out-strength*. *In-strength* designates the sum of the directed edge weights originating from other nodes and ending at a given node. This quantifies how much influence other nodes in the network have on that node. *Out-strength*, on the other hand, is the sum of the directed edge weights originating from a given node and ending at other nodes. This captures the extent to which that node exerts predictive influence on other nodes. Again, higher values equate to greater centrality.

Finally, we computed a directed acyclic graph (DAG) to estimate a directed, potentially causal structure of the system (Pearl, Glymour, & Jewell, 2016). We used a Bayesian hill-climbing algorithm implemented via the R package bnlearn (Scutari, 2010). The structure of the network is estimated through the bootstrap function, which adds, removes, and reverses the direction of edges to ultimately optimize the goodness-of-fit target score, or the Bayesian information criterion (BIC). This involves an iterative process of randomly restarting this calculation with different possible edges connecting symptom pairs and perturbing the system; ultimately, it determines which edges should remain in the network. To ensure the stability of the DAG, we bootstrapped 1,000 samples and averaged across the resulting networks to produce a final network structure (McNally, Heeren, & Robinaugh, 2016; McNally, Mair, Mugno, & Riemann, in press). This involved two steps. First, we determined how frequently a given edge appeared in the 1,000 networks. We then used the optimal cut point method of Scutari and Nagarajan (2013) for retaining edges, which yields networks having both high sensitivity and high specificity. Second, we determined the direction of each surviving edge. If a given edge pointed from node X to node Y in at least 51% of the bootstrapped networks, then this direction was represented in the final network. We then visualized the averaged network in two ways. In the first, edge weights (i.e., thickness) would represent relative BIC values. Higher values and therefore thicker edges indicate greater importance to the network structure. In other words, removing a thick edge from the network would be more damaging to the model fit than removing a thin edge. In the second visualization, edge weights represent directional probabilities. Higher values and therefore thicker edges indicate greater likelihood that the edge points in the direction depicted. Thus, a thick edge pointing from node X to node Y appeared in a larger proportion of bootstrapped networks than a thin edge pointing from node Y to node Z. The DAG model estimates importance and direction in different ways than the graphical LASSO and relative importance network. Thus, if all three models converge in their principal elements despite their varying assumptions and constraints, we can be more confident in the network structure that emerges in this preliminary work despite the modest sample size.

Results

An initial correlation matrix is presented in Table 1. As expected, large pairwise correlations emerged between the rumination variables and more modest correlations between other variables. Figure 1A depicts the resultant graphical LASSO network, which depicts regularized partial correlations and thereby limits spurious associations. Edge weights reflect strength of association and edge color the direction (green represents positive and red represents negative). Several features are immediately apparent. First, self-criticism emerges as central within the group of rumination nodes and is the most strongly connected to the others (min $r = .24$, max $r = .39$). Perseverating on one's performance during the stressor tasks and having those thoughts be negative are also strongly related ($r = .41$), as well as replaying past events and brooding on one's emotional experience ($r = .30$). A negative association remains between n-back performance and flanker score ($r = -.26$) and brooding ($r = -.16$). We also bootstrapped the confidence regions of the edge weights, providing an estimate about the certainty and precision of edges in the networks (see Fig. S1 in the Supplemental Material available online). These dynamics are further reflected in the centrality indices (Fig. 1B). Self-criticism yielded the greatest betweenness, closeness, and strength centrality values in the network. Likewise, we examined the stability of the centrality metrics by using a person-dropping bootstrap procedure. These analyses indicate that the strongest edges are fairly stable and that strength centrality was the most stable centrality metric (see Figs. S1 and S2 in the Supplemental Material).

