The Centrality of Sadness: Networks of Depression, Grief, and Trauma Symptoms in a Spously Bereaved Sample

Matteo Malgaroli

Submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy under the Executive Committee of the Graduate School of Arts and Sciences

COLUMBIA UNIVERSITY
2018
ABSTRACT

The Centrality of Sadness: Networks of Depression, Grief, and Trauma Symptoms in a Spousally Bereaved Sample

Matteo Malgaroli

SIGNIFICANCE: Complicated and persistent grief reactions afflict 10% of bereaved individuals, and are associated with severe disruptions of functioning. These maladaptive patterns were tentatively included in the DSM-5 as Persistent Complex Bereavement Disorder (PCBD). The condition has been studied using network analysis, showing how symptoms activate and reinforce each other into psychopathological configurations. This approach offers unique insights to inform clinical practice and define psychopathology. Despite these strengths, previous studies were based on self-report information from a single archival dataset. To overcome these limitations, we collected clinical data from a community sample of newly bereaved individuals who suffered loss of a spouse (N=305). Symptoms of PCBD from semi-structured clinical interviews were analyzed via a network approach.

METHODS: Ising model Networks of PCBD were generated from symptoms diagnosed at 3 months, 14 months, and 25 months after the loss. Comorbidities with DSM-5 symptoms of Major Depressive Disorder, and PTSD were also explored. The role of risk factors was also assessed. Lastly, longitudinal VAR networks were generated combining the three temporal observations.

RESULTS: Symptoms from the Social/Identity PCBD cluster were central in the network configurations. Yearning and Emotional Pain appeared less strongly interconnected compared to previous research. Meaninglessness activated a cascade of further PCBD symptoms over time.
Loneliness, difficulties trusting others and meaninglessness bridged with comorbid depressive and trauma symptoms.

CONCLUSIONS: Symptoms related to loss of identity and meaninglessness were identified as salient candidates for targeted interventions. The network approach showed potential for an improved understanding of psychopathological distress reactions following potentially traumatic events.
# TABLE OF CONTENTS

LIST OF TABLES AND FIGURES ......................................................................................... ii

INTRODUCTION ................................................................................................................... 1
   Limits of the Diagnostic Approach .............................................................................. 3
   Network Models and Psychopathology ...................................................................... 4

PREVIOUS NETWORK APPLICATIONS ............................................................................ 8
   A new take on psychopathology ................................................................................. 8
   Longitudinal Networks ............................................................................................... 10
   Broader Networks ...................................................................................................... 11

THE CURRENT INVESTIGATION ....................................................................................... 12
   Research Questions .................................................................................................. 13

METHODS .......................................................................................................................... 15
   Participants and procedure ....................................................................................... 15
   Structured Clinical Interviews .................................................................................. 16
   Statistical Analyses .................................................................................................. 17

RESULTS ............................................................................................................................. 21
   Grief Networks ......................................................................................................... 22
   Comorbidity Networks ............................................................................................... 23
   Covariates node communities .................................................................................... 24
   PCBD Longitudinal Networks ................................................................................... 25
   Longitudinal Comorbidity Networks ......................................................................... 26
   Grief Network Comparisons ..................................................................................... 27
   Grief Networks Stability ............................................................................................ 28

DISCUSSION ....................................................................................................................... 30
   Review of Findings .................................................................................................... 32
   Clinical and Nosological Implications ..................................................................... 36
   Limitations and Future Directions .......................................................................... 39

CONCLUSIONS ................................................................................................................. 42

REFERENCES ..................................................................................................................... 44

APPENDIX: TABLES AND FIGURES ................................................................................. 56
Table 1. DSM-5 Diagnostic Criteria of Persistent Complex Bereavement Disorder (PCBD)………………..56
Fig. 1. Example of undirected weighted network graph, consisting of nodes and edges…………………………..57
Fig. 2. Fatigue, disturbed Sleep pattern, and difficulties Concentrating as bridge symptoms between Major Depression (MD) and Generalized Anxiety Disorder (GAD)…………………………………………………………..58
Table 2. Rates of endorsement for DSM-5 Symptoms of MDD (D), PCBD (G), and PTSD (T) at 3 months (N = 260), 14 months (N = 263), and 25 months (N = 271) after the loss………………………59
Fig. 3. Ising Model Networks of PCBD symptoms at 3 months (N = 260), 14 months (N = 263), and 25 months (N = 271) after the loss………………………………………………………………..60
Fig. 4. Ising Model Networks with identical positioning (layout) of PCBD symptoms at 3, 14, and 25 months post loss…………………………………………………………………………………..63
Table 3. Network Centrality Indices for symptoms of PCBD at 3 months (Time 1), 14 months (Time 2), and 25 months (Time 3) post-loss…………………………………………………………………………66
Fig. 5. Comparison of Network Centrality Indices for symptoms of PCBD at 3 months (Time 1), 14 months (Time 2), and 25 months (Time 3) post-loss……………………………………………………………..67
Fig. 6. Centrality Indices for symptoms of PCBD using data only from participants who were administered all interviews (N = 207)………………………………………………………………………………..68
Fig. 7. Ising Model Networks of MDD, PCBD, and PTSD symptoms at 3 months (N = 260), 14 months (N = 263), and 25 months (N = 271) after the loss………………………………………………………..69
Fig. 8. Network Centrality Indices for symptoms of Comorbidity Networks at 3 months (Time1), 14 months (Time 2), and 25 months (Time 3) post-loss…………………………………………………………….72
Fig. 9. Regularized partial correlation network of PCBD symptoms, functioning, demographics, and risk factors at 14 months after the loss (N = 263)……………………………………………………………..73
Fig. 10. VAR Network of temporal, contemporaneous, and between-subject relationships of PCBD symptoms at 3 month, 14 months, and 25 months post loss (N = 207)……………………………………….74
  Fig. 10a. Temporal network…………………………………………………………………………………………..74
  Fig. 10b. Contemporaneous Network……………………………………………………………………………….75
  Fig. 10c. Between Subjects Network………………………………………………………………………………..76
Fig. 11. VAR Network of temporal, contemporaneous, and between-subject relationships between selected symptoms of PCBD, MDD, and PTSD at 3 month, 14 months, and 25 months post loss (N = 207)…………………………………………………………………………………..77
  Fig. 11a. Temporal Network…………………………………………………………………………………………..77
  Fig. 11b. Contemporaneous Network……………………………………………………………………………….77
  Fig. 11c. Between-Subjects Network………………………………………………………………………………..79
Fig. 12. Bootstrapped Confidence Intervals of edge-weights for the PCBD networks……………………………..80
  Fig. 12a. Time 1………………………………………………………………………………………………………….80
Fig. 12b. Time 2 .............................................................................................................. 81
Fig. 12c. Time 3 .............................................................................................................. 82

Fig. 13. Bootstrapped difference tests between non-zero PCBD symptoms edge-weights. Black boxes represent edges that do differ significantly from one-another. ................................................................. 83
Fig. 13a. Time 1 .............................................................................................................. 83
Fig. 13b. Time 2 .............................................................................................................. 84
Fig. 13c. Time 3 .............................................................................................................. 85

Fig. 14. Bootstrapped difference significance tests between node centrality indices. .................. 86
Fig. 14a. Time 1 .............................................................................................................. 86
Fig. 14b. Time 2 .............................................................................................................. 87
Fig. 14c. Time 3 .............................................................................................................. 88

Fig. 15. Average correlations between centrality indices from the original sample and from networks sampled with increasing percentages of dropped participants. ................................................................. 89
Fig. 15a. Time 1 .............................................................................................................. 89
Fig. 15b. Time 2 .............................................................................................................. 90
Fig. 15c. Time 3 .............................................................................................................. 91
ACKNOWLEDGMENTS

I would like to express my thanks to my advisor, Prof. George Bonanno, for his guidance, motivation, knowledge, and friendship. This dissertation stands on the shoulders of his vast body of research. His continuous support of my Ph.D. studies made my academic and personal development possible. He found a seed in Italy and brought it back with him to the US, where it could grow.

I would also like to thank Prof. Helen Verdeli and Prof. Bryan Keller for their precious feedback and assistance during the Dissertation Proposal and Advanced Seminar. The insightfulness of their comments and suggestions both improved and widened the scope of my research. I would also like to thank Prof. Laura Smith and Dr. Fiona Maccallum for their role as Committee members. I would like to further express my gratitude to Dr. Fiona Maccallum, for her mentorship during her time in the LTE Lab. She was the first suggesting me a network approach to psychopathology. Her guidance inspired ground breaking prospective on what complicated grief and more in general psychopathology consist.

I am grateful to Dr. Jeffrey Birk, for all his help with aggregating, organizing, and cleaning the data used in this research. Without his continuous assistance and intelligence, none of my analyses would have been possible.

I thank my fellow LTE lab member, for the stimulating discussions, for the work we shared and for all the fun we have had in the last four years.

Lastly, I would like to thank my parents, for their unrelenting love and support. None of these academic achievements would have been possible without their help and inspiration.
To our participants, who selflessly helped research in their darkest hour.
INTRODUCTION

Psychological science has been facing a replication crisis (Open Science Collaboration, 2015) so pronounced that it received mainstream media coverage. Since the time of Galileo, replication has been one of the pillars of the scientific method: obtaining the same results under the same conditions is evidence of an underlying common mechanism. In the case of psychology, upholding this principle has been difficult due to the intrinsic complexity of its data. Another reason is that psychological constructs sometimes use identical labels while actually referring to different phenomena. Some of the most common examples of such misconceptions are associated with mental disorder diagnoses.

Despite marked heterogeneity between different symptom presentations (Craddock & Owen, 2010), diagnostic labels have been extensively used as clinical and research categories, possibly outliving their purpose as a shared language (Kraemer, 2007). The fifth edition of Diagnostic and Statistical Manual of Mental Disorders (DSM-5; American Psychiatric Association, 2013) is the most used system of psychiatric classification in the US. Despite the assumption that mental disorders are distinct entities, DSM-5 categories present a high degree of overlap and comorbidity (Casey et al., 2013). This is a crucial limitation that affects the validity of clinical diagnosis and their replicability. In fact, NIMH officially moved away from DSM-5 categories, embracing the Research Domain Criteria (RDoC; Insel, 2013). The best possible clinical alternative to the DSM-5 is still a hotly debated topic (McNally, 2016). This is a particularly pressing issue for conditions not fully understood yet, such as complicated bereavement reactions.
The death of a loved one is a potentially traumatic life event followed by heterogeneous reactions (Galatzer-Levy & Bonanno, 2012). While resilience is a common outcome (Bonanno et al., 2002), 10-15% of bereaved individuals will suffer from long term functioning problems (Bonanno, 2004). Among those associated with psychopathological symptoms are intense and prolonged yearnings for the deceased, avoidance of reminders, difficulties accepting the death, a sense that life lacks meaning, emotional numbness, bitterness, loss of trust, distress at the lost relationship, and difficulty re-engaging with life (Prigerson et al., 2009). Grief symptoms have been frequently observed co-occurring with other symptoms of depression and trauma (Simon et al., 2007), and associated with substance abuse (Shear et al., 2011). In the DSM-5 these complicated grief reactions were labeled Persistent Complex Bereavement Disorder (PCBD; Table 1), and included as Conditions for Further Study (APA, 2013). Given the heterogeneity of psychopathological diagnosis, there is need to study these distress reactions in a more empirical way.

