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Research paper

The interplay between cognitive risk and resilience factors in remitted depression: A network analysis

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ABSTRACT

Background: Individuals in remission from depression are at increased risk for developing future depressive episodes. Several cognitive risk- and resilience factors have been suggested to account for this vulnerability. In the current study we explored how risk- and protective factors such as cognitive control, adaptive and maladaptive emotion regulation, residual symptomatology, and resilience relate to one another in a remitted depressed (RMD) sample.

Methods: We examined the relationships between these constructs in a cross-sectional dataset of 69 RMD patients using network analyses in order to obtain a comprehensive, data-driven view on the interplay between these constructs. We subsequently present an association network, a concentration network, and a relative importance network.

Results: In all three networks resilience formed the central hub, connecting perceived cognitive control (i.e., working memory complaints), emotion regulation, and residual symptomatology. The contribution of the behavioral measure for cognitive control in the network was negligible. Moreover, the directed relative importance network indicates bidirectional influences between these constructs, with all indicators of centrality suggesting a key role of resilience in remission from depression.

Limitations: The presented findings are cross-sectional and networks are limited to a fixed set of key constructs in the literature pertaining cognitive vulnerability for depression.

Conclusions: These findings indicate the importance of resilience to successfully cope with stressors following remission from depression. Further in-depth studies will be essential to identify the specific underlying resilience mechanisms that may be key to successful remission from depression.

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1. Introduction

Depression is a highly prevalent, severe mental illness that is related to substantial individual suffering (e.g., Cuijpers et al., 2004; Lima and Fleck, 2007). In terms of disability, estimations suggest that major depressive disorder (MDD) is among the leading causes of burden of diseases worldwide (e.g., Demyttenaere et al., 2004). Current treatment options (psychological, pharmacological, and neurostimulation interventions) are moderately successful in achieving initial symptom reduction but long-term effects are less encouraging, with research showing that recurrence of MDD (i.e., experiencing a depressive episode after having exhibited full and/or partial remission from a previous depressive episode) is high in the general population (35% after 15 years), and even higher in those treated at specialized mental health centers (60% after 5 years and 85% after 15 years; Hardeveld et al., 2010). This has led to the realization that studying individuals remitted from depression (RMD) is crucial in understanding who remains well after initial remission and who is at-risk for new depressive episodes (e.g., De Raedt and Koster, 2010; Marchetti et al., 2012).

Current research has successfully identified a number of interindividual variables that seem to play a key role in risk as well as resilience in RMD. At the level of information-processing, previous depressive episodes have a negative impact on cognitive control processes (Vanderhasselt and De Raedt, 2009), which are crucial for goal-directed behavior. Importantly, cognitive control has been found to play a major role in emotion regulation, the

Abbreviations: ADAPT ER, adaptive emotion regulation strategies; BRIEF-WM, Working Memory scale of the Behavior Rating Inventory of Executive Function; CERQ, Cognitive Emotion Regulation Questionnaire; MALADAPT ER, maladaptive emotion regulation strategies; MDD, major depressive disorder; MINI, Mini-International Neuropsychiatric Interview; OLS, ordinary least squares; PASAT, Paced Auditory Serial Addition Task; Resid Depres, residual depressive symptoms; RDQ, Remission from Depression Questionnaire; RMD, remission from depression / remitted depressed patients; RS, Resilience Scale

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process of influencing which emotions one has, including when and how these emotions are experienced (Gross, 1998). For instance, cognitive control impairments have been associated with maladaptive emotion regulation strategies such as rumination, self-blame, and catastrophizing (e.g., Hoorelbeke et al., accepted for publication; Joormann and Gotlib, 2008; Whitmer and Banich, 2007), known to have detrimental effects on mental well-being (Aldao and Nolen-Hoeksema, 2010; Garnefski and Kraaij, 2006). Moreover, cognitive control moderates the effects of maladaptive emotion regulation on mood in daily life, with for instance low levels of cognitive control predicting a stronger increase in negative affect following rumination (Pe et al., 2013). Furthermore, in the context of remission from depression, impaired cognitive control has shown to predict rumination, linking cognitive control impairments to recurrent depressive symptoms in a RMD sample (Demeyer et al., 2012). Importantly, cognitive control impairments may also disrupt adaptive emotion regulation processes (Cohen et al., 2014; Joormann and D'Avanzato, 2010; Joormann and Vanderlind, 2014), which are key to resilience and mental well-being (Gross and John, 2003; Hu et al., 2014; Kalisch et al., 2015). Despite increasing research linking RMD to information-processing factors that are involved in emotion regulation strategies, which subsequently influence resilience or alternatively increase depressive symptoms, there are limitations to the current available research. Most importantly, research has often tested simple, unidirectional relationships between these constructs, which ignores the notion that many of the constructs involved can have reciprocal relationships. For instance, there is empirical evidence showing that levels of cognitive control can influence ruminative tendencies (Cohen et al., 2015) as well as evidence that levels of rumination influence cognitive control (Philippot and Brutoux, 2008). Currently, there is very little work integrating risk- and protective factors in RMD.