Figure 2A depicts the relative importance network. Self-criticism was strongly predictive of perseveration (*lmg* = .30), negativity (*lmg* = .36), brooding (*lmg* = .28), and replaying (*lmg* = .31). A few apparent loops also stand out. For example, although self-criticism strongly predicts negativity, negativity strongly predicts *n*-back performance (*lmg* = .54), which in turn predicts self-criticism (*lmg* = .33). In addition,

Table 1. Correlation Matrix

Variable	1	2	3	4	5	6	7	8
1. Persev	—							
2. Neg	.81**	—						
3. Critic	.78**	.83**	—					
4. Brood	.61**	.66**	.74**	—				
5. Replay	.63**	.64**	.76**	.70**	—			
6. Nback	−.20†	−.13	−.21*	−.30**	−.20†	—		
7. IST	.20†	.25*	.19†	.09	.20†	.06	—	
8. Flanker	.13	.06	.05	.10	−.08	−.33**	.11	—

Note: Pearson correlations presented. Persev = perseveration or "How much have you been thinking about your performance?" Neg = negativity or "How negative have your thoughts been?" Critic = self-criticism or "How much have you criticized yourself about your performance?" Brood = brooding or "How much have you thought about how upset you felt?" Replay = replaying or "To what extent did you replay parts of what happened in your mind?" Nback = proportion of correct responses in the *n*-back task. IST = difference in reaction times on switch and nonswitch trials in the Internal Shift Task (IST). Flanker = difference in reaction times on congruent and incongruent trials in the Flanker task.
†$p < .10$. *$p < .05$. **$p < .005$.

although self-criticism predicts brooding, brooding predicts flanker performance (*lmg* = .57), which then predicts self-criticism (*lmg* = .24). These relationships can also be quantified along four dimensions of centrality (see Fig. 2B for a full plot). Flanker score, negativity, and *n*-back score showed the highest levels of betweenness centrality. Self-criticism and n-back score showed the greatest closeness centrality. Replaying, negativity, IST score, and self-criticism demonstrated the highest in-strength values, indicating that they are the most influenced by all other nodes in the network.

