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Isvoranu, A.-M.; Epskamp, S.; Cheung, M.W.-L.

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Network Models of Post-traumatic Stress Disorder: A Meta-analysis

Adela-Maria Isvoranu[1]

Sacha Epskamp[1,2]

Mike W.-L. Cheung[3]

[1]Department of Psychology, Psychological Methods, University of Amsterdam, Amsterdam, The Netherlands

[2]Centre for Urban Mental Health, Amsterdam, The Netherlands

[3]Department of Psychology, National University of Singapore, Singapore

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*Corresponding author:

Adela-Maria Isvoranu, Department of Psychology, Psychological Methods, University of Amsterdam, Nieuwe Achtergracht 129B, 1018 WT Amsterdam, The Netherlands; email:

Abstract

Post-traumatic stress disorder (PTSD) researchers have increasingly used psychological network models to investigate PTSD symptom interactions, as well as to identify central driver symptoms. It is unclear, however, how generalizable such results are. We have developed a meta-analytic framework for aggregating network studies while taking between-study heterogeneity into account and applied this framework in the first-ever meta-analytic study of PTSD symptom networks. We analyzed the correlational structures of 52 different samples with a total sample size of n = 29,561 and estimated a single pooled network model underlying the datasets, investigated the scope of between-study heterogeneity, and assessed the performance of network models estimated from single studies.

Our main findings are that: (1) We identified large between-study heterogeneity, indicating that it should be expected for networks of single studies to not perfectly align with one-another, and meta-analytic approaches are vital for the study of PTSD networks. (2) While several clear symptom-links, interpretable clusters, and significant differences between strength of edges and centrality of nodes can be identified in the network, no single or small set of nodes that clearly played a more central role than other nodes could be pinpointed, except for the symptom 'amnesia' which was clearly the least central symptom. (3) Despite large between-study heterogeneity, we found that network models estimated from single samples can lead to similar network structures as the pooled network model. We discuss the implications of these findings for both the PTSD literature as well as methodological literature on network psychometrics.

Keywords: PTSD, PTSS, post-traumatic stress disorder, network analysis, network models, network psychometrics, meta-analysis

General Scientific Summaries (GSS)

In this meta-analysis, we used new statistical routines to analyze 52 datasets used in publications on Post-traumatic Stress Symptoms (PTSS) networks. We find a generalizable network structure that contains the most salient symptom-interactions, but also identify a large degree of heterogeneity across these datasets, indicating that datasets can vastly differ from one-another. We discuss both clinical and methodological implications. Important for PTSS treatment, our meta-analysis indicates that we should not expect a single PTSS symptom to drive other symptoms.

1. Introduction

Over the past decade, a novel theoretical framework proposed in the study of psychopathology grew popular and prominent, especially in clinical and psychiatric research domains: the network approach (Borsboom et al., 2011; Borsboom, 2017; Borsboom & Cramer, 2013; Cramer et al., 2010; Epskamp, van Borkulo, et al., 2018; Fried et al., 2015; Fried, van Borkulo, Cramer, et al., 2016; Fried, van Borkulo, Epskamp, et al., 2016; Isvoranu et al., 2016, 2017; Klaiber et al., 2015; Rhemtulla et al., 2016; Robinaugh et al., 2020; van Rooijen et al., 2018). The network approach to psychopathology proposes that mental disorders result from dynamical interactions between symptoms (e.g., flashbacks of a traumatic event could cause nightmares, which could in turn cause intrusive thoughts and sleep disturbance), and that the symptoms themselves are what constitute a mental disorder, rather than a non-observable common cause (Borsboom, 2008, 2017; Borsboom & Cramer, 2013). From this perspective, symptoms become agents in a causal system and are no longer regarded as merely passive indicators of a latent unobserved entity (i.e., a mental disorder; Borsboom & Cramer, 2013; Kendler, 2016). In response to the network perspective, which was first advanced as theoretical groundwork, the exploratory methodological framework now known as the field of *network psychometrics* (Epskamp, 2017; Epskamp, Maris, et al., 2018) developed, with a large body of growing empirical research across diverse disciplines currently and frequently employing this methodology (Abacioglu et al., 2019; Blanken et al., 2019; Costantini & Perugini, 2016; Kossakowski et al., 2015). The main type of network now commonly used is the *Gaussian Graphical Model* (GGM): a network in which variables (e.g., symptoms) are represented as nodes, which are connected by weighted edges that represent partial correlation coefficients (Epskamp, Waldorp, et al., 2018; Lauritzen, 1996).

One of the fast-expanding research fields focused on identifying associations between a wide array of symptoms and other factors, and commonly utilizing network models, is the

field of post-traumatic stress. Over the past half-decade, numerous studies have been published that investigate associations between symptomatology (McNally et al., 2015; van Loo et al., 2017), potential risk factors (Armour et al., 2017; Choi et al., 2017; Mancini et al., 2019; Simons et al., 2019) and pathways to comorbidity (Djelantik et al., 2020; Gilbar, 2020; Lazarov et al., 2019; Malgaroli et al., 2018; Price et al., 2019; Vanzhula et al., 2019), yielding novel results and hypotheses. In response to this rapid research expansion and in an aim to synthesize current findings in the field, a thorough systematic review of the network approach to posttraumatic stress disorder (PTSD) has been recently carried out (Birkeland et al., 2020). While more general and overarching reviews discussing theoretical, methodological, and empirical contributions of network approaches to psychopathology (including PTSD as a sub-field) already exist (Contreras et al., 2019; Robinaugh et al., 2020), to our knowledge, no other review focused on network approaches to specific research areas has yet been conducted. This further supports the rapid development of the network framework in PTSD research. Of note, while aiming to synthesize current research findings and summarize common features, existing reviews are mainly narrative, based on for instance observation of strongest edges and centrality measures. This is due to the novelty of network models, and the lack of methodological advances at the time, which would have allowed conducting a comprehensive meta-analysis. While certainly important contributions, such narrative work cannot handle cross-study heterogeneity in a systematic way, and results could be impacted by investigating several potentially underpowered (and unstable) results based on individual samples, rather than investigating the results of a single well-powered meta-analytic analysis.

Consequently, and alongside the call for new developments in the field of network psychometrics, we proposed the Meta-Analytic Gaussian Network Aggregation (MAGNA; Epskamp et al., 2020), which is a novel methodology that was derived from meta-analytic

structural equation modeling (MASEM; Cheung, 2015; Cheung & Chan, 2005) and can be used to perform a meta-analysis of network models. MAGNA allows for estimating a single pooled GGM structure from multiple studies, as well as estimate the size of heterogeneity in deviations from this pooled GGM. In this way, it becomes possible to aggregate results across a multitude of studies, providing a statistical and objective framework to summarize these findings, while taking heterogeneity across different study domains (e.g., subjects from different populations that were exposed to different traumatic events) into account.

The goal of the current research was therefore to expand on previous narrative findings relating to network models of post-traumatic stress symptoms (PTSS). We aimed to, for the first time ever, carry out a meta-analysis of existing research focused on the network approach to PTSD. Specifically, we aimed to identify common effects of current research by estimating a pooled network structure of frequently assessed post-traumatic symptoms, to assess centrality of these symptoms in the pooled network structure, and to investigate the size of between-study heterogeneity by assessing deviations from the pooled network structure. Finally, we investigated how similar results from individual network studies are compared to this pooled cross-study network. We discuss implications from these results for PTSD research, but also for the replicability (Borsboom et al., 2017; Forbes et al., 2017a), generalizability (Forbes et al., 2017b), and utility of centrality indices (Bringmann et al., 2019).

2. Methods

2.1. Data sources and search strategies

Consistent with PRISMA (Moher et al., 2009) guidelines, we followed the search strategies employed by Birkeland and colleagues (Birkeland et al., 2020), with an extended timeframe and an additional search term. Specifically, we performed a keyword search in PsychINFO,

Medline, and Web of Science and limited our search to studies published between January 2008 and January 2020. We used a combination of a keyword pertaining to the network approach (i.e., network analysis OR network approach OR network model OR network structure OR network modelling OR network psychometrics) and a keyword denoting a focus on PTSS (i.e., posttraumatic stress disorder OR posttraumatic disorder OR PTSD OR posttraumatic stress symptoms OR PTS or PTS symptom or PTSD symptoms). To further identify records, we examined papers that identified themselves as reviews conducted on the network approach literature and selected articles through cross-referencing.

2.2. Study selection

Studies were included if they: (1) were written in English, (2) were peer-reviewed[1], (3) were accepted for publication between the pre-defined timeframe, (4) estimated a GGM of PTSS, (5) were based on cross-sectional or panel data, (6) made the dataset or correlation matrices available online or via email when requested.

Of note, unlike classical meta-analytic techniques, but similar to MASEM, the MAGNA framework requires correlation matrices of datasets as input. As such, when the data or correlation matrices were not made available online, A.M.I and S.E. contacted all corresponding authors to request either the dataset used when estimating the network structure(s) or, when not possible to share this, summary statistics of the data (i.e., Pearson correlations after listwise deletion, Pearson correlations using pairwise estimation, Spearman correlations after listwise deletion, Spearman correlations using pairwise estimation, the sample size used, the name of the variables, the number of levels per variable in case these were measured on an ordered scale, means and standard deviations, and a description of the

[1]We did not search for unpublished manuscripts and as such our results might be influenced by publication bias. However, we do not expect publication bias to play a role in network papers as these are highly exploratory and typically not designed to test particular hypotheses. Further, the number of unpublished manuscripts is likely very small due to the novelty of the field.

content of each variable). For the convenience of the authors, an *R* (R Core Team, 2020) function was provided in the request email, which solely required the dataset as input, and automatically compiled five files with the requested information (see sAppendix 1 in the Supplement for the *R* code; R Core Team, 2015). Two reminder emails were sent to all authors before deciding to exclude the respective study based on unresponsiveness.