In order to obtain a more comprehensive view on the interaction between information-processing and emotion regulation strategies in relation to risk and resilience we conducted a network analysis on these constructs in a RMD sample. Based on graph theory, network modeling represents an important innovation to examine the interplay between different constructs in a largely data-driven manner (Borsboom and Cramer, 2013). Within a network model each variable is represented by a node, while the edge between two nodes shows the relationship between them. Typically, studies have relied on this type of analysis to explore how observable behaviors (i.e., symptoms) relate to one another, aiming to overcome the use of unobservable, latent variables (i.e., depression) (e.g., Borsboom et al., 2011; Cramer et al., 2010; De Schryver et al., 2015; Fried, 2015; McNally et al., 2014). However, network modeling can also be employed to decipher the interrelationship between constructs (i.e., structural network analysis) and, in turn, explore the nomological universe in which the different constructs are placed (Costantini et al., 2015b). To do so, relying on weighted and directed networks represents a great advancement, in that it is possible to obtain a fine-grained representation of the centrality (i.e., the extent to which a construct plays a central role in the network) of all the constructs considered and the possible directionality among them (Borsboom and Cramer, 2013; Costantini et al., 2015a).

In order to gain further insight in the mechanisms underlying remission from depression, we propose the use of this latter approach to examine how key constructs in the context of vulnerability for depression and resilience are related in a RMD sample. For this purpose, based on the literature, we selected four key risk factors (cognitive control impairments, working memory complaints, maladaptive emotion regulation, and residual depressive symptomatology) and two protective factors (adaptive emotion regulation and resilience) for the network analyses: (1) At the level of information-processing we obtained information about cognitive control measured with a well-validated performance based task, the Paced Auditory Serial Addition Task (PASAT; Gronwall, 1977; for a review see Tombaugh, 2006), and (2) an indicator of experienced working memory complaints, the Working Memory scale of the Behavior Rating Inventory of Executive Function (BRIEF-WM; Roth et al., 2013). Previous studies with MDD and other clinical samples indicate that self-reported cognitive functioning in daily life and performance on cognitive tasks may capture different aspects of cognitive control, as they are not necessarily associated with each other and may differ in their predictive value for well-being and symptomatology (Chan et al., 2008; Middleton et al., 2006; Mowla et al., 2008; Svendsen et al., 2012). Furthermore, the Cognitive Emotion Regulation Questionnaire (CERQ; Garnefski et al., 2001) was used to assess a broad range of emotion regulation strategies, which allows calculation of compound scores for (3) adaptive and (4) maladaptive emotion regulation processes. (5) The Remission from Depression Questionnaire (RDQ; Zimmerman et al., 2013) was used as an indicator of residual symptoms following (partial) remission from depression given that previous work indicates that residual symptomatology increases the chance of recurrence of depressive episodes (e.g., Solomon et al., 2000). This questionnaire provides a more nuanced assessment of remission than standard measures of depressive symptomatology as it combines assessment of residual depressive- and related symptoms with indicators of functioning such as sense of well-being. (6) Finally, given the importance of resilience to mental health (e.g., Griffiths et al., 2015), resilience was selected as a protective factor for the network analysis. Resilience – connoting "inner strength, competence, optimism, flexibility, and the ability to cope effectively when faced with adversity" (Wagnild, 2009, p. 105) – was assessed using the Resilience Scale (RS; Portzky et al., 2010; Wagnild and Young, 1993). This self-report measure is based on five characteristics assumed to be central to resilience: perseverance, equanimity, meaningfulness, being self-reliant, and the realization that each person is unique (for a review, see Wagnild, 2009).

In line with previous literature (Costantini et al., 2015a; McNally et al., 2014), we relied on different types of network models to obtain a more comprehensive representation of factors related to remission from depression. First, we examined simple correlational patterns (i.e, association network). Second, the underlying structure of the network was examined by means of a concentration network, where the correlations between every pair of variables were controlled for all the other variables of the network. Third, we examined a relative importance network to index predictive directionality within cross-sectional data, although this does not necessarily imply causality (McNally et al., 2014). Based on the literature we expected to find a model depicting reciprocal relationships between cognitive control and emotion regulation. Maladaptive emotion regulation strategies would link cognitive control impairments to increased residual symptomatology, whereas adaptive emotion regulation strategies would link cognitive control to resilience, which should show the opposite relation to residual symptomatology.

2. Methods

2.1. Participants

The sample consisted of 69 RMD patients that were recruited for a cognitive control training study registered as NCT02407652 at ClinicalTrials.Gov. The protocol of this training study was published online (Hoorelbeke et al., 2015). For our network analyses, baseline measures were used from the 68 participants of the

Table 1
Sample characteristics.