Therefore, the purpose of this research was to offer an alternative conceptualization to the development of psychopathology in the context of bereavement. In the current study, network analysis was used to model psychopathological symptoms in a sample who suffered spousal bereavement. Data was gathered from clinical interviews, at 3-5 months, 13-15 months, and 25 months after the loss. The network approach was chosen as it could offer insights on what constitutes mental disorders, how symptoms interact, and make temporal predictions. Perhaps these methods could even offer another analogy from the times of Galileo. The geocentric astronomical model was falsified by findings from the telescope: Jupiter was observed having moons that did not orbit around the Earth. Similarly, in network analysis symptoms are observed
directly relating and interacting with each other, offering explanations for facts that are problematic in our current diagnostic system.

**Limits of the Diagnostic Approach**

The concept of defining mental illnesses as a-priori collections of specific symptoms has inherent limitations (Galatzer-Levy & Bryant, 2013). A first issue is that a priori diagnoses exclude sub-threshold people needing services, as they don't possess the specified combination of symptoms (Stein, Walker, Hazen, & Forde, 1997). This is a crucial flaw considering that DSM diagnostic criteria were determined with an expert-committee consensus model, rather than a scientifically driven approach (Kendler, 2013). Moreover, DSM trials did not focus on the validity of its proposed classifications (Obiols, 2012). Instead they focused on diagnostic reliability (Regier et al., 2013), with moderate success (Kraemer, Kupfer, Clarke, Narrow, & Regier, 2012). This approach also explicitly ignored the question of etiology, thus leaving it somewhere between natural kinds or social construction (McNally, 2012). Another conceptual limitation of diagnostic categories is that trying to model heterogeneity with a set of rules can lead to amorphous classifications. In the DSM-5 for example there are 636,120 possible symptom combinations that meet PTSD diagnostic criteria, making the diagnosis broad and error-prone (Galatzer-Levy & Bryant, 2013).

There are also psychometric limits to our current approach to mental disorders, in particular to the idea that latent mental disorders (e.g. depression) manifest through observable psychological variables (e.g. lack of concentration, fatigue, disturbed sleep, etc.). Borsboom (2008) criticized the statistical properties of the current diagnostic system, as this approach
violated the axiom of local independence. The axiom states that the indicators of a latent variable have to be independent from one another. Any shared variance between these variables should be accounted once the latent variable has included in the model (Bauer & Curran, 2004). For example, the measurements obtained from two barometers are the manifestation of the latent variable ‘air pressure’. Should the air density above only one barometer change (modifying its output), the measurements of the other barometer will not be affected. Borsboom (2008) argued that psychological variables by contrast are interconnected and thus not independent. For example, rumination, fatigue, difficulties concentrating, and poor sleep interact with each other, regardless of depression (i.e. rumination leads to worse sleep patterns; insomnia results in experiencing more fatigue; fatigue makes it harder to concentrate; and so forth). Therefore, symptoms are best characterized as existing in a state of mutual causal association, which is only partially accounted for in the latent diagnostic approach (McNally et al., 2015). Another limitation of diagnostic categories is that while medical diagnoses have an etiology that is independent of their symptoms (e.g. one can have the flu virus without high body temperature or sneezing), mental disorders cannot be described in the absence of their symptoms (Borsboom & Cramer, 2013). To cope with these fatal limitations, networks analysis was proposed as a radically different approach to the nature of psychopathology.

**Network Models and Psychopathology**

Network models use graphs to describe statistical relationships between phenomena (Wasserman & Faust, 1994). Graphs are composed by two elements: a set of points, or nodes (the units), and a set of lines, or edges (the connections). Depending on the different network computational
models, edges can be undirected, indicating mutual connection without directionality between nodes, or directed, indicating that one element has directional predictive influence on another. Moreover, edges can also be weighted or unweighted, or can be positive or negative, depending if the activation of one node is respectively directly or inversely proportional to the manifestation of the other. An example of a graph consisting of nodes and edges is reported in Figure 1. The relative importance of each node for the overall network configuration is evaluated by its centrality (Freeman, 1978). There are different measures to calculate nodes’ centrality. As each is based on different assumptions of network information flow (Borgatti 2005), overall centrality is assessed by interpreting these measures in combination. Among the most commonly used centrality measured are Strength (the sum of the weights of connected edges), Closeness (inverse of the sum of the distances of a node from all other), and Betweenness (sum of times in which a given node bridges the shortest path between two other nodes).

In the form of complex networks, the network approach has been used to model multiple branches of knowledge, from physics to biology, including also social sciences (Strogatz, 2001). It was first applied to psychopathology by Borsboom (2008). Given the nature of psychological data, Borsboom argued that a causal system perspective constituted a more appropriate model for psychopathology. In this approach, symptoms are not observable components of an otherwise latent construct (e.g. depression). Instead, they are considered to constitute a system of mutually reinforcing elements (Schmittmann et al., 2013). In other words, the very symptoms are the mental disorder. Their systemic configuration is what constitutes psychopathology, without the need of any underlying latent condition (Borsboom, 2008). In the network approach, it’s not the combination of low mood, anhedonia, fatigue, insomnia, etc. that represents the latent depression disease. Depression coincides with the symptoms activation, connection, and mutual
reinforcement via positive feedback loops. Network analysis visually describes these interactions, offering a visual language to study psychopathology. Graphs the nodes are used to represent the symptoms (e.g. fatigue, disturbed sleep), while the edges are used to represent the relationships and interactions between them. Unlike diagnostic categories, symptoms also have good psychometric properties since they can be measured through direct and often multimodal observation (Schmittmann et al., 2013).

According to this approach, clinical episodes of mental disorders happen whenever a number of symptoms manifests for a sufficient period of time, activating a causal system of dynamic self-reinforcing interactions between symptoms (McNally, 2016). Therefore, symptoms can serve as activators that when triggered spread their influence through their edges, ultimately tipping the system into a disordered state (Cramer & Borsboom, 2015). This perspective would also be consistent with the generally high rates of psychological resilience (Bonanno, 2004). A psychological system that maintains its current stability is resilient, as individual symptom perturbations are eliminated by the overall system’s robustness (Scheffer et al., 2012). Psychopathological symptoms fluctuations would tend to extinguish due to homeostatic effect, unless enough symptoms trigger up to a tipping point (Scheffer et al., 2012). When a psychopathological equilibrium is reached, the casual activations between symptoms mutually reinforce each other and spread through other symptoms. The widespread effects of this process could explain the multiple impairments associated with mental illness (Whiteford et al., 2013). Its pervasiveness could be consistent with modeling psychopathology as a single factor (Caspi et al., 2014). Once the psychological network reached this new configuration, it would take effort via therapeutic intervention to destabilize the network back to a non-pathological configuration (Hofmann, Curtiss, & McNally, 2016).
The network perspective also offers new conceptual and empirical solutions to the problem of diagnostic comorbidity (Figure 2). The absence of diagnostic categories eliminates the need of clear boundaries, allowing heterogeneity in the manifestation of symptoms (Hofmann, Curtiss, & McNally, 2016). In network models, the co-occurrence of symptoms from different conditions is empirically expressed by their higher clustering and short edge distance (Borsboom, Cramer, Schmittmann, Epskamp, & Waldorp, 2011). This conceptualization is consistent with the network analysis of 120 psychiatric symptoms in a large epidemiological sample (Boschloo et al., 2015). One implication of this model is that activated symptoms can spread and trigger symptoms from other clusters they are connected to, resulting in comorbidity (Fried et al., 2017). For example, analyses performed with a bereaved sample showed that loneliness, feeling that life is empty, and emotional pain acted as bridge between depressive symptoms and complex grief symptoms (Robinaugh, LeBlanc, Vuletich, & McNally, 2014).

The benefits of using network analysis to model psychopathology are not limited to increased statistical accuracy, or better descriptive exploratory information. A crucial aspect of the network approach that emerged from previous researches is the possibility of gaining insights that can influence clinical practice. The first implication comes from the possibility of focusing treatment on specific symptoms. The connections between the various symptoms imply that if a highly central symptom could be targeted in treatment and extinguished, this would also effect the symptoms that are interconnected with it, potentially extinguishing the network (Borsboom & Cramer, 2013). Highly central symptoms also carry more risk for potential relapse. Thus identifying and monitoring central symptoms enables rapid early intervention to prevent relapse when in a remission context (McNally et al., 2015). It is also possible to identify the specific symptoms that connect different constellations of symptoms with other psychopathological
clusters (Robinaugh et al., 2014). Specific types of networks can also provide with further causal information. Directed networks can be used to analyze which symptoms predict others (McNally, 2016). Furthermore, temporal networks with time series data can be used to make longitudinal inferences (Bringmann et al., 2013). Finally, it is possible to create within-person individual networks, identifying personal constellations of symptoms and their pathways (Borsboom & Cramer, 2013).

**PREVIOUS NETWORK APPLICATIONS**

The network approach to psychology has been gaining increasing popularity, thanks to the heuristics that distinguish it from the traditional diagnostic approach. It has already seen numerous applications in a number of different (and transcultural) samples, modeling a variety of clinical, self-reported, and even experimental psychological data.

**A new take on psychopathology**

The relationship between depression and Persistent Complex Bereavement Disorder (PCBD, or Complicated Grief, CG) was analyzed with the network approach (Robinaugh et al., 2014). Data was obtained from the Changing Lives of Older Couples database (CLOC). Depression items and adapted grief symptoms from 250 spousally bereaved subjects (65 years or older) were modeled into both directed and undirected networks. Results indicated that emotional pain is the core element of PCBD, and also associated in positive feedback loop with other symptoms.
Thanks to the feedback loops, the activation of an element spreads to all connected elements. Their triggering strengthens the activation of all other connected elements, including the initial one (and so forth). Emotional pain, feeling that life is empty or meaningless, and loneliness were symptoms linking grief symptoms with depressive, especially sadness and depressed mood. Another study on grief and depression based on the same database (Fried et al., 2015) compared the bereaved sample with married control groups. The effect of partner loss was modeled in the network, and results indicated that it was not mediated by a latent variable. Loneliness was indicated as the most central symptom of the loss, which in turn activated depressive symptoms.

McNally and colleagues (2015) used network analysis to analyze the structure of PTSD. Participants consisted of 362 survivors from the Wenchuan earthquake, who had lost at least one child and were exposed to other potential traumas. Network graphs were derived from relations among symptoms reported from a posttraumatic checklist. Results indicated hypervigilance as a highly central symptom of the network, also predicting startle response in the relative importance network. Foreshortened future was another central element, while Anger was connected to sleep and concentration difficulties, suggesting interactions that would have been otherwise not explored.