2.3. Data extraction

From all eligible articles, we extracted the author's last name, year of publication, email address of the corresponding author(s), sample size (both pairwise average and following listwise deletion when missing data were present, if this information was available), number of variables assessing PTSS, population, measure used, diagnostic system, and when available the data or correlation matrices (when not, the automated procedure described in the *Study selection* above was employed).

Given the multitude of measures and PTSS symptoms commonly assessed, for every study included in the meta-analysis, we examined all variables and identified the symptoms that adhere to DSM-IV criteria for PTSD. One reviewer conducted the abstraction of the data, while another reviewer verified its accuracy. For studies in which different samples were available (e.g., different populations or multiple time points), these were treated as multiple samples in the statistical analyses (see Table 1).[2]

2.4. Statistical Analysis

All statistical analyses were conducted in the R statistical software version 4.1.0 (R Core Team, 2020), using the MAGNA framework (Epskamp et al, 2020) implemented in the *R*

[2]Supplementary materials sFigure 4 and sFigure 5 show results based on collapsing multiple dependent samples (repeated measures) into a single correlation matrix instead of treating these as separate samples.

package *psychonetrics* version 0.9 (Epskamp, 2020). We employed a random-effects MAGNA model using an averaged individual estimate of the sampling variation matrix. In random-effects MAGNA, we model the marginal (not partial) pairwise correlation coefficient between two symptoms as the composite of a correlation implied by a single pooled GGM structure, deviation due to between-study random effects, and deviation due to sampling variation:

sample correlation = implied correlation by GGM + heterogeneity + sampling variation.

To do this, the MAGNA analysis first estimates the amount of sampling variation on the reported correlations across studies. Next, the analysis takes each correlation as a 'variable', for which it estimates a mean (fixed-effect) and variance-covariance (random-effects) structure, while taking the previously estimated sampling variation into account. In this analysis, the means of sample correlations are modeled using a GGM, which we term the 'pooled MAGNA network'. Therefore, random-effects MAGNA is a multi-level model with a random effect on correlations (not on the edge parameters themselves). Such a MAGNA analysis can involve many parameters to be estimated: a 17-node network involves 136 network parameters, 136 variances and 9,180 covariances to be estimated.

We investigated reported Pearson correlation matrices—for which MAGNA was developed—in which listwise deletion was used. Sampling variation was handled by first estimating a single averaged sampling variation matrix, which was constructed by averaging estimated sample variation matrices per study (we refer to Epskamp et al., 2020, for more details). We estimated model parameters through maximum likelihood estimation, using the R package *psychonetrics*, which subsequently uses the optimization algorithm implemented in the *nlminb* function for parameter estimation. This routine returns several results of interest:

1. Parameter estimates for the pooled MAGNA network, which we used to investigate edge weights and centrality estimates.
2. An estimated parameter variance-covariance matrix (Fisher information), which we used to test the significance of edges, as well as to assess differences in centrality indices.
3. An estimated variance-covariance matrix of random effects on the implied correlational structure, of which we obtained standard deviations of random effects to assess heterogeneity across studies

We used these to investigate (1) the edge-weights of the pooled MAGNA network, (2) the centrality of nodes in the pooled MAGNA network, (3) the cross-study heterogeneity. Simulations reported by Epskamp et al. (2020) show that the MAGNA method estimates the pooled MAGNA network and cross-study heterogeneity well given sufficient samples: at least 16 samples are needed for acceptable levels of specificity, while more samples (32 & 64) lead to the best levels of sensitivity and parameter accuracy. Furthermore, we investigated (4) how much networks estimated from single studies reflect the meta-analytic results, and the consistency in results across several methodological choices we could have made, we also employed (5) a multiverse analysis. Below we discuss each of these analyses in more detail.

2.4.1. Pooled MAGNA edge weights

The edge weights of the pooled MAGNA network represent the strength of associations between two items in the network structure after conditioning on all other items in the dataset. These are parameterized as *partial correlation coefficients*. The analysis returns a single set of edge weights for a single pooled model containing the expected edge weights across all studies. The parameter variance-covariance matrix in addition returns the *standard*

errors of these edge weights, which can subsequently be used to obtain *p*-values and confidence intervals.

2.4.2. Pooled MAGNA centrality indices

Centrality indices can be used to gauge the importance of nodes in any network structure (Newman, 2010). We investigated three commonly assessed centrality measures for weighted networks: *strength*, *closeness*, and *betweenness* (Opsahl et al., 2010), in addition to two more recently proposed metrics that have grown popular when analyzing psychological networks: *expected influence* (Robinaugh et al., 2016), and the *predictability* of nodes (quantified as explained variance R^2; Haslbeck & Waldorp, 2018)[3]. The metrics strength, expected influence and R^2 quantify direct connectivity, being a function only of the nodes a node is connected to, and the metrics closeness and betweenness also quantify indirect connectivity, being a function of all other nodes in the network. Strength (also termed *node strength* or *weighted degree*) is quantified by summing the absolute values of all edge weights connected to a node. Expected influence is the same as strength but does not take the absolute value of edge weights before summing them. R^2 or predictability is a metric quantifying how much variance can be explained in one node by all other nodes in the network, closeness is computed by taking the inverse of the sum of lengths of edges on the shortest paths between one node and all other nodes (with length defined as the inverse of the absolute edge weight), and betweenness is computed by counting how often a node lies on the shortest paths between all other nodes. For more information on how these measures are computed, we refer to Opsahl et al. (2010) for strength, closeness and betweenness, to Robinaugh et al.

[3]Predictability is technically not a centrality index, as unlike the other metrics the metric is specifically designed for the statistical model underlying the network representation rather than for the network representation itself.

(2016) for expected influence, and to Haslbeck & Waldorp (2018) and Williams (2018) for predictability.

In addition to reporting the obtained centrality indices, we employed a parametric bootstrap routine to obtain centrality difference plots commonly used in reported network analyses (Epskamp et al., 2017). In this method, sampling techniques are used to assess the significance of a difference between centrality indices. This is typically done to gain insight in the stability of centrality, as it is not possible to draw confidence regions on the commonly reported centrality indices due to these relying on absolute values of edge weights and many edge weights being estimated near the boundary of zero. While commonly a non-parametric bootstrap is used, we used a parametric bootstrap routine that did not involve estimating parameters as the estimation routine is very slow.[4] This routine is as follows. First, we simulated 1,000,000 network models using the estimated parameter variance-covariance matrix of the pooled MAGNA network edge weights. Next, for each pair of variables and for each centrality index, we computed the proportion of times the difference was below zero and the proportion of times the difference was above zero. Finally, we took the lowest of these proportions and multiplied the result by two to obtain a *p*-value corresponding to a two-sided difference test. The null-hypothesis for equality in centrality can then be rejected at different α levels using these *p*-values. Of note, Epskamp, Borsboom, and Fried (2018) report that the expected rejection rate given the null model of equal centrality indices may actually be lower than α, indicating that this test can be more conservative than expected.

[4]Performing the MAGNA analysis reported here took over an hour of computation time on a relatively powerful computer, and the multiverse analysis reported in the supplementary materials took several days to run. In addition, these computations relied on GPU computing, and as such could not be parallelized over CPU cores as typically done in non-parametric bootstraps of psychological network models.

2.4.3. Heterogeneity across studies

The MAGNA analysis returns an estimated variance-covariance matrix on the variability around the correlational structure implied by the pooled GGM. To ensure that this matrix is positive semi-definite, we estimated the Cholesky decomposition of this variance-covariance matrix rather than estimating the variances and covariances directly. This routine is further explained elsewhere (Epskamp et al., 2020). To assess cross-study heterogeneity, we computed random effect standard deviations by taking the square root of the estimated variances. These random effect standard deviations give insight in how much the correlation coefficient between two variables differs across studies after taking sampling variation into account.

2.4.4. Comparison to single-study network models

We further investigated how individual network studies correspond to the obtained pooled MAGNA network: if a network is estimated from a single sample, would similar conclusions be drawn from the resulting network structure as would be drawn from the meta-analytic results? To do this, for each correlation matrix (Pearson correlations obtained through listwise deletion), we estimated network models using four techniques that allow for correlation matrices to be used as input: (1) the *EBICglasso* algorithm (Epskamp & Fried, 2018), which combines the graphical LASSO (Friedman et al., 2008) regularization with model selection using the extended Bayesian information criterion (EBIC; Foygel & Drton, 2010) and is estimated through using the *EBICglasso* function in the *qgraph* package (Epskamp et al., 2012), (2) the *ggmModSelect* algorithm using the *qgraph* package (Isvoranu et al., 2019), which performs extensive stepwise unregularized model search, (3) unthresholded partial correlation estimation using the *qgraph* package, and (4) pruning at $\alpha = .05$ using the *psychonetrics* package (Epskamp, 2020b; Epskamp et al., 2020), which

starts with estimating unthresholded partial correlations as in (3), but subsequently removes non-significant edges and re-fits other edges using maximum likelihood estimation while keeping weights of the removed edges fixed to zero. We compared how well on average parameter estimates compared to the pooled MAGNA network.