	RMD patients ($n=69$)
Mean age (SD)	47.13 (11.46)
Gender (male:female)	23:46
Mean age of onset (SD)	27.36 (12.76)
Mean self-reported amount of depressive episodes (SD)	3.28 (4.23)
Mean self-reported episode length in months (SD)	6.96 (4.64)
Mean time since previous episode in years (SD)	6.12 (6.34)
% reporting recurrent MDD	74%
% currently on antidepressant medication	42%
% reporting maintenance contact with psychologist	9%
% reporting maintenance contact with psychiatrist	13%

training study plus one additional participant that was only willing to contribute to the correlational study. To be eligible for participation in this study, participants should be aged 23–65, show a history of MDD and report being in (partial) remission for at least six months. A history of comorbid disorders was allowed, with the exception of severe substance abuse, psychosis and bipolar disorder. However, participants should not meet criteria for a clinical diagnosis at time of assessment nor report neurological impairments. Use of antidepressant medication and psychotherapeutic maintenance treatment was allowed. Sample characteristics are reported in Table 1. Participants received a financial reimbursement for their participation to the training study. This study was approved by the local ethical committee of Ghent University.

2.2. Apparatus and material

The cognitive task was run using the INQUISIT Millisecond software package on a Dell Dimension 4600 computer with a 72 Hz, 17-inch color monitor. Statistical analyses were performed in R version 3.2.2.

2.3. Screening instruments

Eligibility for participation to the study was screened using a two-phased, in time separated, protocol. First, interested candidates were contacted by telephone to give practical information concerning the study and to screen for eligibility using a selection of relevant questions of the screening version of the Mini-International Neuropsychiatric Interview (MINI Screening version; Sheehan et al., 1989; Van Vliet and De Beurs, 2007). Next, participants' eligibility was re-assessed by a clinical psychologist using the MINI Screening version and relevant modules of the corresponding structured clinical interview (MINI structured interview; Sheehan et al., 1989) at the Faculty of Psychology and Educational Science of Ghent University. By default, all participants completed the module on (current and lifetime) depressive episodes. Based on the individual responses to the MINI Screening version during the second phase, relevant modules of the MINI structured interview were added to rule out the presence of other current diagnoses.

2.4. Questionnaires

The working memory subscale of the Behavior Rating Inventory of Executive Function Adult version (BRIEF-WM; Roth et al., 2013; Scholte and Noens, 2011) assesses working memory complaints, which was used as an indicator of *perceived cognitive control* (range: 8–24; e.g., "I find it difficult to concentrate on tasks (e.g., while doing chores, reading, work)"). Adaptive and maladaptive emotion regulation was assessed using the Cognitive Emotion Regulation Questionnaire (CERQ; Garnefski et al., 2001). In line with Vanderhasselt et al. (2014) we calculated two sum scores: (1) *adaptive emotion regulation* (range: 20–100; e.g., "I think I can learn something from the situation") was computed using the subscales acceptance, refocus on planning, positive refocus, positive reappraisal, and putting into perspective, whereas (2) *maladaptive emotion regulation* (range: 16–80; e.g., "I feel that I am the one to blame for it") was computed using the subscales self-blame, blaming others, rumination, and catastrophizing. Remission was assessed using the Remission of Depression Questionnaire (RDQ, range: 0–82; e.g., "I felt sad or depressed"; Peeters et al., 2013; Zimmerman et al., 2013), which combines indicators of depressive residual symptoms and related symptoms with indicators of functioning (e.g., well-being). Provided that a higher score on this scale is indicative for more pathological processes, for convenience we will consistently refer to it as *residual depressive symptoms*. *Resilience* was assessed using the Resilience Scale (RS, range: 25–100, e.g., "I am determined", "I can usually find something to laugh about"; Portzky et al., 2010; Wagnild and Young, 1993). The self-report measures for working memory complaints, adaptive and maladaptive emotion regulation, resilience and residual depressive symptoms demonstrated proper reliability in our sample, with a Cronbach's Alpha of .88, .92, .87, .91, and .96 respectively. For all questionnaires but the RS and the CERQ compound measure for adaptive emotion regulation, a higher score reflects the presence of more symptoms or maladaptive processes. As this study is part of a more extensive training study, other questionnaires were assessed which will not be discussed here.

2.5. Cognitive control task

Participants performed three blocks of the non-adaptive Paced Auditory Serial Addition task (PASAT; Gronwall, 1977; for a review, see Tombaugh, 2006) containing 60 trials each. During this task participants listened to a series of digits and had to continuously respond to the sum of the last two digits. Task difficulty increased over the three blocks, using inter stimulus intervals of 3000, 2000 and 1500 ms respectively. The total accuracy score served as a *behavioral indicator of cognitive control*. The split-half reliability of this measure (Spearman-Brown corrected) was .95.