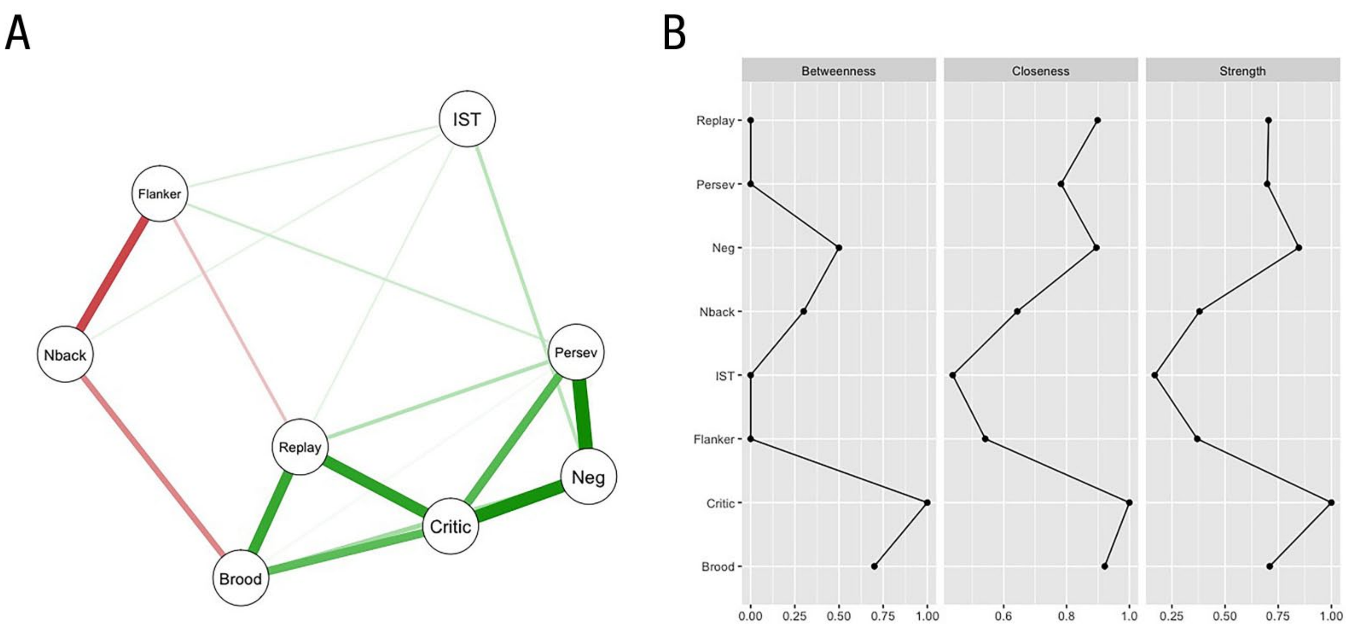

Fig. 1. Graphical LASSO network and centrality plot. (A) Graphical LASSO network in which edge weights reflect relative strength of an association, green denotes a positive association, and red denotes a negative association. (B) Centrality plot. Betweenness = the number of times that a given node lies on the shortest path length between any two other nodes. Closeness = the average distance between a given node and all other nodes, which is calculated from the inverse of the weighted sum of shortest path from a given node to all other nodes. Strength = sum of the edge weights connecting a given node to other nodes. Persev = perseveration or "How much have you been thinking about your performance?" Neg = negativity or "How negative have your thoughts been?" Critic = self-criticism or "How much have you criticized yourself about your performance?" Brood = brooding or "How much have you thought about how upset you felt?" Replay = replaying or "To what extent did you replay parts of what happened in your mind?" Nback = proportion of correct responses in the *n*-back task. Flanker = difference in reaction times on congruent and incongruent trials in the Flanker task. IST = difference in reaction times on switch and nonswitch trials in the Internal Shift Task (IST).