The network approach was similarly used in the context of eating disorders (Forbush, Siew, & Vitevitch, 2016). Structured clinical interview data from 147 adult participants was used to model an undirected network of eating disorder symptoms, with body-checking and excessive exercise as the most central nodes.
**Longitudinal Networks**

Network analysis has also been used to model longitudinal clinical data, particularly with repeated measures in relatively short time frames (Bringmann et al., 2013). In a randomized clinical trial with 182 depressed patients (Bringmann et al., 2015), Beck Depression inventory II data was collected before each session for 14 weeks. Longitudinal network analysis results indicated that all symptoms were positively connected, and that loss of pleasure was the most central item of the depression network. In another study (van Borkulo, Boschloo, Borsboom, Penninx, Waldorp, & Schoevers, 2015), differences in configuration of depressive symptoms between remitters and persisters were studied. Data from 515 patients with a history of major depression and present depressive symptoms was used to model networks. Patients were divided in two group based on traditional diagnostic criteria. Results indicated that the network of persisters was more interconnected, and fatigue and feeling guilty were more central when compared to the remitters network.

The relationship between psychotic symptoms and childhood trauma was also explored using network analysis (Isvoranu et al., 2016). The interaction between clinical symptoms data and a retrospective questionnaire on childhood trauma from 522 patients diagnosed with a psychotic disorder were depicted with network graphs. Results indicated that childhood trauma scores from the scale were not connected directly to positive and negative symptoms. Instead, the relationship was mediated by general symptoms of psychopathology (Isvoranu et al., 2016).
**Broader Networks**

Network analysis can also be used with more than symptoms measures, offering the opportunity to include also other type of insightful data. For example, it was used to explore heterogeneity in autism spectrum disorder presentations (Deserno, Borsboom, Begeer, & Geurts, 2016). Using demographics, self-reported IQ, and self and proxy reported well-being data on 2341 individuals suffering from the disorder. Results indicated that self-reported IQ, living situation, level of daily activity and happiness were the most central nodes of the well-being network.

In another study (Boschloo, Schoevers, van Borkulo, Borsboom, & Oldehinkel, 2016), 95 behavioral and emotional psychological problems were assessed via self-report in a large community sample consisting of 2,175 preadolescents. Using network graphs, the research showed that single emotional or behavioral problems cannot be used to represent clear cut domains, due to the pair interactions of problems between the factors (Boschloo et al., 2016).

Constantini and colleagues (2015) used network analysis to explore personality structure. The authors were able to model the mutual interactions between honesty–humility, emotionality, extraversion, agreeableness vs. anger, conscientiousness and openness to experience, showing the potential of applying the network approach to personality.

Hereen and McNally (2016) proposed to integrate social anxiety disorder symptoms networks with experimental data. In their work, they used data derived from an experimental attentional bias and attentional network tasks with self-report symptoms data, and also impediment of speech ratings from clinical psychologists. Their sample consisted of 61 individuals (of which 49 were female). Weighted directed networks were calculated to assess the potential causal relations among laboratory measures of attentional components and symptoms
of social anxiety disorder. Results indicated that the orienting component of attention, avoidance of social situations, and fear of social situations were the most central nodes of the network, suggesting the potential role of multimodal data for network analysis, and also for psychological mechanisms hypothesis testing.

THE CURRENT INVESTIGATION

While previous studies showed the benefits of applying the network approach to grief related psychopathology (Robinaugh et al., 2014; Fried et al., 2015), these were based on the same CLOC database. The CLOC is a perspective study on spousal bereavement conducted from 1987 to 1993 in Michigan. The study presents a series of important limitations. First, the CLOC did not include all symptoms of distressed bereavement, since they were not identified when the study was undertaken. Secondly, it comprised individual aged 65 years or older. It is unclear if our current understanding of grief reactions can be generalized, in particular to a younger population. Thirdly, a significant portion of studies all studies about PCBD and CG have used the CLOC as sole source of data. Thus it is also fundamental to assess if previous findings can replicate using a new sample.

The current study was designed to cope with these limitations, using data from a new and ongoing bereavement study. Our sample consisted of adult who recently lost a spouse. They were assessed soon after the loss (3-5 months), a year later (13-15 months), and also two years later (23-25 months). Symptoms measures consisted of ratings from clinicians, which are more
reliable than self-reported information. To the best of our knowledge, this is the first research to use data obtained from grief-specific clinical interviews to test PCBD’s symptoms structure. A first component of this research is to determine how grief symptoms networks compare with previous findings. In particular, which symptoms are central for the networks’ configurations at both times. Another fundamental feature is to assess comorbidity. Specifically, how depression and trauma symptoms interact with PCBD, and which symptoms act as bridges. Using data from these time points, we analyzed temporal networks. We examined which symptoms triggering early in grief (when it’s difficult to distinguish pathological from culturally appropriate bereavement) carry a higher risk of spreading into psychopathological networks later on.

Research Questions

1) How do symptoms of complex grief, depression, and trauma manifest after bereavement? How do they relate to each other immediately after the loss and the subsequent year? In other words, what are the symptoms network graphical configurations?

2) Which of the depression, trauma, and proposed PCBD symptoms are crucial for the homeostasis of the psychopathological network? In other words, which symptoms are statistically the most relevant and have the highest centrality measures?

3) Can the symptoms network models immediately after the loss and the subsequent year be considered different manifestations of the same underlying phenomena? In other words, is there any statistically significant difference between the network models obtained at different observations?
4) What grief symptoms immediately after the loss are the predictive of later complex psychopathological bereavement reaction? Is there a symptoms profile recognizable early on that can predict the psychopathological network configuration in the future?
METHODS

Participants and procedure

Our sample consisted of newly bereaved individuals below 65 years of age who had lost a spouse. They were enrolled in a longitudinal study examining predictors of grief reactions, and recruited in the New York metropolitan area. The study was approved by the Institutional Review Board at Teachers College, Columbia University. Recruitment was done by sending letters based on public death listings, obituaries, support group referrals, as well as fliers, internet, and newspaper advertisements (provided that a death certificate was presented). Participants were administered psychological structured clinical interviews at 3 months after the loss (Time 1: M = 2.67; SD = 1.01), 14 months after the loss (Time 2: M = 14.25; SD = .98), and 25 months after the loss (Time 3: M = 24.92; SD = .64). To ensure a consistent number of participants across all time points, we oversampled recruitment at the time of the second session. Prior to their sessions participants filled questionnaire packets at home, while during their visits they also completed in-lab experimental tasks, semi-structured narrative interviews, and various self-report measures. They received a $100 compensation for completing each visit.

The final sample consisted of 305 adult bereaved individuals. The mean age was 55.25 (SD = 7.23) at the time of the first interview. Participants were more than two thirds female (female 66.4%; male 33.6%), and predominantly identified as white (Caucasian 88.2%; African American 4.3%; Hispanic 3.9%; Asian 3.3%; AI or AN 1.3%; Other 1%). The majority of the sample had a college degree or above (HS or less 10%; Some College 20%; Bachelor Degree 37.3%; MA or prof. Degree 31.9; Ph.D. 0.8%), and was working full time (Full Time 61.5%; Part Time 13.5; Unemployed or Retired 30%). Of the total sample, 260 subjects participated to
the first assessment (85.2% of total), 263 participated to the second (86.2%) and 271 to the third interview (88.9%), while 207 participants (67.9%) completed all three sessions.

**Structured Clinical Interviews**

Participants were administered structured clinical interviews to assess psychopathological symptoms corresponding to the DSM-5 criteria (American Psychiatric Association, 2013) of Major Depressive Disorder (MDD), Posttraumatic Stress Disorder (PTSD), and Persistent Complex Bereavement Disorder (PCBD). Other assessed symptoms associated with persistent bereavement reactions were adapted from grief specific structured interview (Bonanno, Keltner, Holen, & Horowitz, 1995), including items from the Structured Clinical Interview for CG (SCI-CG; Bui et al., 2015). Items were scored on a 1-3 scale (1 = symptom absent; 2 = criterion suggested but not fully met; 3 = full manifestation of diagnostic criterion), and then used dichotomically (0 = symptom absent, or criterion not met; 1 = full manifestation of diagnostic criterion). Further structured risk assessment (Shea, 1998) was administered with the patients who endorsed suicidal symptoms. Interviews were conducted by a team of psychologists and advanced doctoral candidates in clinical psychology. Interviews were videotaped, and each interviewer coded a randomly selected set of five additional interviews. The initial scoring scale showed very high interclass correlation (ICC = .94) for absolute agreement (the ICC was computed not only for correlation but for exact same scores). Inter-rater reliability for the interview binary scores was also very high (average K = .87).

After the interview, each subject was assessed on their overall psychological, social, and occupational functioning using the Global Assessment of Functioning scale (GAF; Jones,
GAF scores are considered a reliable method to measure changes and outcomes at a group level (Söderberg, Tungström & Armelius, 2005). Inter-rater reliability was assessed having three external trained raters recode GAF scores on randomly selected subsets of 20 participants each from SCIDs videotapes. Their ratings showed very high interclass correlation (ICC = .92) for absolute agreement.

**Statistical Analyses**

A series of networks models were estimated using R (R Core Team, 2016). Networks are graphical models consisting of two components: nodes and edges. Nodes represent the individual symptom items included in the analysis. Edges represent the relationships between two nodes, after conditioning on all other nodes in the analysis. Cross sectional networks were calculated for the symptoms at each session. A temporal network was also calculated by using data from all three sessions. In the graphical models, thicker edges represent stronger associations between symptoms.

**Grief Networks.** For each time point, undirected networks of PCBD psychopathological symptoms were calculated using the R package Isingfit (van Borkulo, Epskamp & van Borkulo, 2016). Isingfit use eLasso method to estimate networks from binary data (van Borkulo et al., 2014). This approach generates parsimonious network models by applying graphical LASSO penalties (Friedman, Hastie, & Tibshirani, 2008). The estimation method is based on the Ising model, combining LASSO regularized nodewise logistic regression with model selection based on the Extended Bayesian Information Criterion (EBIC; Foygel, & Drton, 2010). The eLasso removes spurious connections between nodes based on indirect relationships with a third node,
causing small connections to shrink, and therefore resulting in more sparse networks (Epskamp, Borsboom, & Fried, 2017). For all network estimations, the EBIC gamma hyperparameter was set to .25. The estimated networks were then plotted using the package Qgraph (Epskamp, Cramer, Waldorp, Schmittmann, & Borsboom, 2012).

**Comorbidity Networks.** We explored the relationship between symptoms of MDD, PCBD, and PTSD at each time point by including all symptoms items in the network (39 nodes in total). The Ising model estimations for all networks used the same parameters as the grief networks.

**Covariates node communities.** The R package Qgraph (Epskamp et al., 2012) was used to analyze the relationships between PCBD symptoms, functioning (GAF scores), risk factors associated with the death (i.e. if the circumstances of the loss were sudden and/or violent, monetary losses after death, and living alone), and selected demographics (i.e., age, gender, length of marriage, and number of children). Analysis were limited to 14 months after the loss (N = 263), given its diagnostic salience. A regularized partial correlation network was estimated using LASSO regularization and EBIC model selection (gamma set to .25).

**Measures of node centrality.** For all grief and comorbidity networks, node centrality was calculated using the R package Qgraph (Epskamp et al., 2012). The importance of each symptom in the network was assessed using three indices of node centrality: Strength, Closeness and Betweenness. Strength corresponds to the sum of the weights of the edges attached to that node. Closeness is calculated using the inverse of the sum of the distances of the node from all other nodes in the network. A closeness-central node is more likely to be affected by changes in
other nodes directly or indirectly. Betweenness is defined as the number of times in which a given node lies on the shortest path between two other nodes.