2.4.5. Consistency due to methodological choices

There were various methodological choices in this work leading to a plurality of possible statistical results that could be obtained, which can be problematic especially given the novelty of our methodology (Epskamp, 2019). Regarding the MAGNA analysis, we chose to use a variant in which sampling variation is handled through using the average of individually estimated sampling variation matrices. Instead of using an average sampling variation matrix we could have also used full-information maximum likelihood estimation and use a different sampling variation matrix per study, and instead of using individually estimated sampling variation matrices we could have also used a pooled sampling variation matrix. As such, there are four variants of MAGNA analysis (Epskamp et al., 2020). Regarding the data, we used Pearson correlation matrices obtained through listwise deletion (as these were most in line with the assumptions underlying the MAGNA model and as we had the most samples with these correlation matrices), but we could have also chosen to analyze Spearman correlations or to use pairwise deletion. Some samples in our study included observations of the same cases measured multiple times, leading to dependencies between these samples that violate the assumption of independent samples. We chose to include these samples in the analysis (to optimize the number of samples and because mostly the time interval between samples was long), but we could have also chosen to collapse correlation matrices of these samples into a single correlation matrix per study. Finally, we chose to analyze the DSM-IV symptoms, but we could have also chosen to analyze only

symptoms shared between the DSM-IV and DSM-5 (analyzing all DSM-5 symptoms was computationally not feasible). To gain insight in the impact of these methodological choices, we performed a *multiverse analysis* by performing the analysis for each of the in total 64 potential analyses that could have been performed (Steegen et al., 2016). Of these 64 analyses, we report the estimated edge weights and centrality indices.

2.5. Bias assessment

As also highlighted in the systematic review carried out by Birkeland and colleagues (2020), to date no established instruments yet exist to assess bias in network studies, and regular meta-analytic instruments are not applicable for this current statistical technique. Of note, the MAGNA framework accounts for the heterogeneity of the data, as well as for the difference in sample size across the studies.

3. Results

In this section, we discuss the main results of our meta-analysis. More detailed results, as well as several figures that were outside the scope of this paper can be found in the online supplementary materials.

3.1. Systematic search

The study selection process is displayed in Figure 1 below; in total, the search returned 260 articles. After removing 140 duplicates, records were screened by title and abstract for eligibility. For 70 articles where this was unclear, the full text was further examined, and articles were excluded based on the criteria described above, resulting in 33 eligible studies to be included in the meta-analysis, with a total of 52 samples that could be used in the analysis Table 1 presents study characteristics for each included study. Supplementary sFigure 2

presents an overview of the cumulative number of articles, as well as the number of articles published per year. Sample sizes ranged from 124 to 1,790, with a median sample size of 418 and a mean sample size of 568.48 (SD = 401.05). The total sample size was 29,561 cases across all samples.

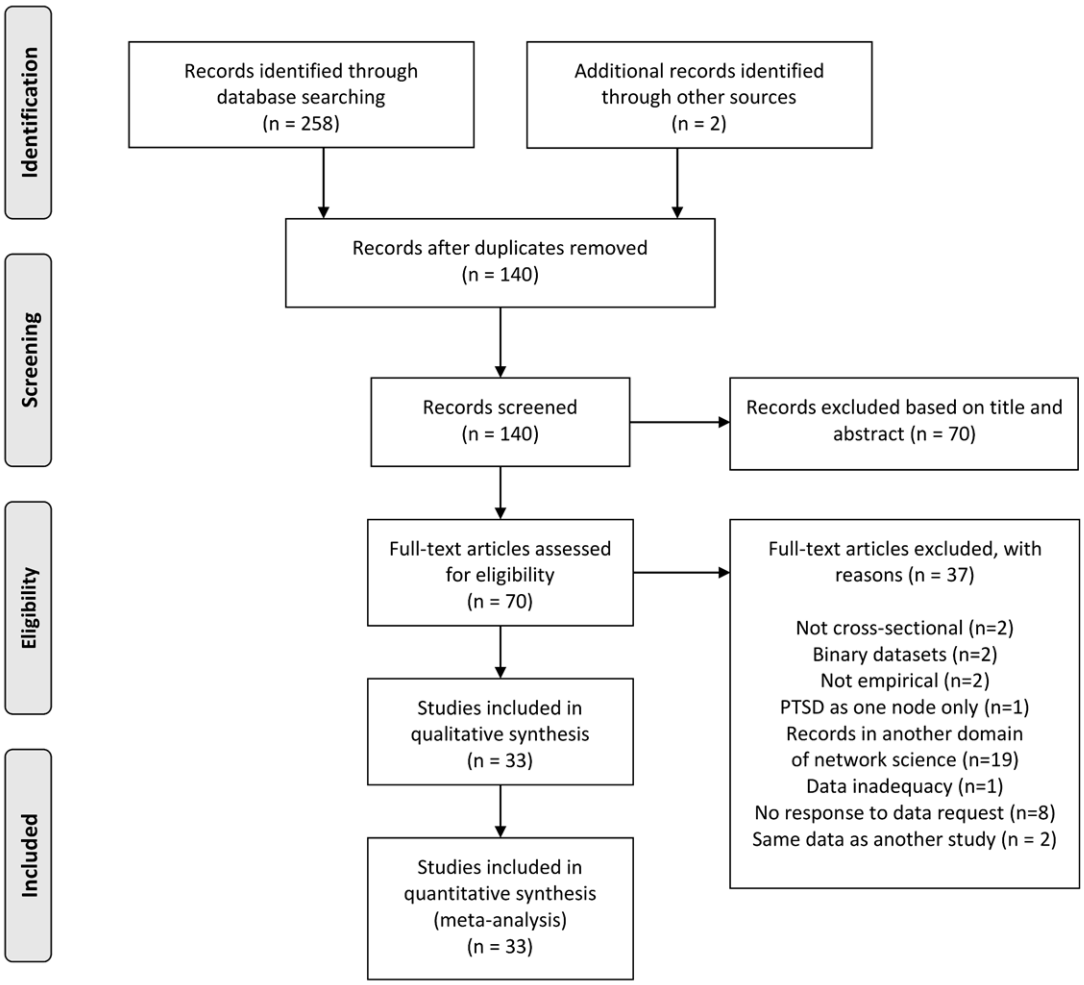

Figure 1. PRSIMA flow diagram.

Based on our variable selection (i.e., symptoms that adhere to DSM-IV criteria for PTSD), we identified 17 symptoms (further described in sAppendix 2): intrusive thoughts, nightmares, flashbacks, psychological reactivity, physiological reactivity, internal avoidance, external avoidance, amnesia, loss of interest, feeling detached, emotional numbing,

irritability/ anger, hypervigilance, easily startled, difficulty concentrating, sleep disturbance, and hopelessness[5]. Thus, we employed MAGNA estimation on all symptoms from the DSM-IV (17 symptoms). Not all studies included all symptoms, but full information maximum likelihood estimation in MAGNA can handle missing nodes. Figure 2 shows the number of studies that report each pair of symptoms analyzed. A higher number of samples for each pair of variables is available for the common DSM-IV and DSM-5 symptoms across different studies (i.e., the item 'hopelessness' is specific to the DSM-IV and not measured across all studies). Some studies featured two variables designed to measure the same symptom, in which case the average correlation with both variables was used as input to MAGNA.

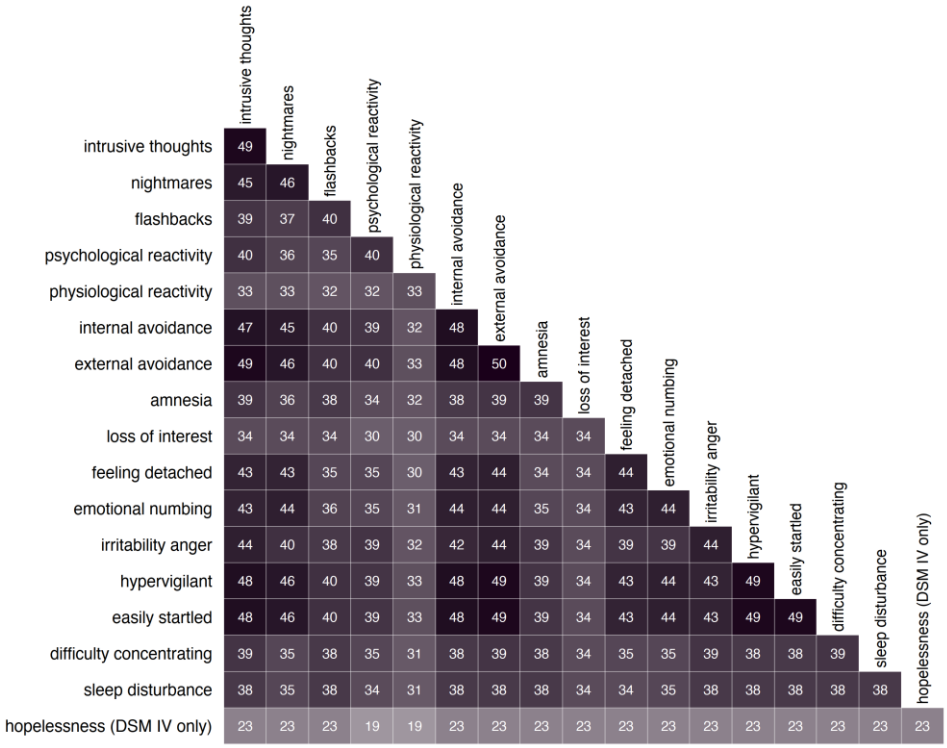

Figure 2. Number of samples for each pair of variables for which Pearson correlations based on listwise deletion were available. Sample sizes for other types of correlations can be seen in sFigure 2 in the supplementary materials.