2.6. Procedure

The data were collected during the baseline assessment of a cognitive control training study (see Hoorelbeke et al. (2015) for the full protocol). Participants were recruited drawing on an existing data-base of potentially interested candidates ($n=23$), and using flyers that were placed in 106 drugstores in Ghent area, advertisements in popular magazines and national newspapers. After a telephone screening, potential participants were invited for a second screening, including a more extensive structured clinical interview at the Faculty of Psychology and Educational Sciences of Ghent University. Candidates that met the inclusion criteria then gave informed consent, completed the questionnaires and completed the cognitive task. Debriefing and reimbursement took place at the end of participation to the training study.

2.7. Data analysis

After inspecting the descriptive statistics and zero-order correlations among the variables of interest, three types of networks were computed using the R package *qgraph* (Epskamp et al., 2012). Importantly, each network was displayed in accordance to the Fruchterman and Reingold's (1991) algorithm, whereby strongly related nodes are positioned in the middle of the figure, while poorly correlated ones appear in the periphery. We proceeded as

follows.

We first computed the association network with all the variables of interest being included (the nodes) and the edges representing zero-order correlations (Borsboom and Cramer, 2013). In both the association and concentration network, node size reflects the (relative) importance of a variable in the network in terms of centrality. The thickness and color saturation of the edge signify the magnitude of the correlation, while green edges represent positive correlations and red edges represent negative correlations. From this, it follows that the association network is weighted and undirected. Although informative, the association network only approximates the underlying structure of the network, in that the association between two nodes could be due to shared connections to a third node, rather than representing a real influence between the two nodes (Borsboom and Cramer, 2013).

To address this concern, we built a concentration network (Cox and Wermuth, 1993), where the association between every pair of nodes was controlled for the influence of all the other variables. By doing so, it is relatively probable that the remaining (partial) correlations reflect relations that are likely/common in the population on which the network analysis has been done (Borsboom and Cramer, 2013). Moreover, sparse networks (i.e., networks characterized by less edges than the maximum possible) are to be preferred, in that they are simpler to interpret and more stable (Costantini et al., 2015a). However, in weighted networks, two nodes are not connected if and only if the weight of the connection is zero, whereas ordinary least squares (OLS) approach virtually never reports estimations exactly amounting to zero. In order to overcome this problem, the adaptive LASSO method represents a widely accepted procedure (Costantini et al., 2015a). Adaptive LASSO method is a technique that assigns different penalties to different weights and causes small weights to automatically shrink to zero (Zou, 2006), thereby producing a more parsimonious and sparse model. Importantly, adaptive LASSO outperforms other types of estimation in terms of reduced false positives (Kraemer et al., 2009). Adaptive LASSO partial correlations were computed using the R package *parcor* (Kraemer et al., 2009).

Then, we computed a relative importance network, including the variables that emerged as linked in the adaptive LASSO concentration network. In a relative importance network, each edge represents the relative importance weights of node X in predicting node Y, after controlling for all the other nodes (McNally et al., 2014; Robinaugh et al., 2014). In other words, relative importance weight quantifies the amount of explained variance attributable to each predictor, after controlling for multicollinearity (Johnson, 2000), and it ranges between 0 and 1. This procedure was repeated for every node of the network. The resulting network was weighted and, importantly, directed. Thus, not only does relative importance analysis provide specific weights, but also directionality. However, it is of crucial importance to note that directionality of these weights represents directionality of the predictions and does not imply causality. To compute non-normalized relative importance weights, we used the *lmg* metric as provided by the R package *relaimpo* (Groemping, 2006).

Furthermore, in order to qualify the importance of each node in the relative importance network, we calculated four indexes of centrality: *betweenness*, *closeness*, *instrength*, and *outstrength* (Borsboom and Cramer, 2013; Costantini et al., 2015a). Betweenness refers to the number of times that a specific node lies on the shortest path between two other nodes, whereas closeness is computed as the inverse of the sum of the total length of all the shortest path lengths between a specific node and the rest of the network. Instrength is calculated as the sum of all the directed weights accounting for a specific node and being originated by all the other nodes of the network, while outstrength summarizes the total influence that a certain node exerts on all the other nodes. In terms of interpretation, betweenness indexes how efficiently a node connects to other nodes, while closeness represents the average distance from a specific node to all other nodes. Additionally, outstrength quantifies the extent to which a certain variable is expected to influence connected variables in the network rather than being influenced by these other variables (instrength). In the relative importance network, we choose to vary the node size as a function of outstrength. Together, these centrality indexes point out the variable(*s*) whose manipulation is most likely to influence the rest of the network, and, by representing different aspects of node centrality, higher levels of each index reflect higher node centrality. All the centrality indexes were computed by means of the R package *qgraph* (Epskamp et al., 2012).