**Longitudinal Networks.** Longitudinal data from all three interviews was analyzed to model symptoms interactions over time. For the purpose of this analysis, only data from participants who completed all three sessions was included (N = 207). The longitudinal networks were calculated using the R package mlVAR (Epskamp, Deserno, & Bringmann, 2016). Vector autoregression (VAR) are multi-level methods that combine multilevel hierarchical and time-series models, and are suited for analyzing clinical longitudinal data (Bringmann, Lemmens, Huibers, Borsboom, & Tuerlinckx, 2015). Estimations in mlVAR generate three different networks: temporal, contemporaneous, and between-subjects. The temporal network is a directed network with edges that model temporal predictive effects between nodes. The contemporaneous is an undirected partial correlation network of within-person relationships. The between-subjects network models mean relationships between nodes over time. Interpreting the temporal together with contemporaneous and between-subjects effects can highlight causal relationships among symptoms (Epskamp, Waldorp, Möttus, & Borsboom, 2016). Temporal effects were estimated as orthogonal, while the contemporaneous network was estimated as fixed.

VAR models were estimated respectively for PCBD symptoms and for the comorbidity network. Currently, VAR estimations via mlVAR show inadequacies with high dimensional data, given limitations in computational power when using more than 20 variables (Epskamp, Waldorp, et al., 2016). Therefore, in the comorbidity network only a subset of 20 symptoms of PCBD, MDD, and PTSD with the greatest Strength (one of the centrality measures) at 3 months was used to generate nodes. To better fit the VAR assumptions of normality, all symptoms were
used based on their initial 1-3 scoring, and a non-paranormal transformation (Liu, Lafferty, & Wasserman, 2009) was applied to the data using the R package Huge (Zhao, Liu, Roeder, Lafferty & Wasserman, 2012). Edges in the graphs can be red (negative relationship), or green (positive relationship). The direction of the arrows in the temporal graph indicates the direction of the prediction (how the activation symptom predicts another over time).

**Networks Comparison.** Data from the subset of participants who completed all sessions (N = 207) was used to test differences between the grief networks obtained from Time 1, Time 2, and Time 3 symptoms data. The global strength of the three networks was compared to assess invariance in connectivity using the R package NetworkComparisonTest (NCT; van Borkulo, 2016). The NCT is a permutation based hypothesis test that analyzes the difference in the weighted sum of the absolute connections for repeated samples of randomly regrouped individuals (van Borkulo et al., 2015). Networks estimation was based on Ising models, and the EBIC hyperparameter gamma was set to 0.25. The sampling procedure was repeated 1000 times for each comparison. Network invariance was tested two observations at a time (Time 1 compared to Time 2; Time 2 compared to Time 3; Time 1 compared to Time 3). Samples at each time point were modeled as dependent. The test suggests disparities in network structures when the test is significant (p ≤ .05). Furthermore, NCT reports when the difference in global strength between two networks is meaningful (p ≤ 0.5).

**Network Stability.** The stability of the three estimated cross-sectional grief network models was analyzed using the R package Bootnet (Epskamp et al., 2017). Non-parametric bootstrapping was performed to compute 95% Confidence Intervals (CI) of estimated edge weights accuracy for each of the networks. Large overlapping bootstrapped CIs imply caution
interpreting edges in the network (Epskamp et al., 2017). Additionally, bootstrapped difference tests were performed to determine significant differences between the estimated network edges, and also between the estimated node strengths. Significant results ($p \leq .05$) suggest that two edges or two nodes meaningfully differ from one-another; not significant results, however, do not necessarily constitute evidence for the null-hypothesis being true (Epskamp et al., 2017).

Lastly, to determine the stability of centrality indices, case-dropping bootstrap methods were performed to compute 95% confidence intervals of correlations between centrality indices with the total sample. Number of bootstraps samples for all analyses was set to 2500. Network estimation was based on regularized Ising models, and EBIC tuning parameter was set to .25.

**RESULTS**

Mean symptoms scores for each interview session are reported in Table 2. Most prevalent endorsed DSM symptoms in the sample on average across all interviews included Yearnings (T1, 54%; T2, 35.7%; T3, 28.8%), Preoccupation with the Circumstances of the Death (T1, 53.1%; T2, 26.6%; T3, 27.3%), Disturbed Sleep (T1, 47.7%; T2, 33.5%; T3, 23.6%), Distress at Exposure of Loss Reminders (T1, 43.8%; T2, 25.1%; T3, 23.2%), and Difficulties Pursuing Interests (T1, 31.9%; T2, 24.7%; T3, 24%). Symptoms with initially high but decreasing rates of endorsement over time included Weight loss or gain (T1, 41.2%; T2, 12.2%; T3, 12.5%), Difficulties Concentrating (T1, 44.6%; T2, 20.9%; T3, 15.1%), and Emotional Pain (T1, 44.2%; T2, 19.8%; T3, 12.5%). The mean number of endorsed symptoms per participant were 9.37 (SD
= 6.96) at the first interview, 5.73 (SD = 6.18) at the second interview, and 4.76 (SD = 5.62) at the final interview.

Grief Networks

The Ising model networks representing the constellations of grief symptoms at Time 1, Time 2, and Time 3 are presented respectively in Figure 3. Another representation of the same networks, this time using identical overlays, are presented in Figure 4 (i.e. for better comparison of differences in the number and strength of edges over time). The centrality indices of Strength, Closeness and Betweenness for each network are reported in Table 3 and graphically compared in Figure 5.

The symptoms with the highest centrality at 3 months after the loss were Confusion about one’s role in life, Preoccupation with the Circumstances of the death, Numbness, Meaninglessness, and Emotional Pain. Furthermore, Difficulties having Positive Reminiscing about the deceased appeared unconnected to the other symptoms, as per its position and lack of connected edges in the network (Figure 3), resulting in an absent Closeness score. At 14 months after the loss, the aforementioned Time 1 symptoms remained among those having the highest centrality, with the exception of Numbness and Emotional Pain. Moreover, feeling Alone increased in its centrality Time 2 scores, becoming one of the most salient symptoms. What emerged from the overall the symptoms configuration 14 months post loss was the increased sparseness of connections between many of the proposed PCBD symptom criteria. Specifically, Difficulties Trusting others, Preoccupation with the Deceased, Numbness, Positive Reminiscing difficulties, and Emotional Pain were not connected to other symptoms (as indicated by their
lack of Closeness scores in Figure 4). Lack of connections between symptoms was also observed 25 months after the loss, where Avoidance of Reminders of the deceased, Positive Reminiscing, and Preoccupation with the deceased appeared separated from the rest of the network. Confusion about one’s Role in Life, Numbness, Difficulties Trusting others, and persistent Yearning were among the symptoms with highest centrality scores at Time 3.

To assess whether differences in symptoms centrality at Time 2 were due to changes in the samples used to model the networks, PCBD networks were generated using data only from subjects who participated to all three interviews (N = 207). Figure 6 reports the centrality indices for the networks, which were broadly similar to those obtained from using the entire sample available at each time point (Figure 5). Therefore, results suggested that changes in the symptoms’ centrality across time points were not due to differences in samples.

**Comorbidity Networks**

The Ising model networks that included symptoms of MDD and PTSD as well as PCDB are presented in Figure 7. The centrality scores of the networks nodes at respectively 3, 14, and 25 months post-loss are reported in Figure 8. Commonalities emerged in the constellations at different observations. In particular, symptoms that referred to negative emotions tended to have higher importance in the network. Specifically, Depressed Mood, Anhedonia, and Worthlessness (MDD), Negative Emotional States (PTSD), Numbness and somewhat Emotional Pain (PCBD). Lastly, Difficulties Pursuing Interests, Meaninglessness, Preoccupations with the Death, and Suicidality were among the most central symptoms across all observations.
In terms of bridge symptoms cross diagnoses, the edges suggested connections between Difficulties Trusting and selected PTSD and MDD symptoms, such as Sleep disturbances, Concentration problems, Hyper vigilance, and Inability experiencing positive emotions. The latter was also connected with feeling Alone, which also bridged with other symptoms including low Mood and Anhedonia. Meaninglessness further bridged symptoms of MDD across all three observations (particularly low Mood). The networks also indicated connections between Preoccupation with the Circumstances of the death and Distress at exposure of reminders of the loss, already part of both PCBD and PTSD criteria. Numbness was to some extent connected with PTSD symptoms, while Suicidality and Wishing to Join the Deceased appeared strongly connected symptoms at all three time points.

**Covariates node communities.**

The regularized partial correlation model (Figure 9) explored the role of risk factor and other covariates in the symptoms network at 14 months. The edges of the network indicated that a loss following violent circumstances had stronger connections with Bitterness, Difficulties Positive Reminiscing, and Preoccupation with the Circumstances of the Death. Furthermore, symptoms such as Emotional Pain, Loneliness, Confusion about role in life, Difficulty pursuing interests, and Avoidance of reminders were linked with lower functioning. The other covariates and risk factors did not have direct interactions with the other nodes of the network.
PCBD Longitudinal Networks

The VAR temporal and between-subjects networks of PCBD over the three time points are reported in Figure 10. The temporal graphical model’s edges indicated directionality in the relationships between symptoms over time (Figure 10a). Of particular interest given previous cross-sectional networks were the relationships between specific PCBD symptoms. Endorsing meaninglessness (from the PCBD social/identity cluster) would tend to activate Preoccupations with the Deceased, and Difficulty accepting the loss - which would also activate Yearning, Preoccupation with the Circumstances of the Death and Emotional Pain. Difficulties having Positive Reminiscing activated Maladaptive Appraisal and Numbness, while in conjunctions with dying to Be with the Deceased it also activated Bitterness and Preoccupation with Death. Numbness also increased Emotional Pain, which further activated Preoccupation with the Deceased.

The contemporaneous network (Figure 10b) showed multiple but overall loose within-person associations between symptoms. These edges can be understood using temporal effects, as a prominent feature emerging from temporal network was that the self-loops of symptoms (i.e. the prediction of a symptom based on its own activation in the past) were depicted as negative. This finding was consistent with the overall decrease in symptoms endorsement shown on Table 2. Overall, the VAR model suggested that the general tendency for PCBD symptoms in our sample was to extinguish over time.

The between-subjects network of PCBD symptoms across time points (Figure 10c) showed stronger connections between Meaninglessness, feeling Alone, wanting to Be with Deceased, and also significant edges with difficulties Pursuing Interest, and Difficulties
Accepting the Loss. Furthermore, through loneliness, there were connections with Confusion about Role in Life, Numbness, and Difficulties trusting others – which was also connected with Diff. Positive Reminiscing. Emotional Pain and Yearning were strongly connected. These edges configurations showed broad similarities with the PCBD cross-sectional networks (Figure 3).