[5]Of note, analyses including all symptoms measured across all studies, as well as analyses including only DSM-5 symptoms were not feasible due to a too high model complexity for the software to handle, as well as a low number of studies including either DSM-5 symptoms or a wide array of other symptoms.

3.2. Pooled MAGNA edge weights

Figure 3 shows the estimated pooled MAGNA network for the DSM-IV PTSD symptoms, and supplementary materials sAppendix 3 presents numeric results in a table. In Figure 3, all edges not significant at $\alpha = .05$ are hidden. Figure 4 and sFigure 3 in the supplementary materials furthermore show the estimated edge weights, the 95% confidence regions of edges all edges, and the significance of these edges. The significance level of $\alpha = .0004$ corresponds to an α level of .05 corrected for 136 tests and rounded to 4 digits. Within the pooled MAGNA network structure across all DSM-IV symptoms, notably all significant edges between all pairs of items were positive. Further, several strong and stand-out links between symptoms emerged. The three strongest edges were 'easily startled' – 'hypervigilant', 'external avoidance' – 'internal avoidance' and 'emotional numbing' – 'feeling detached'. Also strong were the edges 'physiological reactivity' – 'psychological reactivity', 'feeling detached' – 'loss of interest', and 'flashbacks' – 'intrusive thoughts', and three edges linked to the node 'nightmares': 'sleep disturbance', 'intrusive thoughts', and 'flashbacks'. The network model furthermore showed some clustering, most notably a cluster emerged with the nodes 'nightmares', 'flashbacks', 'sleep disturbance' and 'intrusive thoughts', and another cluster emerged with the nodes 'emotional numbing', 'feeling detached', 'loss of interest', and 'hopelessness'.[6]

[6]Of note, the placement of nodes is performed via the Fruchterman-Reingold algorithm (Fruchterman & Reingold, 1991), which is a chaotic algorithm that generally places nodes that are strongly connected closer to one-another. This creates a 2-dimensional representation of a high-dimensional object (the network model). Here we define clusters as groups of nodes between which there are relatively strong edges, as well as based on previous DSM (American Psychiatric Association, 2013) distinction of clusters.

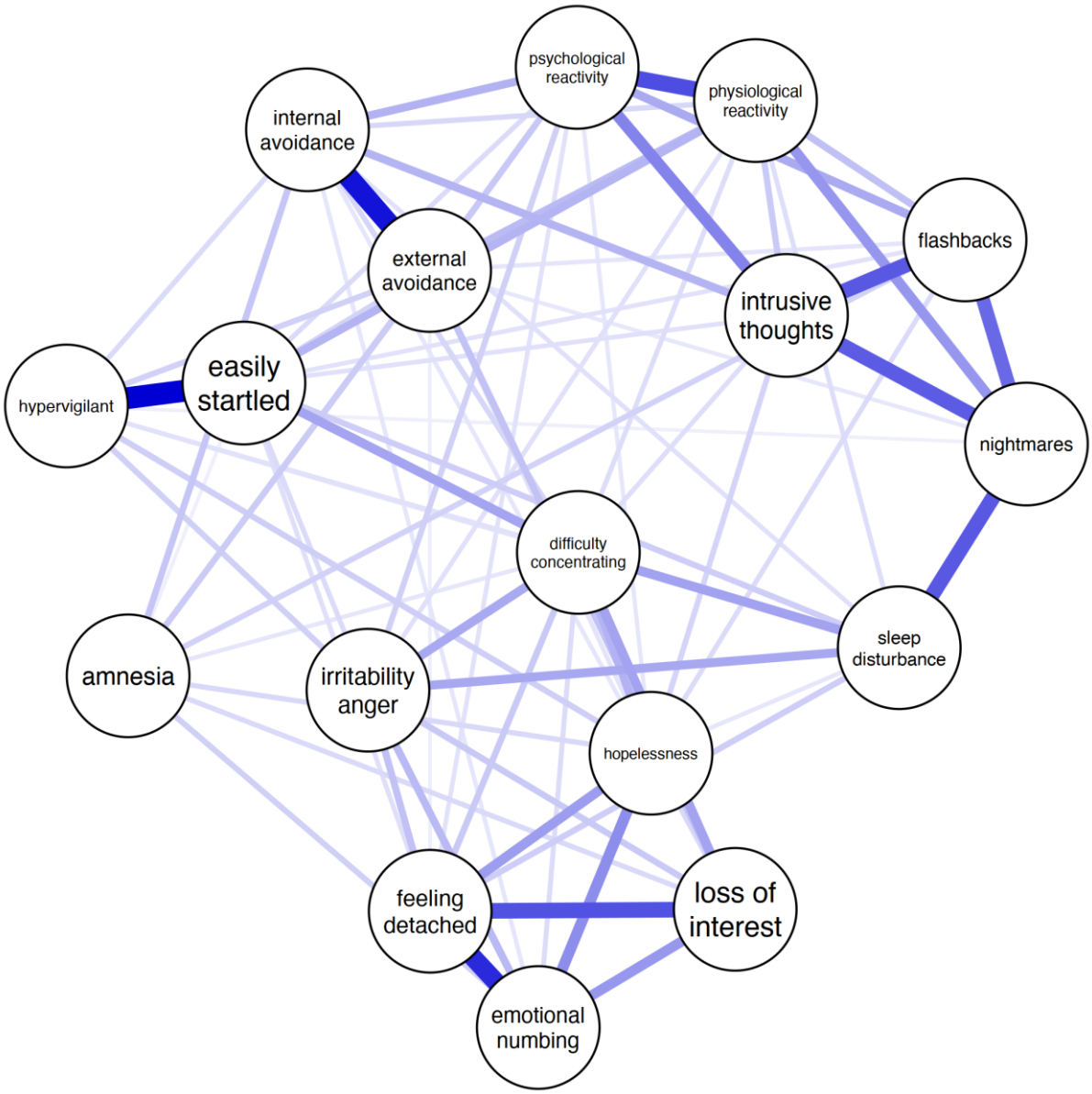

Figure 3. Estimated pooled MAGNA network for Pearson correlation matrices (listwise deletion) including all DSM-IV PTSD symptoms. Nodes represent PTSD symptoms, and edges represent partial correlation coefficients (all partial correlations in this plot are positive). Edges with weights that were not significant at $\alpha = .05$ are not shown.

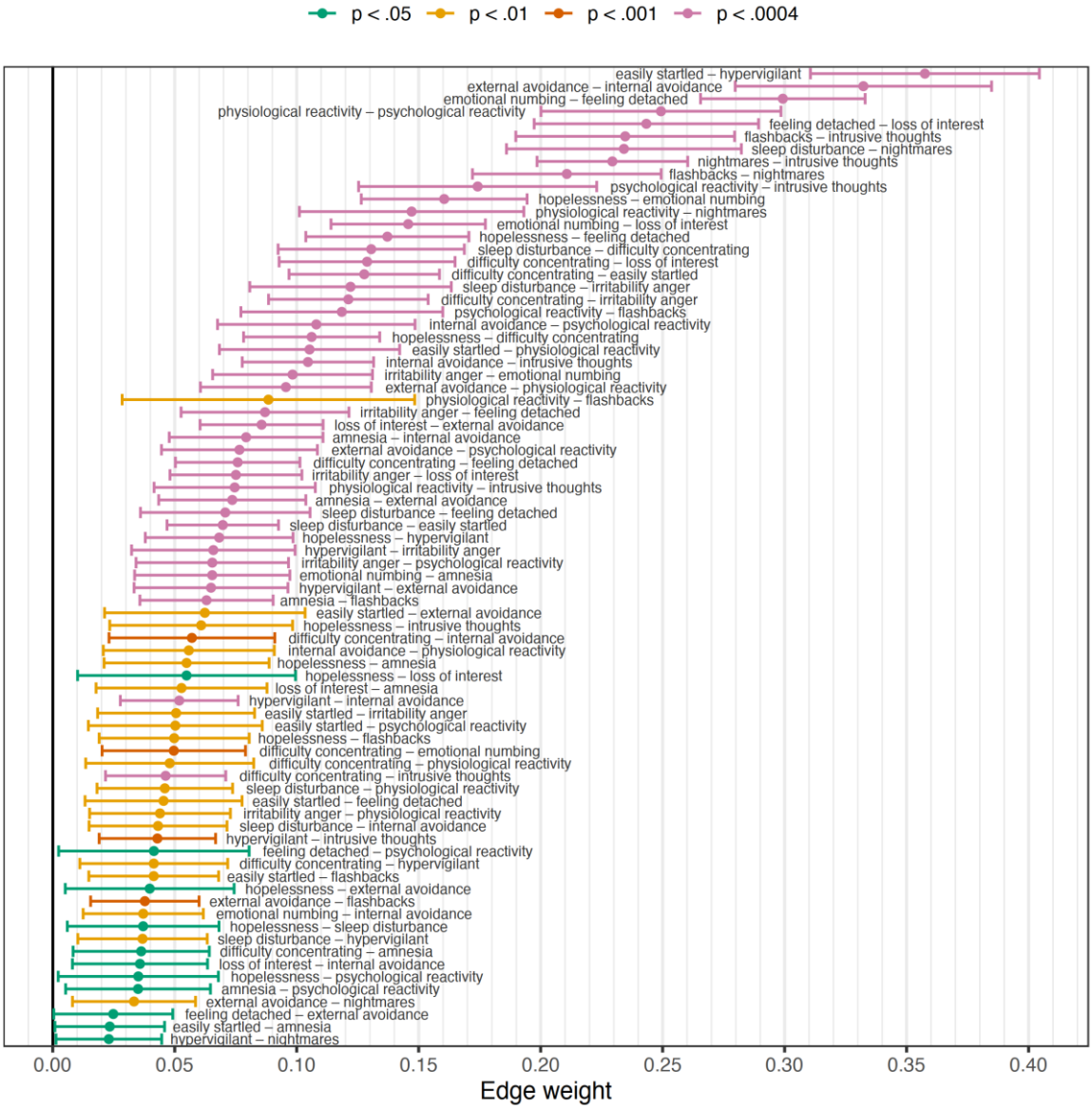

Figure 4. Estimated edge weights of the pooled MAGNA and 95% confidence regions based on the estimated standard errors. Only edges significant at $\alpha = .05$ are shown. For estimates and confidence regions of all edges, see sFigure 3 in the supplementary materials. The α = .0004 level corresponds to a Bonferroni corrected α level of .05.