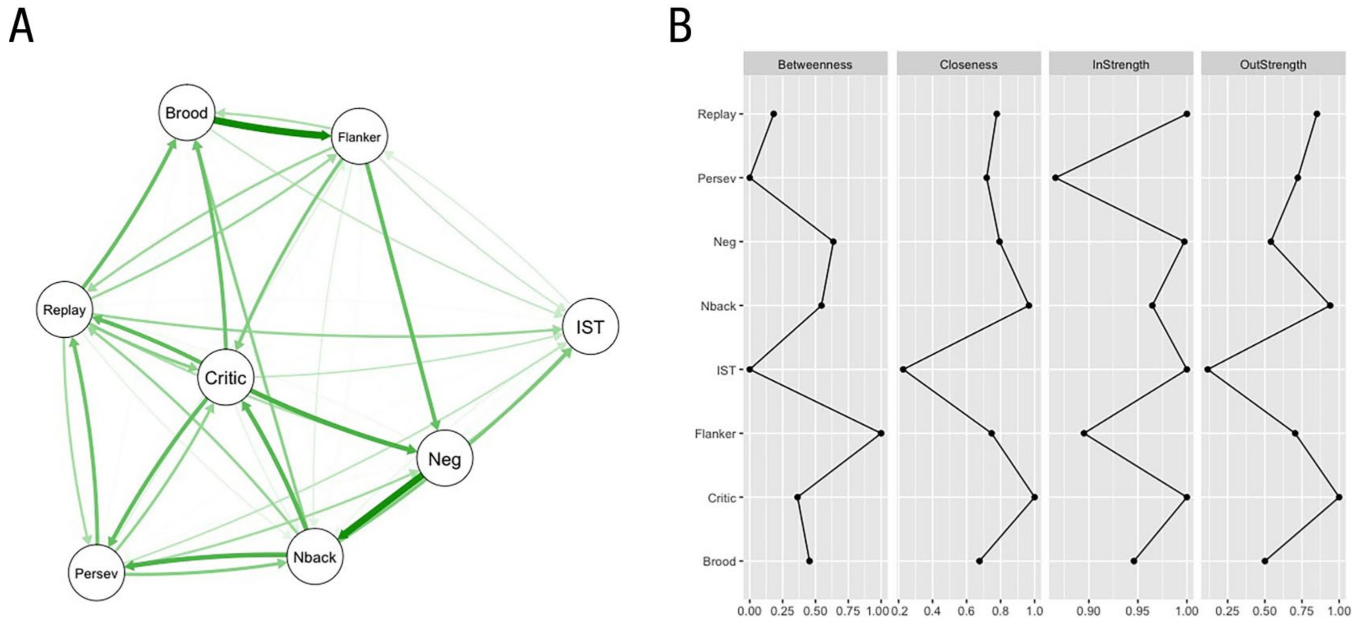

Fig. 2. Relative importance graph and centrality plot. (A) Relative importance network in which edge weights reflect relative contribution the predictor makes to R^2 and arrows denote predictive directionality. (B) Centrality plot. Betweenness = the number of times that a given node lies on the shortest path length between any two other nodes. Closeness = the average distance between a given node and all other nodes, which is calculated from the inverse of the weighted sum of shortest path from a given node to all other nodes. In-strength = sum of the directed edge weights originating from other nodes and ending at a given node. Out-strength = sum of the directed edge weights originating from a given node and ending at other nodes. Persev = perseveration or "How much have you been thinking about your performance?" Neg = negativity or "How negative have your thoughts been?" Critic = self-criticism or "How much have you criticized yourself about your performance?" Brood = brooding or "How much have you thought about how upset you felt?" Replay = replaying or "To what extent did you replay parts of what happened in your mind?" Nback = proportion of correct responses in the *n*-back task. Flanker = difference in reaction times on congruent and incongruent trials in the Flanker task. IST = difference in reaction times on switch and non-switch trials in the Internal Shift Task (IST).

Self-criticism, n-back score, and replaying yielded the greatest out-strength values, indicating that these nodes are the strongest predictors in the network.

Finally, the DAG provides another perspective on the plausible causal relations between nodes. In Figure 3A, edge strength or thickness indicates in what percentage of the networks fitted through the bootstrap procedure that connection appeared. Arrow thickness is drawn proportionately such that the thicker arrows indicate higher connection strength. Structurally, self-criticism emerged at the top of the model and as productive of perseveration, negativity, brooding, and replaying. The strongest connections in the network were self-criticism to negativity, self-criticism to brooding, and self-criticism to replaying. In Figure 3B, edge weights represent directional probabilities. Higher values and therefore thicker arrows indicate greater likelihood that the edge points in the direction depicted. Thus, a thick edge pointing from node X to node Y appeared in a large proportion of bootstrapped networks, whereas a thin edge pointing from node Y to node Z appeared in fewer. The highest value belongs to the connection between self-criticism and replaying (.65), and the lowest value belongs to the connection between self-criticism and negativity (.50). The IST connections did not exceed the significance threshold for inclusion.

Discussion

Computing three types of networks, we examined the interplay between components of a ruminative response style to an in-lab stressor, and their relationships to working memory, inhibitory control, and task shifting. Perhaps the most striking result across analyses was the significant role of self-criticism within the three networks. The extent to which participants criticized themselves about their performance yielded the highest centrality, especially in terms of strength centrality in the graphical LASSO network. It is interesting that in the relative importance network, self-criticism's high out-strength, reflecting its influence on other variables, was largely driven by its connections to the other rumination items (perseveration, negativity, brooding, and replaying). This points to an important potential clinical application of network analyses. In addition to identifying central or core nodes, the relative importance network can also identify which of