Longitudinal Comorbidity Networks

The VAR networks representing the constellations of symptoms with the initial highest Strength centrality are reported in Figure 11. In the temporal network (Figure 11a), Meaninglessness activated other symptoms over time, including Difficulties Concentrating, Negative Beliefs, and Negative Emotions - which in turns predicts the activation of further symptoms, such as Numbness, Bitterness, Emotional Pain, and Maladaptive Appraisals. Worthlessness also activated Difficulties concentrating and most importantly activated the Desire to Die to be with the Deceased, which activated Anhedonia, Bitterness, Distress Reaction at exposure, and Preoccupation with the circumstances of the death. Interestingly, endorsing Negative Beliefs about oneself or the world (e.g., that the world is a dangerous place), decreased the activation of Distressing Reactions, Confusion about the Role in Life, and also Negative Emotional States.

In the contemporaneous network (Figure 11b), Meaninglessness was among the most connected symptoms, as indicated by its central position in the graphical network (assigned by the Fruchterman-Reingold algorithm). Worthlessness, trough Preoccupation with the Death, was part of a cluster of symptoms, which included Anhedonia, Dissociative Reactions, Negative Emotions, and Difficulties pursuing Interests. Anhedonia was further connected to Emotional
Pain and Preoccupation with the Deceased. In the between-subjects network (Figure 11c), Meaningless showed stronger connections also with other PCBD symptoms via Negative Beliefs, such as Difficulties Trusting, Alone, Confusion about Role in Life and Difficulty pursuing interest. Worthlessness was connected with Maladaptive Appraisal and Negative Emotions. These connections were similar to the edges seen in the Comorbidity network at three months post loss (Figure 7).

**Grief Network Comparisons**

Data from participants who were administered all three interviews was used to test differences between PCBD networks structures. This was a subset (N = 207) of the total sample (N = 305). All three observations points were used, compared two at a time. Based on the current version of the NCT parameters, the symptoms data was assumed to entail one group measured twice (van Borkulo, 2016). The NCT results indicated no meaningful differences between Time 1 and Time 2 networks in terms of global strength (difference = 10.51, p = .07) and network structure (Test statistic M = 1.511, p = .48). Results indicated that also the networks at Time 2 and Time 3 had similar connections in terms of strength (difference = 4.60, p = .38) and structure (Test statistic M = 1.97, p = .29). Finally, the NCT did not suggest differences between Time 1 and Time 3 networks structure (Test statistic M = 1.57, p = .58) and strength (difference = 5.91, p = .31). Overall, these results suggest that the connections among grief symptoms and their strength did not change between the three examined time points.
**Grief Networks Stability**

Network stability analyses were run on the constellation of grief symptoms at Time 1, Time 2, and Time 3. Edges Confidence Intervals (CI) are presented in Figure 12. Results indicated a degree of overlapping among the edges’ 95% CI. Figure 13 reports the results of the significance tests of pairwise differences between edge-weights that were non-zero. Results suggested that the connection between Yearning and Emotional pain appeared significantly stronger than most other edges between other symptoms at Time 1 and Time 3. Also the edge between Role Confusion and Meaninglessness were significantly stronger than other edges at Time 1. Many of the remaining edges were shown not to be as reliably different from one another. Pairwise bootstrapped significance tests were performed to assess differences between node centrality indices (Figure 14). In the results, Confusion about Role in life emerged as significantly stronger than other symptoms at Time 1. The test also indicated that Difficulties Positive Reminiscing had meaningful differences in Strength with Preoccupation with the Death at Time 1 and 2, and with Maladaptive Appraisal at Time 1. Significant differences in Strength were also indicated between Preoccupation about Deceased and Preoccupation about the Death at Time 2. Yearning had significant differences in Strength with Difficulties Positive Reminiscing and Avoidance of Reminders at Time 3.

Case-dropping bootstraps was used to test the overall stability of the networks centrality indices. Figure 15 shows the correlations between the networks centrality indices at Time 1, Time 2, and Time 3 with the centrality indices extracted from increasingly smaller subsets of cases. The Correlation Stability (CS) coefficient identified the percentage of cases that could be dropped to maintain a significant correlation with the original centrality indices. The value for
the CS-coefficients at Time 1 indicated that Strength was the relatively more stable centrality indices (CS = .13) compared to Betweenness (CS = .05) and Closeness (CS = .00). Results at Time 2 indicated comparable results for Strength (CS = .13), Betweenness (CS = .00) and Closeness (CS = .00), while the same coefficients emerged for Strength (CS = .13), Closeness (CS = .00) and Betweenness (CS = .05) at Time 3.

Taken together, results from the stability analyses suggested that more power was needed to more reliably estimate the network models. While clear guidelines for power analysis of psychological networks are still lacking (Epskamp et al., 2017), caution is suggested in drawing conclusions about the differential strength or centrality for all but the strongest edges and nodes in the networks.
DISCUSSION

The inclusion of PCBD in the DSM-5 as a condition for further study attested the need for an improved empirical understanding of long-term grief distress reactions. This addition has been met with controversy (Boelen, & Prigerson, 2012), also due to the diverging perspectives on psychopathological grief and bereavement from which PCBD originated (Prigerson, Vanderwerker, & Maciejewski, 2008; Shear et al., 2011). Moreover, no consensus has yet been reached regarding which symptoms better capture psychiatrically significant grief reactions (Maercker et al., 2013; Maciejewski, Maercker, Boelen, & Prigerson, 2016). The proposed DSM-5 PCBD diagnostic algorithm results in 37,650\(^1\) possible combinations of symptoms meeting criteria for PCBD, potentially making the construct broad and error prone (Galatzer-Levy & Bryant, 2013). Consistently, Cozza and colleagues (2016) showed that PCBD had poor sensitivity with clinical samples, further intensifying the dispute about the most significant diagnostic configuration for grief (Prigerson, & Maciejewski, 2017; Reynolds, Cozza, & Shear, 2017). Taken together, these issues amplify some of the inherent limitations of a diagnostic approach to grief and more in general to psychopathology (Fried et al., 2015).

Network analysis offers an alternative approach in the context of bereavement research (Robinaugh et al., 2014) that provides a more flexible, data-driven methodology to understand and tease out symptom heterogeneity. In the network approach, symptoms are not considered to be the manifestation of an otherwise latent mental disorder. Rather, psychopathology arises as the expression of the mutually reinforcing interactions among symptoms. Network theory is

\(^1\)PCBD diagnostic criteria include: Cluster B (need 1 or more of 4 symptoms) and Cluster C (need 6 or more of 12 symptoms). The possible combinations of symptoms can be calculated, as per Galatzer-Levy and Bryant (2013). The possible PCBD symptom combinations can be calculated, as per Galatzer-Levy and Bryant (2013). The possible PCBD symptom combinations to meet minimum diagnostic criteria are: \(\binom{4}{k}\cap\binom{12}{k}\) = 3,696 combinations. The number of all possible PCBD symptom combinations that would meet PCBD diagnostic criteria are:

\[
\sum_{k=1}^{4} \binom{4}{k} \cap \sum_{k=6}^{12} \binom{12}{k} = 37,650 \text{ combinations.}
\]
considered a highly promising approach to cope with the limitations of our current diagnostic-based model (Fried et al., 2017), holding the potential to provide new tools for both clinical theory and practice (Borsboom, & Cramer, 2013). Unlike latent constructs (e.g., PTSD), which have proved difficult to reliably quantify, symptoms can be directly measured and quantified (e.g., startle response). By using network analysis it is possible to identify the most important (central) elements of the symptoms constellations (Borsboom, & Cramer, 2013). These symptoms in turn may become the target of clinical interventions aimed at extinguishing the entire psychopathological network (McNally, 2016). Furthermore, the analysis of macroscopic changes in network structure (composed by the multiple relationships among individual symptoms) offers a framework to understand how individuals transition from psychological health to psychopathological states, and the nature of therapeutic change in between (Hofmann et al., 2016). Network graphs also offer visual clarification of psychiatric comorbidities, showing which symptoms bridge across different diagnoses (Schmittmann et al., 2013). Lastly, temporal networks can show causal pathways of symptoms’ interactions, identifying which symptoms activated early on will lead to the manifestation of other symptoms in the future (Epskamp et al., 2016).

Previous studies that have explored the psychopathological network structure of PCBD and bereavement (Robinaugh et al., 2014; Fried et al., 2015) used data that presented significant limitations. These studies relied on the same archival data garnered from the CLOC study, a sample of older adults with a mean sample age of about 70. This feature limited the generalizability of the findings, particularly, as Fried and colleagues pointed out (2015), concerning the different ability in emotion regulation of older compared to younger adults (Charles, & Carstensen, 2007). Furthermore, because the CLOC study was conducted in the
1980s, it predated the development of diagnostic categorization for grief-related pathology. As a result, symptoms comprising the currently used diagnostic category, PCBD, had to be deduced from other survey items, resulting in some PCBD symptoms entirely missing from the network (Robinaugh et al., 2014). Moreover, all symptom data was based on self-report questionnaires. Only interactions with depressive symptoms were included and no comorbidity with PTSD was explored. Lastly, the stability of the resulting psychopathological networks was not explored, as the appropriate methods were at that time in the process of being developed (Epskamp et al., 2017).

To address these limitations, in the current study we used the network approach to analyze PCBD symptoms and their mutual interactions at three time points over the first two years of conjugal bereavement. Primary analyses focused on cross-sectional and longitudinal networks of PCBD symptoms with emphasis on the stability of the networks obtained at the different observations. We also explored interactions of PCBD symptoms with comorbid MDD and PTSD symptoms. All symptom data were obtained using a structured clinical interview format.

**Review of Findings**

**Grief Networks.** The cross-sectional PCBD models indicated that symptoms such as Confusion about one’s role in life, Preoccupations about the death, Meaninglessness, and Numbness had a highly central and relatively stable role in the networks. The central role of these symptoms was consistent with the findings of Robinaugh et al. (2014). A notable exception was the role of Emotional Pain, which was highly central in Robinaugh et al. (2014), but was less prominent in
the current analyses. Among the other symptoms identified as core features (Maciejewski et al., 2016) of PCBD (i.e., cluster B), only Preoccupation with the Death and Yearning emerged as strongly central elements in the constellation of PCBD symptoms. The remaining symptoms had a less consistent role in the three networks. In particular, symptoms such as Difficulties positive reminiscing and Avoidance had little to no centrality across time points, or otherwise intermittent connections. Based on the results from the current network analysis and also the network analyses of the CLOC data (Robinaugh et al. 2014), symptoms related to role transitioning after the loss emerged as core elements of psychopathological grief reactions. The activation of these symptoms was also associated with lower GAF scores. Somewhat strikingly, although these symptom are included in the current DSM-5 PCBD diagnostic criteria they are not of crucial importance. In fact, based on the current PCBD diagnostic algorithm, a diagnosis is possible without endorsing any of symptoms related to Social/Identity disruptions (e.g., Confusion about role in life and Meaninglessness).

In terms of edges, the networks showed heterogeneous configurations of symptoms at the different time points. A notable example is the edge between Yearning and Emotional Pain, prominent in Robinaugh et al. (2014). In the current study, although these symptoms were present at each time point their network association was less consistent over time. Part of the heterogeneity could be accounted for by the parsimony of the Ising model, particularly when compared with networks obtained via other estimation methods (Epskamp, Kruis, & Marsman, 2016). Nonetheless, our findings could also suggest that, although related, yearning and sadness appeared to be two different phenomena. This interpretation is consistent with previous literature associating grief with long term and profound cognitive appraisals such as identity and worldview, while instead linking emotion with more short-term coping (Bonanno, Goorin, & Coifman,
Furthermore, these differences are consonant with different neurological substrata, as bereavement studies have identified unique patterns of neural activity in association with both yearning or reward seeking and emotional pain (O’Connor et al., 2008; Schneck et al., 2017). In particular, yearning has been associated with activity in the nucleus accumbens (O’Connor et al., 2008), while sadness has been associated with activity in the anterior insula and subgenual cingulate (Mayberg et al., 1999).