3. Results

Descriptive statistics of the variables of interest are reported in Table 2 (added as supplemental material). The association network (Fig. 1) highlights that all the nodes were related to one another, with resilience, residual depressive symptoms (RDQ), and self-reported working memory complaints (BRIEF-WM) showing the strongest connectivity and being positioned at the center of the network. In general, resilience showed the strongest correlations compared to RDQ and BRIEF-WM, therefore suggesting a possible primary role in the network. Surprisingly, PASAT accuracy index was unrelated to BRIEF-WM (r=.06), maladaptive emotion regulation strategies (r=.03), and RDQ (r=.09), and weakly and negatively correlated to resilience (r=−.21) and adaptive emotion regulation strategies (r=−.26).

In order to shed light on which nodes exert real influences rather than spurious ones (Borsboom and Cramer, 2013; Costantini et al., 2015a), the adaptive LASSO concentration network (Fig. 2) was built to refine the model suggested by the association network. Interestingly, resilience emerged to be the main hub of the network, in that it connected all the variables, which were not connected otherwise (Table 3; supplemental material). When estimated with adaptive LASSO, resilience appeared to be strongly related to BRIEF-WM (pr=−.52) and RDQ (pr=−.41), and weakly to moderately related to maladaptive and adaptive emotion regulation strategies (pr=−.21, and pr=.26, respectively). Moreover, the PASAT accuracy index emerged to be unrelated to the rest of the nodes (i.e., sparse network), therefore suggesting that PASAT task performance does not play a substantial role in accounting for

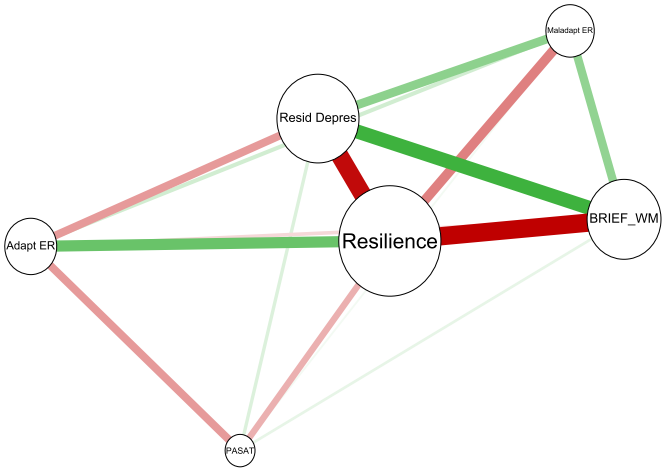


Fig. 1. Association network.

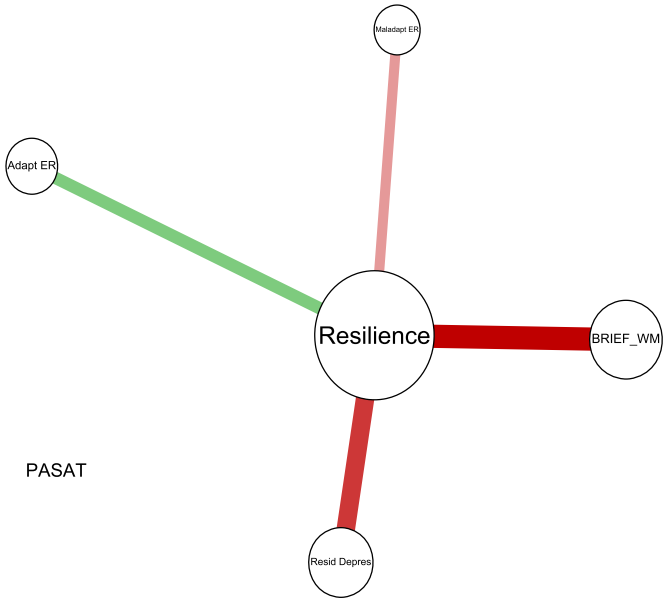


Fig. 2. Adaptive LASSO concentration network.

resilience, residual depressive symptoms, and (mal)adaptive emotion regulation strategies in RMD.

Finally, the directed relative importance network (Fig. 3) was constructed including all the variables that emerged as related to other nodes of the network in the concentration network. Thus, PASAT accuracy was excluded. Importantly, the directed relative importance network highlighted that resilience was the main hub of the network, in that it exerted a major influence on all the other nodes, as confirmed by centrality analysis (Fig. 4; Table 4, added as supplemental material). In fact, resilience showed the highest levels of betweenness, closeness, and strength. In keeping with this, unlike all the other nodes, resilience had higher outstrength values (0.77) than instrength values (0.64). In other words, although the other nodes accounted for 64% of the resilience variance, resilience – in turn – could explain about 77% variance of the other variables, across different regression models. This seems to imply that, although highly related to all the other constructs, resilience exerted a larger influence on the rest of the network than vice versa.[1]