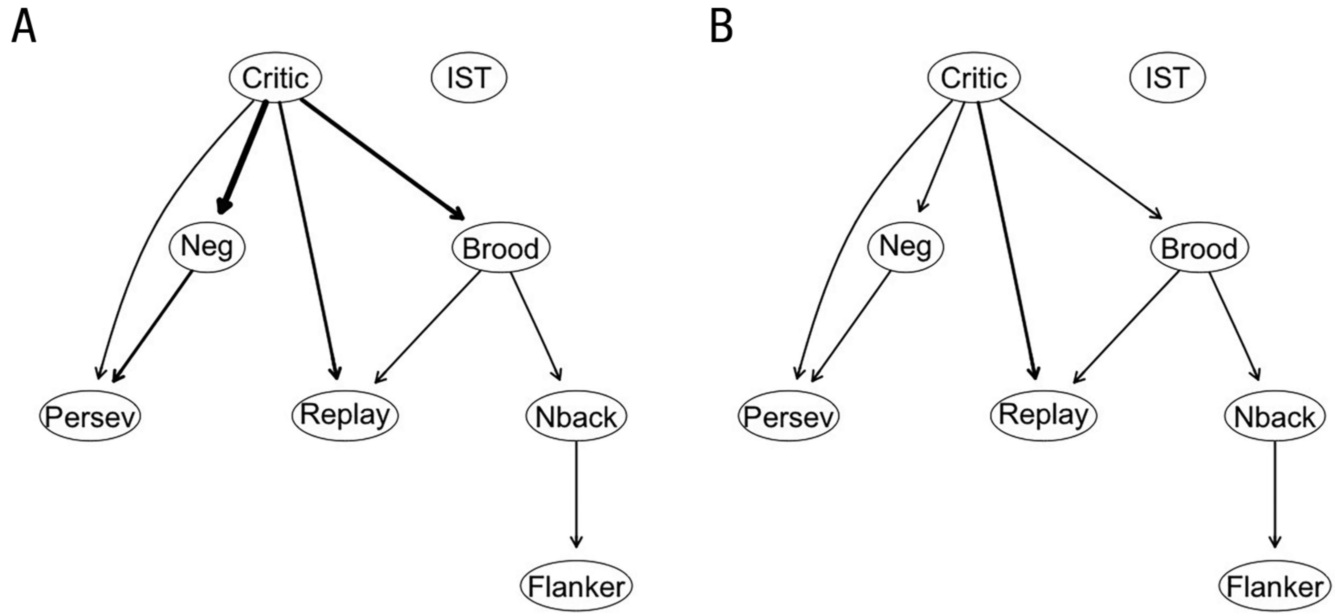

Fig. 3. Directed acyclic graphs (DAGs). (A) Connection strength indicates in what percentage of the networks fitted in the bootstrap procedure that connection appeared. Arrow thickness is drawn proportionately such that the thicker arrows indicate higher connection strength. (B) Direction probability indicates in what percentage of the fitted networks the connection went in that direction. Arrow thickness is drawn proportionately such that the thicker arrows indicate higher direction probability. Persev = perseveration or "How much have you been thinking about your performance?" Neg = negativity or "How negative have your thoughts been?" Critic = self-criticism or "How much have you criticized yourself about your performance?" Brood = brooding or "How much have you thought about how upset you felt?" Replay = replaying or "To what extent did you replay parts of what happened in your mind?" Nback = proportion of correct responses in the *n*-back task. Flanker = difference in reaction times on congruent and incongruent trials in the Flanker task. IST = difference in reaction times on switch and non-switch trials in the Internal Shift Task (IST).

these are central because they predict activation of other nodes. This finding generates a new hypothesis: Given its high out-strength, self-criticism could be a prime target for clinical intervention (McNally, 2016). This was echoed in the DAG, in which self-criticism topped the cascading network, and leads us to theorize that it could be a driving force for each of the other rumination items. If this were confirmed, diminishing self-criticism could deactivate other nodes, precipitating a downstream cascade of beneficial changes throughout the network. Thus, after identifying promising targets for intervention through this type of analysis, we would need to evaluate their malleability, and if such a target is malleable, to experimentally test whether changes to the target initiate the broader, expected changes in the network.

Self-criticism also showed high in-strength in the relative importance network, which was largely driven by connections with the flanker and *n*-back tasks. This finding is suggestive of loops within the network. Bidirectional edges in the relative importance network tended to be asymmetrical, indicating that one of the directions of prediction connecting two nodes was much stronger than the other. Directed edges connecting three or more nodes though emerged and could point to feedback effects. It is important that these purported relationships must be interpreted as conjectural and meriting further investigation, particularly those speculating about the direct effects of rumination components on executive control. In the present study, executive control was always measured first and at rest, and rumination second and as a state measure after the stressor. Repeated measurement of these variables in the future would allow for a more rigorous analysis of the reciprocal connections. Among potential loops to explore, for example, it appears that perseveration and negative thinking predicted lesser working memory capacity and that brooding on one's emotional experience predicted lesser inhibitory control. Lowered working memory capacity and inhibitory control appear to predict exacerbated self-criticism and may thus maintain or amplify these loops. In other words, it is plausible that a self-critical reaction to the stressor would promote repetitive, negative, and analytical thoughts, and that these responses would induce cognitive loads sufficient to limit cognitive reserves (Curci, Lanciano, Soleti, & Rimé, 2013). When capacity becomes limited, it could become harder to ignore or alter self-critical thoughts and thus interrupt the ruminative cycle. In this way, strengthening cognitive flexibility could help individuals to disrupt some of this problematic feedback and potentially dampen the impact of negative perseverations. This speculation is echoed in the DAG, in which repetitive negative thinking is predictive of cognitive impairments. DAGs do not permit loops (i.e., activation flows in a single direction). However, the modest directional probabilities could be indicative of potential "hidden" loops (McNally et al., in press). It is plausible that as criticism activates brooding and subsequently induces executive control deficits, a feedback loop could be drawn connecting the cognitive nodes back to self-criticism. Thus, although the cognitive nodes are at the bottom of the present DAG, appearing as consequences of other nodes, they may serve a feed-forward role in maintaining self-criticism. But, even if these causal interrelationships were confirmed, such an intervention alone may be insufficient. The centrality of self-criticism and strength of interrelationships among the rumination nodes themselves suggest that other edges would likely need disruption as well. In addition, self-loops could be involved and require intervention.