**Comorbidity Networks.** In the comorbidity networks, depressed mood, difficulties pursuing interest, yearning, preoccupation with the circumstances of the death, negative emotional states, emerged as the most central symptoms. A significant proportion of the most central symptoms were related to negative emotions. This finding was consistent with previous research, showing that low emotional stability was predictive of poor outcome in response to bereavement (Galatzer-Levy, & Bonanno, 2012). Symptoms from the Social/Identity Disruption PCBD cluster once more appeared highly central in the networks configurations across time points, even after including MDD and PTSD symptoms.

In terms of overall structure, and in contrast to previous studies (Robinaugh et al., 2014), PCBD, MDD, and PTSD did not emerge in our analyses as separate communities of symptoms. It may be that the unique clustering observed in prior research stemmed from the fact that the different diagnoses had been measured using different questionnaires, with different numeric response scales, rather from a similar structured interview format as in the current study. Consistently with Fried and colleagues (2015), loneliness was related to symptoms of depression such as low mood and anhedonia. Additionally, loneliness was connected to the inability of experiencing positive emotions, a PTSD symptom. This finding highlights the importance of
loneliness as a risk factor (Heinrich, & Gullone, 2006), particularly for bereavement outcome (Yan, & Bonanno, 2015) given its role as gateway for depressive symptoms (Fried et. al, 2015). Similarly, difficulties in trusting other people were strongly connected to depressive and traumatic symptoms, including sleep and concentration problem, hypervigilance, and once again difficulties experiencing positive emotions. Lack of interpersonal trust was characterized in the literature as strongly connected with loneliness (Rotenberg, 1994) and as a risk factor for mortality outcomes (Barefoot et al., 1998). In addition to these findings, Meaninglessness and preoccupation with the death maintained their interconnected role also when including the other symptoms. Suicidality and wanting to join the deceased appeared strongly connected, potentially manifesting the consequences rather than being a feature of prolonged grief (Prigerson, 2009).

**Temporal Network.** The longitudinal PCBD networks suggested that endorsing Meaninglessness early in bereavement carried the risk of activating a cascade of other grief symptoms. The activation over time of the psychopathological network configuration was further reinforced by two other symptoms (Difficulties positive reminiscing and Wish to join the deceased), which were also connected to meaninglessness in the between-subject network. This cascade of symptoms over time originating from Meaninglessness was consistent with Robinaugh and colleagues’ (2014) hypothesis suggesting that Meaninglessness could be the gateway to activating the other PCBD symptoms over time. In particular, it clarified how Yearning and Emotional pain were intermittently associated in the PCBD networks. Instead of having a direct connection, both symptoms were activated by Difficulties accepting the loss, which was in turn activated Meaninglessness.
In addition, the comorbidity longitudinal networks showed that endorsing Meaninglessness and Worthlessness predicted subsequent activation of a broader series of depressive, grief, and trauma symptoms over time. Specifically, the temporal network in particular indicated that Meaninglessness predicted the later manifestation of Negative beliefs, Negative Emotions, Preoccupation with the deceased, and Difficulties concentrating. Worthlessness activated the subsequent Wish to die to be with the deceased, and also Difficulties concentrating. In turn, these symptoms would activate a cascade of further elements in the network. Combined, PCBD and comorbidity longitudinal networks accentuated the role of Meaningless as core element of PCBD and of psychopathological configurations of grief more in general.

Clinical and Nosological Implications

Our findings suggested a number of implications regarding both conceptualization and clinical intervention for PCBD. Difficulties around transitioning to a new role after the loss appeared crucial in the PCBD networks. Therefore, confusion about one’s role in life after the loss as well as meaninglessness would appear to be ideal candidates for targeted treatment (Borsboom, & Cramer, 2013). Additionally, the role of meaninglessness in the network as a gateway to more symptoms over time inversely emphasized how finding new sources of meaning could be fundamental in coping with the loss (Neimeyer, Klass, & Dennis, 2014). As such, addressing these symptoms early on could potentially forestall or at least minimize the network spread of psychopathological symptoms (McNally et al., 2015). Given the longitudinal and often persistent
quality of clinically relevant grief reactions this would be a highly desirable treatment approach (Prigerson, 2009).

Despite the novelty of the network approach, previous findings are concordant in identifying meaning-making and role transaction as key elements of bereavement (Stroebe, & Schut, 2001). Consequently, developing associated strategies was shown to increase the likelihood of successful coping reactions to bereavement. For example, Currier and colleagues (2006) identified meaning-making as the mediating factor between bereavement after a violent loss and complicated grief symptoms. The capacity for finding meaning after the loss also emerged as the strongest predictor of positive adjustment in bereaved parents (Keesee, Currier, & Neimeyer, 2008). More generally, meaning-making was shown to be significant in being able to flexibly integrate confrontational or avoidance strategies to cope with emotions and situations surrounding the experience of the loss (Stroebe, Hansson, Stroebe, & Schut, 2001). In addition, the importance of role transitions after a loss was already present in the clinical literature (de Mello, de Jesus Mari, Bacaltchuk, Verdeli, & Neugebauer, 2005; Mackay, & Bluck, 2010). In fact, role transitioning is considered a core aspect of the grieving process, having to redefine interpersonal identity in a world that is now without the deceased (Parkes, & Prigerson, 2013). Interpersonal Therapy in particular focused on the development of strategies for transitioning to new interpersonal roles as treatment for grief-related depression (de Mello et al., 2010). Psychotherapy focused on one’s place in the world after a loss would be consistent with previous therapeutic approaches to bereavement as a constructivist (Gillies, & Neimeyer, 2006) and interpersonal process (de Mello et al., 2005). Such therapeutic endeavors could be strengthened using a network approach. For example, identifying the unique pathways by which meaning making influences symptoms and functioning at an individual level (Borsboom, & Cramer,
Compared to a “one-size fits all” manualized treatment, individual networks would offer the possibility of more “personalized” interventions. Actively taking into account individual differences would also further clarify the heterogeneous outcomes associated with grief reactions (Bonanno et al., 2002).

The implications of our findings also suggested insights regarding the nosology of psychiatrically significant grief and bereavement reactions. While networks offer a promising nosological framework (Epskamp, Maris, Waldorp, & Borsboom, 2016), the approach is still early in its development to have a clear social function beyond clinical research (e.g., for medical billing purposes). Such cautiousness becomes crucial if considering that the statistical models used for network analysis could in theory support multiple causal interpretations, including a latent one (Kruis, & Maris, 2016). While progress is being made to move psychopathology into a more empirical framework (Insel, 2013), psychiatric diagnoses presently could still serve a role in mental health (Kendell, & Jablensky, 2003; Stein, Lund, & Nesse, 2013).

To this end, the results from network analyses of grief symptoms may also be useful in guiding revision of the current proposed PCBD symptoms. In particular, these analyses offer insights regarding which symptoms should be considered to be the essence of the diagnosis. Our results suggest for example that based on their significance in the psychopathological network, greater importance should be given to elements related to the social/identity cluster, particularly loss of one’s identity and meaning in life.
Limitations and Future Directions

Despite its advantages, there were also a number of limitations to the network approach as used in the current study.

Sample. Our bereaved sample was limited to individuals who suffered a spousal loss. Although previous research had suggested surprisingly few differences in the longitudinal course of bereavement following different types of loss (Maccallum, Galatzer-Levy, & Bonanno, 2015), it would nonetheless be advantageous to explore how longitudinal networks may vary across loss types. Moreover, our sample was predominantly composed by white females with minimal ethnic or racial variation. As such we could not explore gender or cultural differences in bereavement.

Another limitation was that our subjects were recruited from the community and participation to the study was voluntary. As such, the proportions of clinically distressed individuals could be different when compared to a prospective sample, particularly at 3 months post loss. Moreover, our bereaved community sample had low rates of endorsement for psychopathological symptoms at 14 and 25 months post loss. Limited presence of psychopathology made the sample dissimilar to a clinical population, given grossly different symptoms endorsement rates (Reynolds et al., 2017). In fact, only a portion of the participants (9.5%) met criteria for PCBD at 14 months. While this percentage was consistent with population rates of complex grief (Bonanno et al., 2002), their number was insufficient for independent network modeling. Consequently, the findings might not generalize to entirely clinical samples, which would contrast with their heightened need of appropriate clinical
formulations and interventions (Prigerson et al., 2008). Therefore, future studies should try to replicate these findings using samples with more consistent and abundant psychopathology.

**Nodes.** Networks analysis offers powerful empirical tools to visualize interactions among the network elements. Nevertheless, the choice of which items to include in the network is made a priori. In this study, as in all previous network analyses of grief symptoms, only symptoms coming from DSM-5 diagnoses were included. The DSM symptoms are grouped based on decision made by expert committee (Kendler, 2013). However, it is possible that there are other elements that if included would have had better explicative proprieties in defining grief reactions. Ideal network modeling candidates include alternative grief symptoms (Maciejewski et al., 2016) and biological variables, such as immune markers (Kiecolt-Glaser, Derry, & Fagundes, 2015) or neuroendocrine makers like cortisol (Goodyer, Park, Netherton, & Herbert, 2001). Another related limitation is that some of the edges in the network may represent the same semantic cluster (e.g. suicidality and joining the deceased), rather than the interaction of otherwise independent constructs. Therefore, future studies should include further symptoms in addition to those listed in DSM-5 and also experimental measures, to assess their role in relation to the grief symptoms (Gupta, & Bonanno, 2011; Maccallum, & Bryant, 2011; Maccallum, Sawday, Rinck, & Bryant, 2015).

**Analyses.** The PCBD longitudinal networks were based on three temporal “snapshots” (at 3, 14, and 25 months), rather than true time-series data. Therefore, the resulting temporal and contemporaneous VAR networks should be interpreted only as exploratory attempts to assess PCBD’s temporal dynamics. To more accurately study granger causality in the context of longitudinal networks, future studies would need a proper time series study design (multiple
observations very close in time). It is important to note, however, that such an approach would suffer from limitations of its own. For example, repeated and temporally proximal assessments of the same symptoms over time could bias participant’s responses. For these reasons, indirect and possibly biological variables would be the most appropriate candidate for such a study design. Nevertheless, it is also possible that frequent contact with clinical researchers for these assessments might constitute a form of intervention or exert placebo effects, particularly among individuals suffering more extreme grief reactions, and thus inadvertently altering the structure of the network.