3.3. Pooled MAGNA centrality indices

Figure 5 shows common centrality indices of nodes in the pooled MAGNA network, and Figure 6 shows the results of our parametric bootstrapped difference tests. The main finding was that there was no single or small set of nodes that clearly played a more central role than other nodes. While several significant differences could be detected between nodes on some of the metrics, these differences tended to be small, with the exception of 'amnesia' clearly being the least central symptom, both visually as well as significantly according to all metrics.

Overall, the metrics of direct connectivity (strength, expected influence, and R^2) strongly aligned with one-another. These results showed that 'feeling detached', 'intrusive thoughts' and 'physiological reactivity' were the most central nodes, being significantly higher than all other nodes in terms of expected influence, than all but one node in terms of R^2, and significantly higher than several other nodes in terms of strength. These nodes were followed by a large set of nodes of which with similar levels of centrality: 'easily startled', 'psychological reactivity', 'nightmares', 'difficulty concentrating', 'external avoidance', 'internal avoidance', 'loss of interest', 'emotional numbing', and 'flashbacks'.

The metrics of indirect connectivity, closeness and betweenness, diverged more from one-another, with the exception that the symptoms 'nightmares' and 'sleep disturbance' were the highest in both and also significantly higher than several other nodes. The symptom 'difficulty concentrating' was also significantly higher than several other symptoms in terms of closeness, but not in terms of betweenness. The closeness metric revealed very little deviance between nodes, while betweenness revealed more deviance. Betweenness, however, also featured fewer significant differences, and more deviations across methodological choices in our multiverse analysis (see supplementary figure sFigure 5). As such,

betweenness centrality may not be very stable even in our meta-analytic results, which is in line with commonly reported instability of this metric (Epskamp et al., 2017).

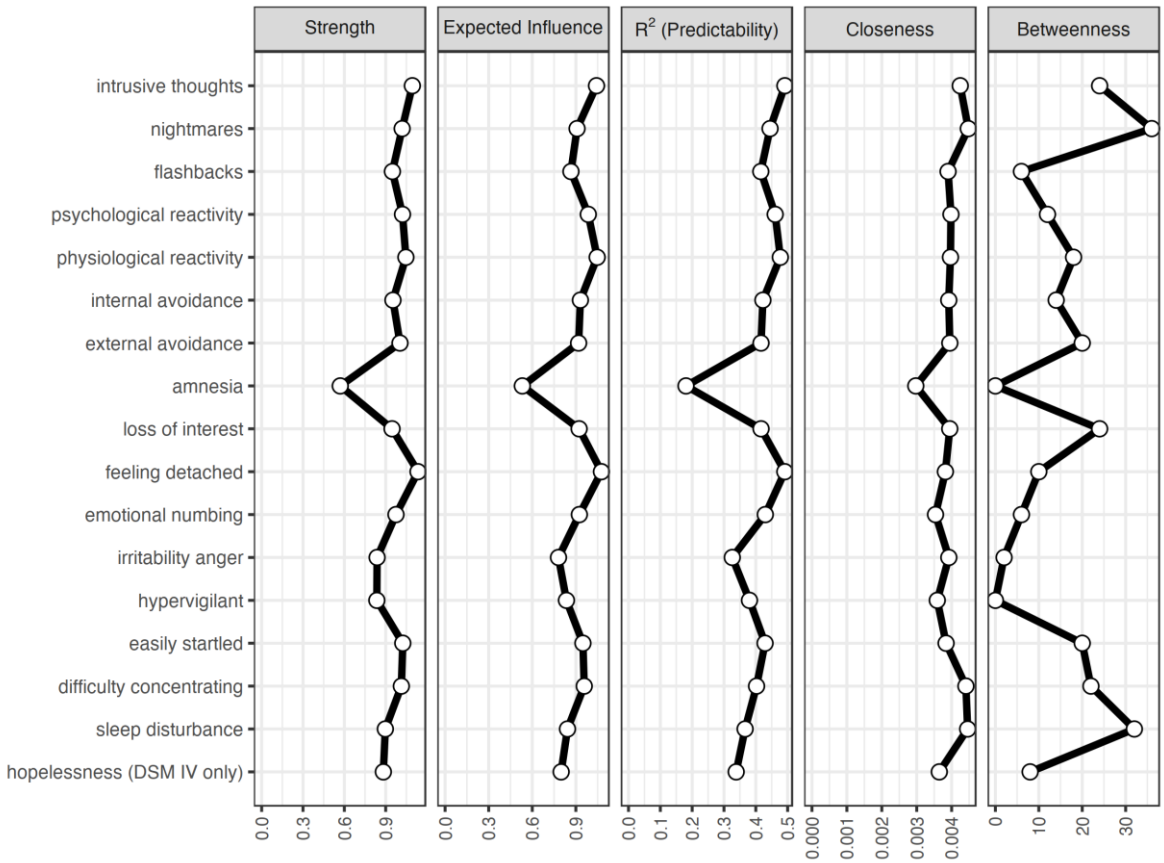

Figure 5. Estimated centrality indices of the pooled MAGNA.

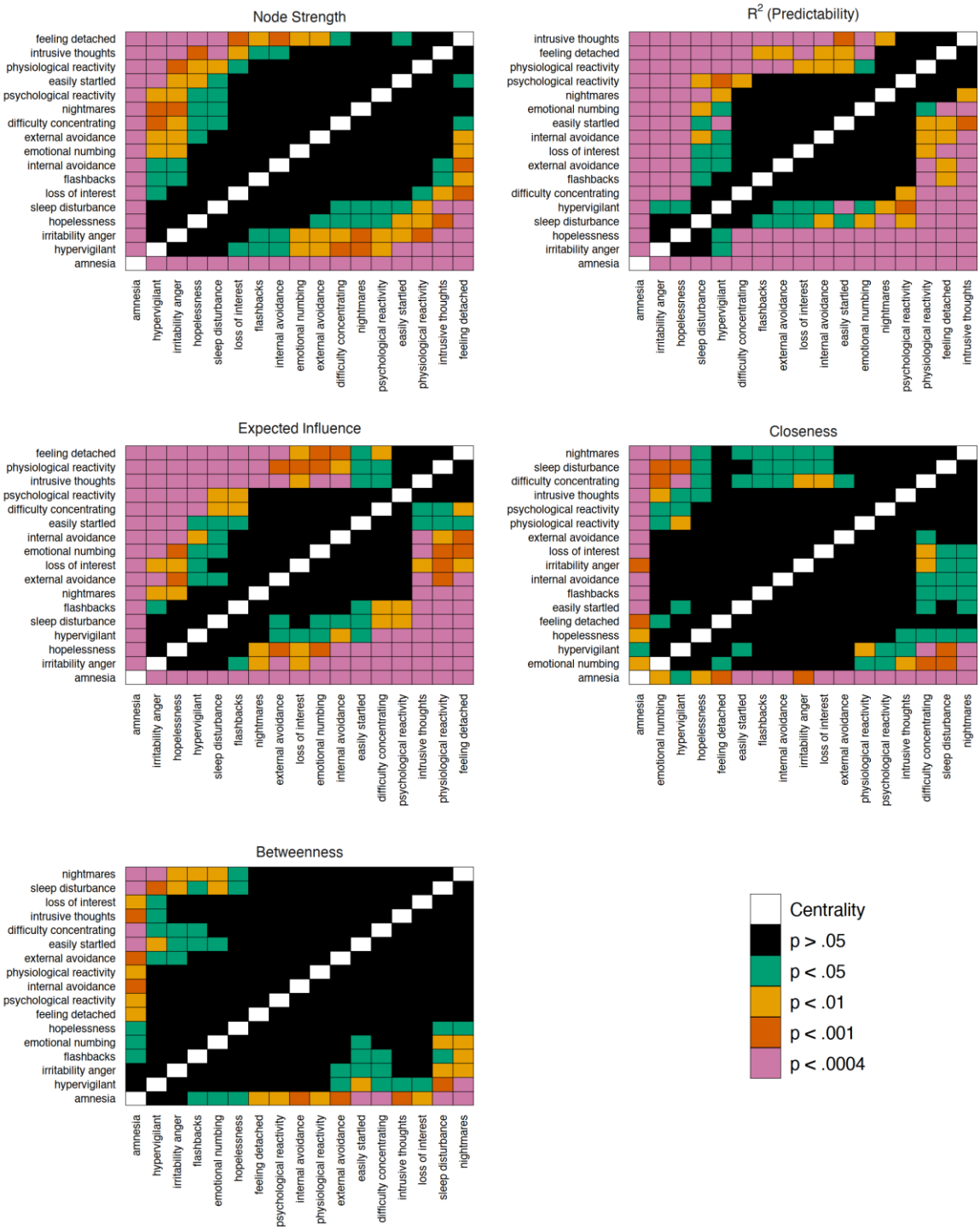

Figure 6. Centrality difference plots obtained through a parametric bootstrap. Each block indicates the significance of the difference between centrality indices of two nodes. These were obtained by sampling 1,000,000 network structures from the estimated asymptotic parameter variance-covariance matrices. The $\alpha = .0004$ level corresponds to a Bonferroni corrected α level of .05 rounded to 4 digits.