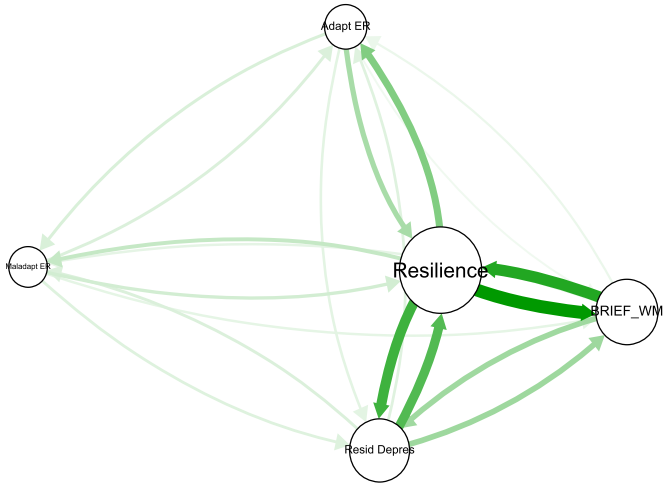


Fig. 3. Directed relative importance network. Note: In contrast to the association network and adaptive LASSO concentration network where green represents a positive association and red a negative association, no such distinction can be made in relative importance networks. That is, here all edges represent amount of variance, therefore no negative values (i.e., red edges) are allowed. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

4. Discussion

Provided that individuals who remit from depression have a larger chance to develop new depressive episodes, we aimed to obtain a comprehensive view on how risk- and protective factors relate in this population. Based on previous work we identified cognitive control, adaptive and maladaptive emotion regulation as well as resilience and residual depressive symptoms as key constructs. The relationships between these constructs were examined using network analyses in order to obtain a comprehensive, data-driven view on the interplay between these constructs. We will below discuss the main results in relation to the different type of network analyses applied in the current study.

The association network revealed that resilience forms a key hub, showing a strong negative association with residual depressive symptomatology and working memory complaints. That is, participants with high resilience scores are likely to report fewer residual depressive symptoms and working memory complaints. Furthermore, resilience showed a moderate positive association with adaptive emotion regulation strategies and a negative association with maladaptive emotion regulation strategies. Moreover, the latter construct showed a moderate positive association with residual depressive symptomatology. Finally, working memory complaints showed a strong association with residual depressive symptoms. All other edges of the association network represented minor associations ($r < .30$).

The adaptive LASSO concentration network confirmed the central role of resilience in the network, in that resilience was related to a number of key variables in RMD such as adaptive and maladaptive emotion regulation, residual depressive symptoms, and self-reported working memory complaints. Moreover, after the correlations between every pair of variables were controlled for all the other variables of the network, the remaining constructs in the network were only indirectly connected to one another via resilience, whereas the direct associations between the other constructs disappeared (e.g., maladaptive emotion regulation and residual symptomatology). The absence of an association between performance-based and self-reported working memory performance is in line with previous literature (e.g., Mowla et al., 2008; Svendsen et al., 2012). However, in contrast to our expectations, the PASAT node had no edges in the adaptive LASSO concentration network, indicating that associations between PASAT task performance and the other constructs in the network were negligible. Importantly, self-reported working memory functioning was strongly associated with resilience in this network, linking experienced cognitive functioning indirectly to emotion regulation and residual depressed symptoms.

Subsequently, the directed relative importance network clearly showed bidirectional influences among the constructs. Interestingly, the indexes indicated that resilience played a central and key role in RMD, in that its influence over the other variables was stronger than the reverse influences of the other variables in the network on resilience. The stability of these findings was

[1] In order to determine stability of these findings (i.e., the central role of resilience), a post-hoc association network, adaptive LASSO concentration network and relative importance network was generated using alternative operationalizations of residual symptomatology (depressive symptomatology, assessed using the Beck Depression Inventory 2nd edition), adaptive- (positive appraisal, assessed using the Cognitive Emotion Regulation Questionnaire) and maladaptive emotion regulation (Brooding, assessed using the Ruminative Response Scale). This provided similar results, demonstrating the central role of resilience in remitted depressed patients. These data are available upon request.