We included stability analyses as part of an effort toward a more empirically-based (and therefore replicable) approach to psychopathology. Given the recommended minimum of one subject per estimated parameter of the network (Epskamp, Kruis, et al., 2016), the sample size for the PCBD networks was adequate. Nevertheless, stability results obtained via Bootnet (Epskamp et al., 2017) recommended caution in interpreting the differences in magnitude of all but the strongest edges. Different types of bootstrapping comparisons suggested that only few nodes and edges were significantly different. Finally, the centrality indices CS-coefficient (i.e. the proportion of cases that can be dropped while maintaining a correlation of 0.7 or higher with the original sample) fell below the recommended 0.25 cut-off. This instability could have been more prominent in the comorbidity network, where the presence of 39 nodes made the analysis underpowered. Simulation studies on the Ising model indicated that networks estimated with suboptimal sample sizes had more sparse edges than the true network (Epskamp, Kruis, et al., 2016). Such sparseness may have affected some of the edges in our network (i.e., explaining the intermittent connections between Yearning and Emotional Pain).
Previous studies that analyzed stability of their network showed similarly large confidence intervals for the edges of their network (Armour, Fried, Deserno, Tsai, & Pietrzak, 2017; Epskamp et al., 2017; Santos, Fried, Asafu-Adjei, & Ruiz, 2017). Given that psychological networks embody a relatively new field of research, norms about the stability of networks are still being developed (Epskamp et al., 2017). Current recommendations suggest caution in accepting nongnificant differences between nodes or edges as evidence for lack of accuracy in the estimations (Epskamp et al., 2017). For example, the aforementioned CS-coefficient cutoff of 0.25 was not recommended as a definite guideline (Epskamp et al., 2017). Regardless, increasing the number of subjects would likely provide more robust and stable findings, while also allowing more items to be modeled in the network. As such, future network studies of PCBD should use a larger sample size, although it could prove challenging given the nature of the examined condition.

**CONCLUSIONS**

Despite these limitations, our study provided further evidence of the advantages of understanding psychopathology using a network approach. To our knowledge, this is the first study that explored PCBD networks using clinical data obtained from multiple in-person diagnostic interviews. Our findings have both clinical and research implications, that will serve as a step toward a more integrated understanding of the interactions between symptoms of a distressed bereavement reaction. In particular, we demonstrated the importance and the difficulties related
to identity disruptions in bereavement, and their role as initiators of a cascade of other symptoms. Further studies are needed to understand more accurately changes in the network over time, and the role of other empirically observable elements in maintaining the symptoms’ activation. These studies should use a time-series design, to address the research question using in a predictive fashion. Particularly important would be to analyze in the network the influence of biological factors already associated with psychopathology, such as inflammatory responses (Kiecolt-Glaser et al., 2015).
REFERENCES


global mental health in the era of DSM-5 and ICD-11. *Current opinion in psychiatry, 26*(5),
493.

stress disorder: findings from a community survey. *American journal of psychiatry, 154*(8),
1114-1119.

bereavement research: Consequences, coping, and care*. American Psychological
Association.

bereavement.


Cambridge university press.

Burstein, R. (2013). Global burden of disease attributable to mental and substance use
1575-1586.


van Borkulo, C. D., Borsboom, D., Epskamp, S., Blanken, T. F., Boschloo, L., Schoevers, R. A.,
reports, 4*, 5918.


APPENDIX: TABLES AND FIGURES

Table 1.
DSM-5 Diagnostic Criteria of Persistent Complex Bereavement Disorder (PCBD).

<table>
<thead>
<tr>
<th>PCBD</th>
<th>Criterion A</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>The person experienced the death of a close relative or friend at least 12 months earlier.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Criterion B</th>
</tr>
</thead>
<tbody>
<tr>
<td>Since the death at least 1 of the following symptoms is experienced on more days than not and to a clinically significant degree:</td>
</tr>
<tr>
<td>B1. Persistent yearning or longing for the deceased.</td>
</tr>
<tr>
<td>B2. Intense sorrow and emotional pain because of the death.</td>
</tr>
<tr>
<td>B3. Preoccupation with the deceased person.</td>
</tr>
<tr>
<td>B4. Preoccupation with the circumstances of the death.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Criterion C</th>
</tr>
</thead>
<tbody>
<tr>
<td>Since the death at least 6 of the following symptoms are experienced on more days than not and to a clinically significant degree:</td>
</tr>
<tr>
<td><strong>Reactive distress to the death</strong></td>
</tr>
<tr>
<td>C1. Marked difficulty accepting the death.</td>
</tr>
<tr>
<td>C2. Feeling shocked, stunned or emotionally numb over the loss.</td>
</tr>
<tr>
<td>C3. Difficulty in positive reminiscing about the deceased.</td>
</tr>
<tr>
<td>C4. Bitterness or anger related to the loss.</td>
</tr>
<tr>
<td>C5. Maladaptive appraisals about oneself in relation to the deceased or the death (e.g., self-blame).</td>
</tr>
<tr>
<td>C6. Excessive avoidance of reminders of the loss (e.g., avoiding places or people associated with the deceased).</td>
</tr>
<tr>
<td><strong>Social/Identity disruption</strong></td>
</tr>
<tr>
<td>C7. A desire not to live in order to be with the deceased.</td>
</tr>
<tr>
<td>C8. Difficulty trusting other people since the death.</td>
</tr>
<tr>
<td>C9. Feeling alone or detached from other people since the death.</td>
</tr>
<tr>
<td>C10. Feeling that life is meaningless or empty without the deceased, or the belief that one cannot function without the deceased.</td>
</tr>
<tr>
<td>C11. Confusion about one’s role in life or a diminished sense of one’s identity (e.g., feeling that a part of oneself died with the deceased).</td>
</tr>
<tr>
<td>C12. Difficulty or reluctance to pursue interests since the loss or to plan for the future (e.g., friendships, activities).</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Criterion D</th>
</tr>
</thead>
<tbody>
<tr>
<td>The disturbance causes clinically significant distress or impairment in social, occupational, or other important areas of functioning.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Criterion E</th>
</tr>
</thead>
<tbody>
<tr>
<td>The bereavement reaction is out of proportion to or inconsistent with cultural, religious, or age-appropriate norms.</td>
</tr>
</tbody>
</table>
Fig. 1. Example of undirected weighted network graph, consisting of nodes and edges.
Fig. 2. Fatigue, disturbed Sleep pattern, and difficulties Concentrating as bridge symptoms between Major Depression (MD) and Generalized Anxiety Disorder (GAD). Adapted from “Network analysis: an integrative approach to the structure of psychopathology” by D. Borsboom and A. O. Cramer, 2013, Annual review of clinical psychology, 9, 99.
Table 2.
Rates of endorsement for DSM-5 Symptoms of MDD (D), PCBD (G), and PTSD (T) at 3 months (N = 260), 14 months (N = 263), and 25 months (N = 271) after the loss.

<table>
<thead>
<tr>
<th>Symptom</th>
<th>3 Months (%)</th>
<th>14 Months (%)</th>
<th>25 Months (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>D-A1. Depressed Mood</td>
<td>28.5</td>
<td>19.8</td>
<td>22.5</td>
</tr>
<tr>
<td>D-A2. Anhedonia</td>
<td>24.6</td>
<td>11.0</td>
<td>14.8</td>
</tr>
<tr>
<td>D-A3. Weight Loss/Gain</td>
<td>41.2</td>
<td>15.6</td>
<td>12.2</td>
</tr>
<tr>
<td>D-A4. Disturbed Sleep Pattern</td>
<td>47.7</td>
<td>33.5</td>
<td>23.6</td>
</tr>
<tr>
<td>D-A5. Psychomotor Agitation/Retardation</td>
<td>24.6</td>
<td>12.9</td>
<td>11.8</td>
</tr>
<tr>
<td>D-A6. Fatigue / Loss of Energy</td>
<td>32.7</td>
<td>23.2</td>
<td>18.1</td>
</tr>
<tr>
<td>D-A7. Worthlessness/Guilt</td>
<td>23.8</td>
<td>12.2</td>
<td>12.5</td>
</tr>
<tr>
<td>D-A8. Difficulty Concentrating</td>
<td>44.6</td>
<td>20.9</td>
<td>15.1</td>
</tr>
<tr>
<td>D-A9. Suicidal Ideation</td>
<td>18.5</td>
<td>17.5</td>
<td>14.4</td>
</tr>
<tr>
<td>G-B1. Persistent Yearning/Longing</td>
<td>54.6</td>
<td>35.7</td>
<td>28.8</td>
</tr>
<tr>
<td>G-B2. Emotional Pain</td>
<td>44.2</td>
<td>19.8</td>
<td>12.5</td>
</tr>
<tr>
<td>G-B3. Preoccupation with Deceased</td>
<td>23.8</td>
<td>7.6</td>
<td>9.2</td>
</tr>
<tr>
<td>G-B4. Preoccupation circumst. death</td>
<td>53.1</td>
<td>26.6</td>
<td>27.3</td>
</tr>
<tr>
<td>G-C1. Marked difficulty accepting loss</td>
<td>27.3</td>
<td>11.8</td>
<td>8.9</td>
</tr>
<tr>
<td>G-C2. Numbness</td>
<td>31.5</td>
<td>10.6</td>
<td>9.2</td>
</tr>
<tr>
<td>G-C3. Difficulties positive reminiscing</td>
<td>7.7</td>
<td>3.4</td>
<td>2.2</td>
</tr>
<tr>
<td>G-C4. Bitterness/Anger related to loss</td>
<td>26.5</td>
<td>15.2</td>
<td>14.0</td>
</tr>
<tr>
<td>G-C5. Maladaptive Appraisal</td>
<td>21.2</td>
<td>11.8</td>
<td>10.0</td>
</tr>
<tr>
<td>G-C6.T-C1/C2. Avoidance reminders</td>
<td>27.3</td>
<td>15.6</td>
<td>12.9</td>
</tr>
<tr>
<td>G-C7. Wish to die to be with deceased</td>
<td>15.8</td>
<td>11.4</td>
<td>11.4</td>
</tr>
<tr>
<td>G-C8. Difficulties trusting others</td>
<td>11.9</td>
<td>8.4</td>
<td>8.1</td>
</tr>
<tr>
<td>G-C10. Life meaningless</td>
<td>26.9</td>
<td>11.8</td>
<td>12.2</td>
</tr>
<tr>
<td>G-C11. Confusion role in life</td>
<td>26.5</td>
<td>21.3</td>
<td>21.4</td>
</tr>
<tr>
<td>G-C12. Difficulties pursue interest</td>
<td>31.9</td>
<td>24.7</td>
<td>24.0</td>
</tr>
<tr>
<td>T-B1. Rec. Intrusive memories</td>
<td>36.2</td>
<td>20.2</td>
<td>11.1</td>
</tr>
<tr>
<td>T-B2. Rec. distressing Dreams</td>
<td>10.4</td>
<td>5.3</td>
<td>4.4</td>
</tr>
<tr>
<td>T-B3. Dissociative Reactions</td>
<td>23.5</td>
<td>19.4</td>
<td>14.8</td>
</tr>
<tr>
<td>T-B4. Distress at exposure</td>
<td>43.8</td>
<td>25.1</td>
<td>23.2</td>
</tr>
<tr>
<td>T-B5. Physiological react. on exposure</td>
<td>26.9</td>
<td>15.6</td>
<td>11.1</td>
</tr>
<tr>
<td>T-D1. Inability remembering</td>
<td>13.8</td>
<td>11.0</td>
<td>9.2</td>
</tr>
<tr>
<td>T-D2. Negative beliefs</td>
<td>10.4</td>
<td>13.7</td>
<td>12.2</td>
</tr>
<tr>
<td>T-D3. Distorted Blame</td>
<td>19.2</td>
<td>16.0</td>
<td>10.7</td>
</tr>
<tr>
<td>T-D4. Negative emotional state</td>
<td>25.8</td>
<td>13.7</td>
<td>8.1</td>
</tr>
<tr>
<td>T-D7 Inability positive emotions</td>
<td>11.5</td>
<td>9.5</td>
<td>9.2</td>
</tr>
<tr>
<td>T-E1. Irritability/Agressive bx</td>
<td>33.8</td>
<td>20.9</td>
<td>17.7</td>
</tr>
<tr>
<td>T-E2. Reckless/Self-destructive bx</td>
<td>2.3</td>
<td>1.1</td>
<td>1.1</td>
</tr>
<tr>
<td>T-E3. Hypervigilance</td>
<td>19.2</td>
<td>16.3</td>
<td>11.1</td>
</tr>
<tr>
<td>T-E4. Startle Response</td>
<td>21.2</td>
<td>16.0</td>
<td>12.9</td>
</tr>
</tbody>
</table>
**Fig. 3.** Ising Model Networks of PCBD symptoms at 3 months (N = 260), 14 months (N = 263), and 25 months (N = 271) after the loss.
Fig. 3 cont’d