3.4. Heterogeneity across studies

Figure 7 shows the estimated random effect standard deviations on the *correlational structure* implied by the pooled MAGNA network. As can be seen in the figure, the standard deviations of the random effects are fairly large among all possible correlations, ranging from .10 to .18. These values therefore are larger than prior reported random effect sizes when only four of the samples were analyzed using MAGNA estimation, and were also larger than the largest random effect sizes used in simulation studies (Epskamp et al., 2020). While random effect sizes were quite uniformly distributed over all possible correlations, it can be noted that in general pairs of variables that featured a strong edge in the pooled MAGNA network also featured higher random effect sizes on the correlations.

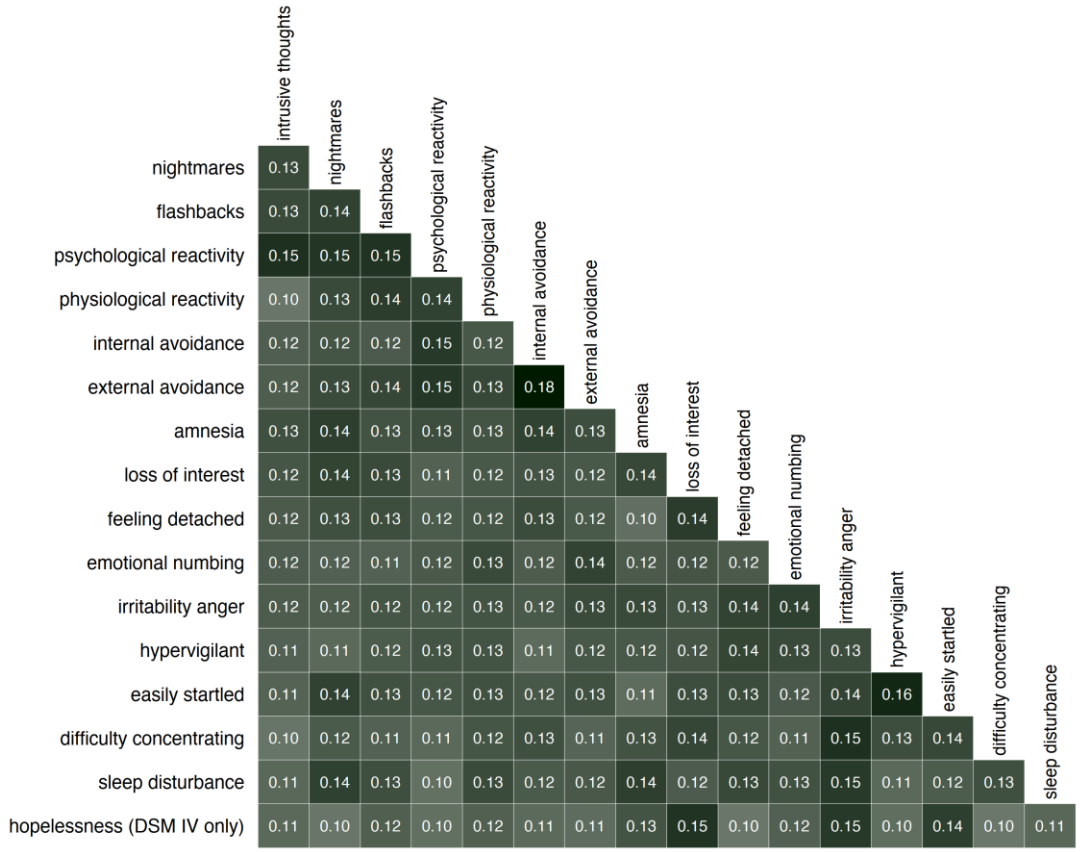

Figure 7. Estimated random effect standard deviations on the model-implied marginal correlation structure among DSM-IV symptoms over studies. Higher values indicate larger differences between studies in correlational structure.

3.5. Comparison to single-study network models

Figure 8 summarizes the single-study networks and how these relate to the pooled MAGNA network structure. The top panels investigate if single-study network models retrieve similar *parameter weights* (i.e., partial correlation estimates) as obtained through MAGNA analysis when edges are included in a network, and the bottom panels investigate if single-study network models identify the same edges as MAGNA analysis with significance thresholding at $\alpha = .05$. The top panels show that when edges are set to non-zero, unthresholded partial correlations (*pcor*) and *EBICglasso* estimation give, on average, parameter estimates that are closer to the parameter values obtained through MAGNA analysis, compared to *ggmModSelect* and *psychonetrics* (pruned at $\alpha = .05$): the average deviation between the edge weight in a single-study network compared to the pooled MAGNA network was centered around zero with *pcor* and *EBICglasso* estimation, but generally larger than zero in *ggmModSelect* and *psychonetrics* estimation. Investigating the bottom panels: on average, single-study networks would include the strongest edges from the pooled MAGNA network almost always (bottom right panel). The bottom left panel shows that *EBICglasso* tended to include more edges that were not included in the pooled MAGNA network than *ggmModSelect* and *psychonetrics*. However, the top left panel shows that these edges were subsequently also estimated to be weaker when included in the network, compared to *ggmModSelect* and *psychonetrics*. The *EBICglasso* also included more often edges that were significant in the MAGNA analysis than the *ggmModSelect* and *psychonetrics*. The *pcor* method did not perform model selection, and as such always includes all edges.

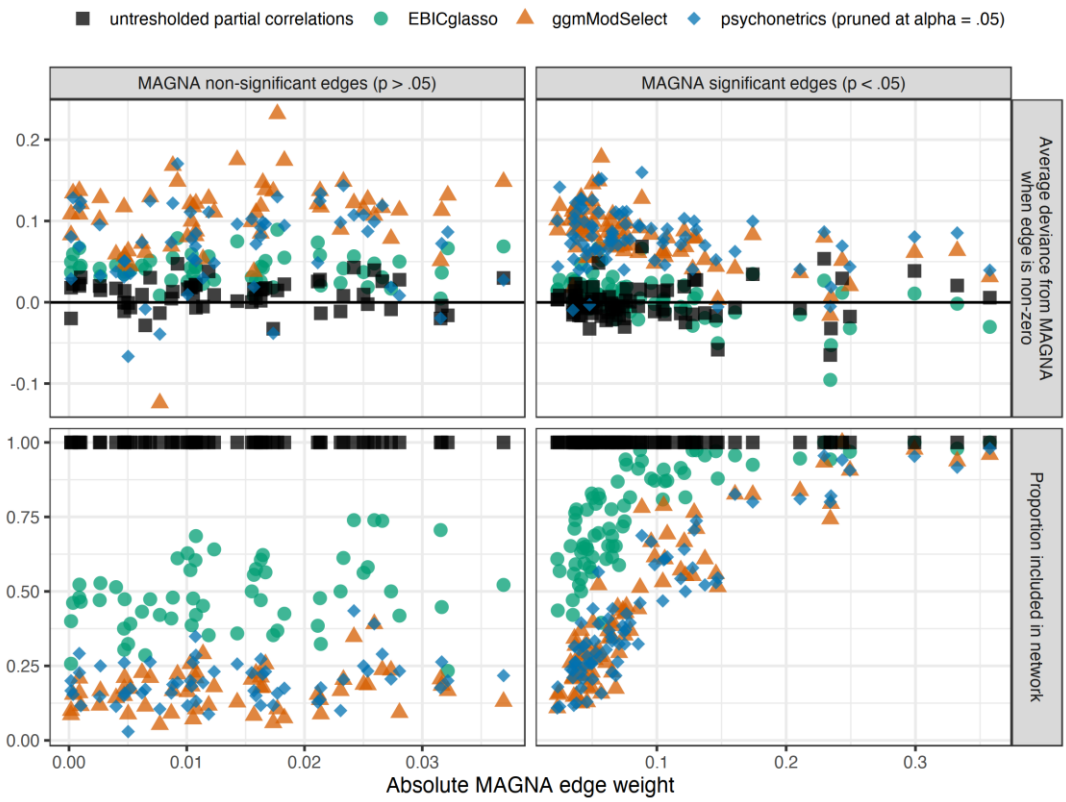

Figure 8. Edge weight estimates based on separate analyses of the analyzed correlation matrices as single studies, compared to the results of the pooled MAGNA network. Each correlation matrix was analyzed using four network estimation routines that take a correlation matrix as input (unthresholded/saturated partial correlation networks, the *EBICglasso* algorithm, the *ggmModSelect* algorithm, and pruned partial correlation networks using the *psychonetrics* package). Each symbol represents one of the 136 potential edges that can be included in a 17-node DSM-IV PTSD symptom network. The top panels show the average estimated edge weight for edges *when these were included in the model* (estimated to be non-zero), and the bottom panels show the proportion of times an edge was included in the model. The left panels show edges that were estimated to not differ significantly from zero at $\alpha = .05$ in the pooled MAGNA network, and the right panels show edges that were estimated to differ significantly from zero at $\alpha = .05$ in the pooled MAGNA network. The x-axis shows the edge weight in the pooled MAGNA network. Of note, unthresholded partial correlation estimation includes all edges.