Results should be interpreted within the context of additional limitations. First, the sample size (N = 91) is modest for network analyses. Replications would benefit from a larger group of participants to corroborate the stability of these networks. On the other hand, the network is low-dimensional (i.e., few nodes relative to the number of participants), and complementary analyses of stability and robustness (see Supplemental Materials) indicate that the network is stable, even when a large part of the sample is removed. Second, our data are cross-sectional and therefore suggest, but cannot confirm, causal connections among nodes. Amassing longitudinal and more experimental work would move us closer to a definitive, causal understanding of the network. In addition, participants in this study were not selected for clinical symptoms and thus clinical levels of rumination were underrepresented. Although this is not necessarily a problem for the present study, as these processes are not confined to clinical samples, a critical next step of this work is to replicate findings in a clinical sample, to consider how networks may differ among clinical and nonclinical samples, and to evaluate how the dynamics within a network could change over time or with increasing clinical severity. Impairments in executive control and a ruminative response style are risk factors for emotional disorders and conceptualized as dimensional, rather than taxonic; thus there is value in understanding how the component variables operate at differing levels of severity. Finally, network analyses, like any statistical tool, can only examine variables that are entered into a model. Therefore, though the current graphs are parsimonious, with only five rumination items and three executive control items, there could be important variables left out. With a larger sample size and more thorough battery of questions and behavioral tasks, a larger network could be analyzed.

Despite these limitations, the results are still valuable. This new approach is primarily aimed to be hypothesis-generating. Each network approach has its strengths and limitations, providing different perspectives on plausible connections between rumination and executive control that merit further study. Although other analytic approaches may reproduce similar associations between variables, the network perspective bears unique ontological implications. Here, we are prompted to consider each node as a distinct process and each edge as a potentially causal connection between them, instead of viewing clusters as necessarily reflecting a single, latent cognitive capacity or feature (van der Maas et al., 2006). Our network analyses suggest that components forming the rumination construct were related, but not interchangeable. Accordingly, our study implies that rumination should be conceptualized as multifaceted and experimentally tested as such. Moreover, claims that cognitive deficits *underlie* rumination or that rumination *causes* impairments in executive control seem oversimplified. In reality, these basic cognitive processes may be strongly predictive of—and may activate—specific components constitutive of rumination while also being exacerbated by other component processes. This complex network of bidirectional and multinode loops may provide a more rich and accurate view of the cognitive and psychological underpinnings of rumination. Ultimately, network models like this may help to guide treatment research, as they are increasingly able to represent directional and even causal structures and to highlight nodes that when deactivated might precipitate the greatest clinical changes.

Author Contributions

E. E. Bernstein and R. J. McNally developed the study concept and design. E. E. Bernstein performed testing and data collection. E. E. Bernstein and A. Heeren completed the data analysis and interpretation under the supervision of R. J. McNally. E. E. Bernstein drafted the manuscript, and A. Heeren and R. J. McNally provided critical revisions. All authors approved the final version of the manuscript for submission.

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The authors declared that they had no conflicts of interest with respect to their authorship or the publication of this article.

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Supplemental Material

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