25 Months post loss
Fig. 4. Ising Model Networks with identical positioning (layout) of PCBD symptoms at 3, 14, and 25 months post loss.
Fig. 4 cont’d

14 Months post loss

- Alone
- Dif Interests
- LifeMeanless
- ConfRoleLife
- BeWithDecd
- DifAccLoss
- Malad Appr
- Yearning
- Em Pain
- AvoidRemind
- Dif Trust
- Numbness
- Bitterness
- PreocCircDth
- Preoc Decd
- DifPosRem
Fig. 4 cont’d

25 Months post loss
Table 3.
Network Centrality Indices for symptoms of PCBD at 3 months (Time 1), 14 months (Time 2), and 25 months (Time 3) post-loss. Symptoms with no Closeness coefficient have only distant neighbors.

<table>
<thead>
<tr>
<th></th>
<th>3 Months</th>
<th></th>
<th>14 Months</th>
<th></th>
<th>25 Months</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Strength</td>
<td>Closeness</td>
<td>Betweenness</td>
<td>Strength</td>
<td>Closeness</td>
<td>Betweenness</td>
</tr>
<tr>
<td>B1. Persistent Yearning/Longing</td>
<td>0.05</td>
<td>0.45</td>
<td>-0.06</td>
<td>0.12</td>
<td>-0.61</td>
<td>-0.50</td>
</tr>
<tr>
<td>B2. Emotional Pain</td>
<td>0.25</td>
<td>-0.48</td>
<td>-0.06</td>
<td>-1.09</td>
<td>NA</td>
<td>-0.73</td>
</tr>
<tr>
<td>B3. Preoccupation Deceased</td>
<td>-0.43</td>
<td>-0.27</td>
<td>-0.58</td>
<td>-1.09</td>
<td>NA</td>
<td>-0.73</td>
</tr>
<tr>
<td>B4. Preoccupation circumstances death</td>
<td>1.44</td>
<td>0.91</td>
<td>1.73</td>
<td>1.10</td>
<td>-0.40</td>
<td>-0.66</td>
</tr>
<tr>
<td>C1. Marked difficulty accepting loss</td>
<td>-0.91</td>
<td>-1.50</td>
<td>-0.58</td>
<td>0.14</td>
<td>-0.29</td>
<td>-0.28</td>
</tr>
<tr>
<td>C2. Numbness</td>
<td>1.10</td>
<td>0.79</td>
<td>0.71</td>
<td>-1.09</td>
<td>NA</td>
<td>-0.73</td>
</tr>
<tr>
<td>C3. Difficulties positive reminiscing</td>
<td>-2.05</td>
<td>NA</td>
<td>-0.83</td>
<td>-1.09</td>
<td>NA</td>
<td>-0.73</td>
</tr>
<tr>
<td>C4. Bitterness/Anger related to loss</td>
<td>0.18</td>
<td>0.18</td>
<td>0.19</td>
<td>0.10</td>
<td>-0.26</td>
<td>-0.28</td>
</tr>
<tr>
<td>C5. Maladaptive Appraisal</td>
<td>-0.62</td>
<td>-1.55</td>
<td>-0.83</td>
<td>0.15</td>
<td>0.04</td>
<td>0.17</td>
</tr>
<tr>
<td>C6. Avoidance reminders</td>
<td>-0.71</td>
<td>0.25</td>
<td>-0.19</td>
<td>-0.76</td>
<td>-1.72</td>
<td>-0.73</td>
</tr>
<tr>
<td>C7. Wish to die to be with deceased</td>
<td>-0.76</td>
<td>-1.11</td>
<td>-0.83</td>
<td>-0.51</td>
<td>-1.05</td>
<td>-0.73</td>
</tr>
<tr>
<td>C8. Difficulties trusting others</td>
<td>-0.06</td>
<td>-0.25</td>
<td>-0.06</td>
<td>-1.09</td>
<td>NA</td>
<td>-0.73</td>
</tr>
<tr>
<td>C9. Alone/Detached</td>
<td>0.03</td>
<td>0.25</td>
<td>-0.58</td>
<td>1.32</td>
<td>1.36</td>
<td>1.73</td>
</tr>
<tr>
<td>C10. Life meaningless</td>
<td>0.67</td>
<td>0.96</td>
<td>0.06</td>
<td>1.73</td>
<td>0.90</td>
<td>2.18</td>
</tr>
<tr>
<td>C11. Confusion role in life</td>
<td>2.10</td>
<td>2.12</td>
<td>2.76</td>
<td>1.08</td>
<td>1.54</td>
<td>1.73</td>
</tr>
<tr>
<td>C12. Difficulties pursue interest</td>
<td>-0.30</td>
<td>-0.73</td>
<td>-0.83</td>
<td>1.00</td>
<td>0.47</td>
<td>0.39</td>
</tr>
</tbody>
</table>
Fig. 5. Comparison of Network Centrality Indices for symptoms of PCBD at 3 months (Time 1), 14 months (Time 2), and 25 months (Time 3) post-loss. Symptoms with no Closeness coefficient have only distant neighbors.
Fig. 6. Centrality Indices for symptoms of PCBD using data only from participants who were administered all interviews (N = 207).
Fig. 7. Ising Model Networks of MDD, PCBD, and PTSD symptoms at 3 months (N = 260), 14 months (N = 263), and 25 months (N = 271) after the loss.
Fig. 7 cont’d

14 Months p.l.
Fig. 7 cont’d

25 Months p.l.
Fig. 8. Network Centrality Indices for symptoms of Comorbidity Networks at 3 months (Time 1), 14 months (Time 2), and 25 months (Time 3) post-loss. Symptoms with no Closeness coefficient have only distant neighbors.
Fig. 9. Regularized partial correlation network of PCBD symptoms, functioning, demographics, and risk factors at 14 months after the loss (N = 263).
**Fig. 10.** VAR Network of temporal, contemporaneous, and between-subject relationships of PCBD symptoms at 3 month, 14 months, and 25 months post loss (N = 207). Arrows depict the strength of a symptom as a predictor of another symptom over time. Self-loops represent symptoms temporal predictions stemming from its previous states. Only significant arrows are shown.

Fig. 10a. Temporal network
Fig. 10b. Contemporaneous Network
Fig. 10c. Between Subjects Network.
Fig. 11. VAR Network of temporal, contemporaneous, and between-subject relationships between selected symptoms of PCBD, MDD, and PTSD at 3 month, 14 months, and 25 months post loss (N = 207).

Fig. 11a. Temporal Network
Fig. 11b. Contemporaneous Network

- **MDD**
  - Mood: Depressed Mood
  - Anhed: Anhedonia
  - Worth: Worthlessness/Guilt
  - ConCent: Difficulty Concentrating
  - Suicid: Suicidal Ideation

- **PCBD**
  - EmPain: Emotional Pain
  - PreocDecd: Preoccupation Deceased
  - PreocCircDth: Preoccupation circumstances death
  - Numbness: Numbness
  - Bitterness: Bitterness/Anger related to loss
  - MaladAppr: Maladaptive Appraisal
  - BeWithDecd: Wish to die to be with deceased
  - DifTrust: Difficulties trusting others
  - Alone: Alone/Detached
  - LifeMeanless: Life meaningless
  - ConfRoleLife: Confusion role in life
  - DifInterests: Difficulties pursue interest

- **PTSD**
  - DisReact: Distress at exposure
  - NegBifs: Negative beliefs
  - NegEmo: Negative emotional state
Fig. 11c. Between-Subjects Network.
**Fig. 12.** Bootstrapped Confidence Intervals of edge-weights for the PCBD networks. Red lines represent edges, ordered by edge weight magnitude, and the gray areas represent their bootstrapped CIs.

Fig. 12a. Time 1
Fig. 12b. Time 2
Fig. 12c. Time 3
Fig. 13. Bootstrapped difference tests between non-zero PCBD symptoms edge-weights. Black boxes represent edges that do differ significantly from one-another. Colored diagonal boxes correspond to the color of the edge in the network.

Fig. 13a. Time 1
Fig. 13b. Time 2
Fig. 13c. Time 3
**Fig. 14.** Bootstrapped difference significance tests between node centrality indices. Black boxes represent nodes that do differ significantly from one-another. Numbers show the values of the node’s Strength.

**Fig. 14a. Time 1**

<table>
<thead>
<tr>
<th>Node</th>
<th>Visibility</th>
<th>Strength</th>
<th>Closeness</th>
<th>Betweenness</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yearing</td>
<td>2.7</td>
<td>4.5</td>
<td>0.0</td>
<td>12.0</td>
</tr>
<tr>
<td>ProceedDh</td>
<td>4.1</td>
<td>2.1</td>
<td>0.0</td>
<td>4.0</td>
</tr>
<tr>
<td>Proceed</td>
<td>1.9</td>
<td>3.5</td>
<td>0.0</td>
<td>24.0</td>
</tr>
<tr>
<td>Number</td>
<td>1.5</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Mbled Appr</td>
<td>1.6</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>LMMeasless</td>
<td>2.3</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Em Pain</td>
<td>2.6</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>DiffusRem</td>
<td>5.4</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Diffinterests</td>
<td>1.7</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>DiffLocLow</td>
<td>1.7</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Def Trust</td>
<td>2.9</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>ConflRelLife</td>
<td>4.0</td>
<td>56.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Biterness</td>
<td>16.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Sad/Wht&amp;Ded</td>
<td>10.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>AcidRend</td>
<td>4.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Alone</td>
<td>2.7</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
</tbody>
</table>
Fig. 14c. Time 3
**Fig. 15.** Average correlations between centrality indices from the original sample and from networks sampled with increasing percentages of dropped participants. Lines indicate the centrality scores means and areas indicate their 95% CIs. Centrality estimates can be considered stable when the correlation after dropping a substantial amount of participants remains high.

**Fig.15a.** Time 1
Fig. 15b. Time 2
Fig. 15c. Time 3