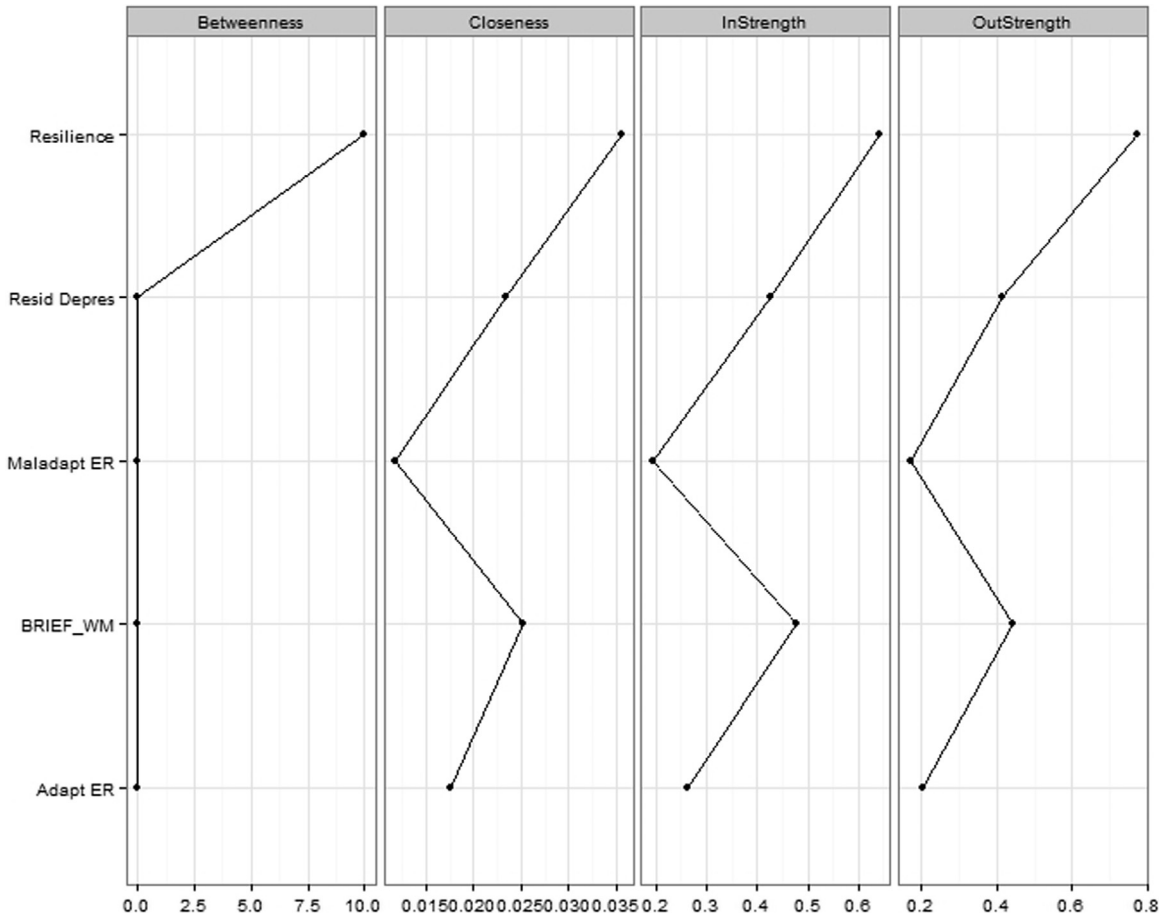


Fig. 4. Indexes of centrality.

confirmed using additional operationalizations for some of the key constructs (e.g., 'brooding' as indicator of maladaptive emotion regulation, 'positive appraisal' as indicator of adaptive emotion regulation, and an alternative measure for 'depressive symptomatology'; available upon request). Provided a dynamic conceptualization of resilience as a protective factor that may be insufficiently represented in remitted depressed patients (Waugh and Koster, 2015), these findings suggest that manipulating resilience may be an efficient way to increase other protective factors (e.g., adaptive emotion regulation), as well as decrease risk factors for recurrent depression (e.g., cognitive dysfunctioning, maladaptive emotion regulation, and residual symptomatology). This is in line with recent views on the importance of resilience in stable remission from depression (Garland et al., 2010; Waugh and Koster, 2015).

Importantly, these findings are not fully in line with the hypothesis that emotion regulation strategies would be important predictors of resilience. Furthermore, in contrast to our prediction, the lack of inclusion of the PASAT in the final model indicates that this specific measure of cognitive control did not significantly contribute to the resilience network, although these findings might be task-specific. Furthermore, the lack of such contribution to the network may be due to the specific operationalization of cognitive control as a behavioral measure whereas all other constructs are assessed using self-report measures. In contrast, self-reported cognitive control (i.e., working memory complaints) contributed to emotion regulation processes and remission, but mostly via the central hub resilience. Several factors may have contributed to this discrepancy between the current findings and our hypothesis based on the literature. First, previous studies have typically used standard analytical techniques to investigate relationships between constructs, testing specific directed models (e.g., De Lissnyder et al., 2012; Demeyer et al., 2012). In contrast, we used a data-driven approach. Because the models are empirically rather than theoretically derived, the solutions might be sample-specific. Second, the behavioral measure for cognitive control relied on neutral stimuli, whereas in previous studies effects were often found using emotional relevant stimuli (e.g., De Lissnyder et al., 2012; Demeyer et al., 2012; Joormann and Gotlib, 2008; Pe et al., 2013). It would be interesting for future studies to include several indicators of cognitive control (e.g., updating, inhibition) over neutral and emotional information to further test how this factor is related to resilience and remission.