3.6. Consistency due to methodological choices

Supplementary figures sFigure 4 and sFigure 5 show the results of the multiverse analysis. The first figure shows that across all methodological choices very similar parameter estimates would have been obtained, and the second figure shows that across all methodological choices also very similar centrality indices would have been obtained, especially with regard to strength and closeness. The multiverse analysis showed the most differences on betweenness, and as such, betweenness centrality may not be stable in these networks, which is in line with previous discussions on this centrality index (Epskamp et al., 2017).

4. Discussion

This article introduced the first ever meta-analysis of network models of PTSD. Using the novel MAGNA (Epskamp et al., 2020) methodology, we identified and discussed common effects of current research by estimating a singled pooled network structure of frequently assessed post-traumatic symptoms, as well a single pooled centrality plot of these symptoms. Further, we investigated the size of between-study heterogeneity by assessing random-effect deviations from the correlational structure that is implied by the pooled network structure. Finally, we examined how well individual network studies perform in retrieving this pooled cross-study network study. Through a multiverse analysis reported in the supplementary materials, we showed that these results were consistent through various methodological choices that could have been made.

4.1. PTSD symptom associations

Overall, the identified common network structure was relatively dense, with high intercorrelations between symptoms. Some especially stronger connections stood out, most of

these being within-cluster associations, as defined by the DSM-IV. These included associations within a cluster of symptoms related to cognition and mood: 'emotional numbing', 'feeling detached', 'loss of interest', 'hopelessness', a cluster of symptoms related to re-experiencing: 'nightmares', 'intrusive thoughts', 'flashbacks', a cluster of the reactivity symptoms that is tightly linked to the re-experiencing cluster, a cluster of the two symptoms on avoidance and a cluster of the symptoms 'hypervigilant' and 'easily startled'. Between these clusters, the symptom 'sleep disturbance' formed a major connection between the cognition and mood and re-experiencing clusters, the symptom 'difficulty concentrating' formed bridges between several clusters and the avoidance and hyperactivity/ startle clusters, and there were strong links between the avoidance and the reactivity clusters. Finally, the node 'amnesia' did not clearly cluster together with any of the other symptoms.

4.2. Centrality of PTSD symptoms

A main finding of the current meta-analysis is that there were no symptoms that clearly played a most central role in the network. While the three symptoms 'feeling detached', 'intrusive thoughts' and 'physiological reactivity' featured consistently amongst the most central across metrics of direct connectivity, the symptoms 'nightmares' and 'sleep disturbance' featured higher on metrics of indirect connectivity (because of their role in connecting the cognition and mood and re-experiencing clusters). Further, several more symptoms were high across several metrics (such as 'psychological reactivity' and 'difficulty concentrating'), but few of these most central nodes showed strong significant differences among each-other across all metrics, nor did their raw centrality values differ much visually.

This is an important finding, especially in light of previous research that identified high heterogeneity in terms of what individual studies determine as central items (Birkeland et al., 2020). If we assume central symptoms to be especially relevant for treatment, as

suggested by previous research (Borsboom & Cramer, 2013; Fried et al., 2018; Rodebaugh et al., 2018; Schmittmann et al., 2013) current results—at least within the PTSD framework—indicate symptoms are mostly indistinguishable in centrality. Future research expanding the MAGNA methodology to other mental disorders may identify whether this is a general result extendable to most psychopathology, or whether it is a specific finding of the PTSD network literature. In addition, while the current analyses identified little evidence for a specific set of symptoms that are especially central across all subgroups, it may be that in individual subgroups, more pronounced differences in centrality exist, which could ultimately become important intervention targets.

While we did not identify symptoms that played a clear most central role, we did identify a symptom that clearly was the least central: The symptom 'amnesia' was significantly less central than most other symptoms on all five centrality indices. This aligns well with previous studies in the field, including factor analytic studies in which amnesia clearly stands out due to weak loadings (Armour et al., 2016; Berntsen & Rubin, 2014; Birkeland et al., 2020; Rubin et al., 2008). In line with such findings, the current meta-analysis further raises the question of whether amnesia is indeed part of PTSD, whether it arises from external factors or other comorbid disorders, or whether the item, dating back to the outset of PTSD research, requires serious reconsideration in the light of this accumulating evidence.

Finally, we identified the least significant differences and the most variability across methodological choices in the betweenness centrality metric. In addition to interpretative difficulties of betweenness centrality (Bringmann et al., 2019), betweenness is often identified as the most unstable centrality measure (Epskamp et al., 2017) and many studies do not identify the centrality stability coefficient for betweenness to be above the recommended cut-off scores (Birkeland et al., 2020b). Thus, our study provides further evidence to

recommend caution when interpreting betweenness centrality of psychological network models.

4.3. Heterogeneity and generalizability of PTSD networks

In line with our previous analysis of only four samples (Epskamp et al., 2020) we estimated large random effect sizes on the correlational structure, indicating large differences between study domains. This has some important implications for the literature on PTSD network models. First, we cannot expect a single sample to recover a structure that is fully generalizable across all possible PTSD samples, regardless of quality (e.g., sample size, reliability of measurement) of the study. This is not surprising, as PTSD samples can consist of vastly different samples of subjects from different cultures exposed to different types of trauma. Second, we previously studied the performance of estimating a single pooled network without taking study-heterogeneity into account (Epskamp et al., 2020) and found that this performs poorly in the presence of strong random effect deviations. In particular, specificity could severely drop in such an aggregated network model, indicating that the model would include many spurious edges. To this end, PTSD network literature that aims to aggregate over multiple studies should use methods that take heterogeneity across study domains into account, such as the random-effects MAGNA methodology used in this paper. Finally, large cross-study heterogeneity means that, even when comparing high quality samples such that expected replicability given the estimation method is high (Williams, 2020), it cannot be expected that PTSD network models replicate perfectly across such diverse samples. This marks an important finding that is relevant especially also to an ongoing discussion on replicability of PTSD symptom networks. For example, in several studies Forbes and colleagues (2017b, 2019, 2021) showcase differences in—mostly very weak—edges in analyses based on multiple PTSD samples, and describe these differences as

"evidence for limited replicability" of network estimation tools. Such differences however can readily be explained as a result of cross-study heterogeneity in addition to sampling variation (Fried et al., 2020; Williams, 2020) and the performance of network estimation tools (Isvoranu & Epskamp, 2021).

In the current paper we identified very heterogeneous correlations between both symptoms that also featured strong edges in the network (such as 'internal avoidance' and 'external avoidance'), but also between symptoms with less prominent edges in the GGM network structure, connecting different clusters (such as 'nightmares' and 'easily startled'). It is important to note that the estimated random-effect size is on the implied correlational structure, not on the GGM network itself. However, we may expect that large random effects on marginal correlations between two variables will translate to larger differences in direct edges between these variables when a network model is estimated from a single sample. To this end, it could be that large between-study differences are also to be expected in which edges will be found to bridge different clusters in the network. As more and more studies on PTSD are being conducted, more data will be able to address the heterogeneity discussed above. Future meta-analytic studies carried out on specific sample subpopulation and measures, when these become sufficient, may be able to identify such differences.

4.4. How do single-study network analyses compare to meta-analytic network analyses?

In addition to estimating a pooled meta-analytic network structure, we studied the correspondence between network models estimated from single datasets to the network models estimated using MAGNA analysis on all datasets. We investigated both *regularized* network estimation as well as *non-regularized* model search. To summarize, we found that all methods estimated similar structures (absence and presence of edges) as well as parameter values (size of the partial correlation) to the MAGNA network. Network models estimated

using regularization techniques led to more generalizable *network parameters* (partial correlation sizes), whereas single-study network models estimated through unregularized model search led to more generalizable *network structures* (absence and presence of edges). This is in line with previous literature, as regularization techniques have, in part, been developed with the specific aim to obtain parameter estimates that are less prone to overfitting and work better in new samples (Hastie et al., 2009), but have also been shown to perform poorer in retrieving network structures in simulation studies (Williams & Rast, 2018).

4.5. Comparison to previous work

We compared our results with previous studies to check for consistency in our findings. Mainly, we compared our results to those by Birkeland and colleagues (2020b), who reviewed many of the same studies that were included in our meta-analysis, and the results by Duek and colleagues (2020), who recently published a PTSD symptom network analysis of 158,139 veterans. This study was not included in our search, as it was published after the selected timeframe of publication. Supplementary figure sFigure 6 shows a visual comparison of our meta-analytic results, the estimated network by Duek and colleagues, and a visual representation of the most common strongest edges reported by Birkeland and colleagues (edges that significantly differed from two-thirds of the included edges of a given network). Supplementary sFigure 6 reveals overall a strong overlap between our results and those of Birkeland and colleagues and Duek and colleagues.

Within both our pooled network structure and the review by Birkeland and colleagues, the associations between ‘hypervigilant’ and ‘easily startled’, between ‘nightmares’ and ‘intrusive thoughts’, between ‘internal avoidance’ and ‘external avoidance’, between ‘emotional numbing’ and ‘feeling detached’, and between ‘feeling detached’ and

'loss of interest' were visibly the strongest edges. Duek and colleagues likewise also identified strong edges between all the above-mentioned pairs of nodes. Both Duek and colleagues and our pooled network model also featured a strong edge between 'psychological reactivity' and 'physiological reactivity', which was not often among the strongest edges according to Birkeland and colleagues. These findings indicate that in spite of high heterogeneity in terms of type of sample (e.g., clinical, community, veteran, general population etc.), these associations are likely to be common and emerge in most network structures. Aligned with these findings, in the multisite study of PTSD symptoms carried out by Fried and colleagues (Fried et al., 2018) in four trauma sample patients, these associations were also consistently identified.