At the theoretical level, the current findings are of interest in directing attention to the mechanisms that play a major role in remitted depressed individuals. Especially given that individuals who have recovered from depression still face significant stressors, frequently due to consequences of having experienced a depressive episode (e.g., unemployment, loss of social roles, etc.). These stressors may interact with cognitive and neurobiological vulnerability factors to predict recurrence of depression (e.g., De Raedt and Koster, 2010), stressing the considerable role of resilience to maintain remission. For instance, previous studies have shown that depression is associated with impaired stress- and emotional reactivity (Burke et al., 2005; Bylsma et al., 2008), which may continue during remission (e.g., O'Hara et al., 2014). In line with these findings, Waugh and Koster (2015) argue that stress recovery, positivity or promotion, and flexible application of coping responses – among other intra- or interpersonal factors contributing to resilience – may play an important role in preventing

recurrence of depressive symptoms (but also see Southwick et al., 2005). These factors match the operationalization of resilience in this study, in line with Wagnild (2009), referring to concepts such as optimism, effectively coping with adversity, and flexibility.

In this context, it is noteworthy that one influential framework for resilience, the broaden-and-build theory, proposes that positive emotions may play an important protective role, as they broaden cognitive and behavioral processes (Fredrickson, 2001; Fredrickson et al., 2003). This may foster adaptive emotion regulation processes and prevent psychopathological processes from occurring. Given the bidirectional nature of these processes, this may then further increase resilience. Indeed, research indicates that levels of positive affect moderate the detrimental effects of stressful events on mood in daily life and may even buffer negative effects of genetic vulnerability for depression (e.g., Wichers et al., 2007). This resilience model is in line with our network models, showing stronger outstrength than relative instrength values for our central hub, resilience, which connected perceived working memory functioning (i.e., working memory complaints) and adaptive emotion regulation with residual depressive symptoms in our RMD sample. This indicates the importance of directly targeting resilience next to focusing on specific vulnerabilities. At the clinical level, it is interesting to note that the central role of resilience also parallels an increased interest in treatments that focus on resilience (Garland et al., 2010; Geschwind et al., 2011; Keng et al., 2011; Waugh and Koster, 2015). Indeed, our findings indicate that patients may benefit from interventions targeting resilience mechanisms. Among more common cognitive behavioral interventions (e.g., Songprakun and McCann, 2012; Steinhardt and Dolbier, 2008), Waugh and Koster (2015) argue that patients may benefit from well-being training, stress inoculation training, meditation and mindfulness-based cognitive therapy (for a meta-analytical review on the efficacy of resilience training programs, see Leppin et al., 2014).

To our knowledge this study is the first to provide a data-driven test of how key constructs such as (perceived) cognitive control, emotion regulation processes, and resilience relate to remission from depression in a RMD population. However, several limitations should be taken into account. A first and most important limitation is the cross-sectional nature of the data. Although the analytical techniques deployed here give an indication of direction of associations, this does not allow drawing conclusions concerning the causal nature of these relationships. Related to this, our network models visualize how key constructs such as cognitive control, (mal)adaptive emotion regulation, resilience and residual depressive symptoms relate at one certain moment in time following (partial) recovery from depression. However, the observed relations may behave in a different manner when observed over multiple time points. Future studies should take this into account, for instance using experience sampling and an experimental approach (Hoorelbeke et al., accepted for publication). Third, the selected nodes for the network were theory-driven and limited to a fixed set of key constructs in the literature pertaining cognitive vulnerability for depression. It is possible that the network is currently overlooking additional nodes which may link factors such as cognitive control to resilience in RMD. Fourth, given that we only included one behavioral measure, the lack of contribution of the behavioral measure for cognitive control to the network – while self-reported working memory functioning was included in the network – is not fully conclusive given that effects may be task-specific. For this purpose, future studies exploring how cognitive control relates to other proposed risk- and protective factors in remitted depressed patients should deploy multiple measures of cognitive control. Furthermore, repeated studies are necessary to identify rather stable connections, focusing on the generalization both within and between different populations (De Schryver et al., 2015). Fifth, we relied on a broad indicator of resilience. Given its central role, future in-depth prospective studies are essential to further elucidate the specific resilience facet(s) that may be key to successful remission from depression.

4.1. Summary

The current study explored how several cognitive processes relate to remission of depression in a RMD sample. The relationships between cognitive control, experienced cognitive functioning, (mal)adaptive emotion regulation, resilience, and residual depressive symptomatology were examined cross-sectionally using network analyses in order to obtain a comprehensive, data-driven view on the interplay between these constructs. Over a series of network models, resilience was found to be a central hub consistently linking working memory complaints and emotion regulation processes to residual symptoms. However, performance on the Paced Auditory Serial Addition task, a behavioral measure of cognitive control, was unrelated to the other variables. These findings indicate the importance of resilience to successfully cope with stressors following remission from depression.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.jad.2016.02.001.

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