In terms of between-cluster associations, our results diverged more from previous findings. Our analysis, like Duek and colleagues, showed that 'nightmares' and 'sleep disturbance' connected the main clusters of the network, but this was less profound in the results by Birkeland and colleagues. The main differences can be seen in the weaker edges connecting the various clusters. Our analysis showed quite a large number of moderately strong positive edges connecting the clusters, whereas Birkeland and colleagues identified far fewer connecting edges and Duek and colleagues identified overall weaker edges including several negative edges. It should be noted that Birkeland and colleagues only aimed to identify edges that are often stronger than other edges, not at identifying all edges. As such, their summary likely does not include smaller edges connecting clusters. The discrepancy between the results by Duek and colleagues and our results could be due to differences in estimation techniques, differences in samples, or possibly due to Berkson's bias in the analysis by Duek and colleagues inducing negative edges (de Ron et al., 2019).

In terms of centrality, Birkeland and colleagues only investigated strength centrality as closeness and betweenness were not deemed stable in the reviewed studies themselves,[7] And Duek and colleagues only reported expected influence and R^2 (predictability). Duek and colleagues made available their estimated network structure through supplementary materials, however, which allows us to also investigate the other centrality indices (see supplementary figure sFigure 7). Birkeland and colleagues identified 'intrusive thoughts' as the most often occurring most central symptom and 'amnesia' as the most often occurring least central symptom, which aligns with our results. Birkeland and colleagues furthermore identified the symptoms 'loss of interest', 'physiological reactivity', 'feeling detached', 'difficulty concentrating' and 'hypervigilance' as often occurring strong central symptoms, most of which were also relatively central nodes according to our direct metrics of connectivity, with the exception of 'hypervigilance'. Duek and colleagues identified 'feeling detached', 'intrusive thoughts', 'psychological reactivity', 'physiological reactivity' and, to a lesser extent, 'loss of interest' as central nodes according to expected influence and R^2, and 'amnesia' as the least central node. These results align well with our findings. Supplementary figure sFigure 7 shows a strong overlap between our centrality metrics and the ones based on the network reported by Duek and colleagues, with the exception of 'betweenness'. Of note, R^2 is on average a bit higher in the network reported by Duek and colleagues, but this can be explained also by our findings that edge weights from the *ggmModSelect* algorithm (the algorithm used by Duek and colleagues) leads to slightly higher estimated edge weights than the meta-analytic results.

In sum, previous results align well with our meta-analytic results. The review of Birkeland and colleagues, the comparison with the results by Duek and colleagues, and the

[7]Of note, while our analysis includes many of the same studies reviewed by Birkeland et al. (2020), our analysis does not depend on the estimated network structures of these studies. As such, our analysis is not impacted by potential instability in network models estimated from single studies.

results from our single study analysis show that conclusions drawn from networks estimated from single studies can align with meta-analytic results, regardless of whether the meta-analytic results are based on the same samples (as is the case with our own single dataset study, as well as the results of Birkeland and colleagues) or not (as is the case with the results from Duek and colleagues). Often, the same edges were identified as being the strongest and the same nodes were identified as being among the most central. In addition, consistently the symptom 'amnesia' was shown to be the least central.

4.6. Limitations

An important limitation of the current study consists of the restricted number of symptoms included in the MAGNA analyses. While here we focused on DSM-IV symptomatology (due to these being the symptoms assessed by most articles), many studies included many more symptoms that we were unable to include in the network structure. The multiverse results in supplementary figures sFigure 4 and sFigure 5 show estimated edge weights based on using either DSM-IV symptoms or only the shared symptoms between the DSM-IV and the DSM-5 (all DSM-IV symptoms except 'hopelessness'). This figure shows a strong symmetry between these results. Due to a lack of studies investigating only DSM-5 symptoms we could not perform the analysis for DSM-5 symptoms, which would be an important avenue of future research.

A further limitation is the restricted availability of bias assessment methods for network models. While the MAGNA methodology is able to address bias due to heterogeneity and distinct sample sizes, other sources of bias were not accounted for here, such as correlation bias[8] due to the sample population (i.e., risk of Berkson's bias due to

[8]The MAGNA framework relies on correlation matrices as input, and not on effect sizes. Therefore, the risk of bias here is equivalent to the risk of bias for correlation structures.

selection criteria; de Ron et al., 2019), or due the data type used as input when calculating the correlations (e.g., risk of biased estimates by calculating Pearson correlations based on ordinal data (Epskamp, 2017). We recommend future research to focus on the investigation of potential sources of bias in network studies, as well as identifying the size of such bias. Since network studies do not use significance testing, publication bias is not an issue with the current analysis.

Final limitations involve the novel aspects of MAGNA estimation, which is not yet capable of handling all characteristics found in real datasets. For example, MAGNA treated data as continuous, while in fact many samples were ordered categorical in nature and measured on a Likert scale with 3 to 5 response categories. In the supplementary materials (see sFigure 4 and sFigure 5) we also investigated Spearman correlations (of which we obtained fewer samples), which shows results to align with the ones reported in this paper. Nonetheless, a proper way of handling ordered categorical data is still lacking. This is a general limitation that also holds to MASEM modeling; while ordered categorical data can in principle be handled in structural equation modeling and network psychometrics through the use of polychoric correlations (Muthén, 1984), such polychoric correlations cannot be used as input to MAGNA, as it uses the normal likelihood to compute the sampling variation matrix. As such, a future direction may be to better handle ordered categorical data in meta-analytic network modeling. Possible future directions would be to extend MAGNA for handling potential violations of independence. Alternatively, one could only include one sample or average the samples. However, we opted to include all samples instead as the number of studies with multiple samples of the same participants were low, usually included large time-lags between samples, and we aimed to include all available data in the analysis.

4.7. Conclusions & Future Directions

The field of network psychometrics has grown extremely popular within the past decade, with numerous studies being published using this novel methodology. Within this field, the PTSD research area has been especially fast expanding, allowing for the first ever meta-analysis of PTSD network models.

The current study summarized and synthesized findings in the field of network models of PTSD, with the aim of advancing current knowledge and bringing together existing results. Our results highlighted common associations between symptoms that are likely to emerge across distinct studies and populations, but also very high heterogeneity between studies. Notably, there may not be such a thing as *one* overall PTSD network structure and future research may benefit from focusing on sub-populations (e.g., veterans) when aiming to construct a pooled PTSD network structure. To date, the amount of data available is not sufficient for such an analysis. In addition, and of note, over 16 different measures of PTSD symptomatology were used across the pool of studies included in this meta-analysis, further highlighting also high heterogeneity in measurement. Summarizing results when the measures employed are themselves heterogeneous across studies is an important challenge in the field of psychopathology. Finally, it may be that research on PTSD symptom networks may not be fruitful in trying to present a generalizable PTSD symptom network, but future studies would benefit by focusing on specific types of trauma and more homogeneous samples (such as war veterans). An increase in the number of such studies that are more homogenous could result in specific meta-analytic research in these subpopulations, leading to estimated meta-analytic network models that are representative for those select subpopulations.

Further, an important finding here is that most centrality estimates were indistinguishable from each other, except for the symptom ‘amnesia’ which was clearly the

least central symptom. A wide array of research to date has argued that centrality may be important for treatment interventions, though recent research also argued that centrality measures for network models are not as straightforward as previously thought (Bringmann et al., 2019; Rodebaugh et al., 2018b). Based on our results, centrality estimates for PTSD symptoms, especially those taken directly from graph theory (strength, closeness and betweenness) show few strong differences, thus intervening on one symptom may not bring a substantial change to the network structure. Of note here, it may be that in individual subgroups, more pronounced differences in centrality exist, which could ultimately become important intervention targets. Investigating this in more homogeneous samples may be an important next step for research.

Finally, our results provide, for the first time, empirical insight in how well network models estimated from single studies compare to generalizable network structures across studies. Overall, most existing methods perform adequately in retrieving a network structure which is close to the pooled network structure. As such, networks estimated from a single PTSD sample can give results that may also generalize to other PTSD samples, especially when investigating strongest edges. However, at the same time we should not expect a single sample to result in a network model that will hold true for all other potential samples, nor should we expect that a single network model will hold true for all potential samples, as we identified large between-study heterogeneity. Possibly, applying meta-analytic techniques to other fields of interest in network psychometrics—such as depression, anxiety and schizophrenia—may lead to similar conclusions. If this is true, then we cannot expect network studies to fully replicate in new samples regardless of the quality of sample, simply due to the presence of heterogeneity between study samples. To this end, the development of meta-analytic techniques to aggregate samples of interest for network models while taking

between-study heterogeneity into account may be an important avenue for future research in many fields of interest.

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7. Conflict of interest

The authors have declared that there are no conflicts of interest in relation to the subject of this study.

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Table 1. Study characteristics

No	Study	Sample	Sample size (pairwise)	Sample size (listwise)	Measure	DSM / ICD	Pearson (pairwise)	Pearson (listwise)	Spearman (pairwise)	Spearman (listwise)
1	McNally, 2015	Chinese adults who survived the Wenchuan earthquake, and who had lost at least one child in the disaster	359.4	344	PCL-C	DSM-IV	✓	✓	✓	✓
2	De Schryver, 2015	War-affected youth in northern Uganda	442	430	IES-R	DSM-IV	✓	✓	✓	✓
3	Armour, 2017	Veterans (US)	221	221	PCL-5	DSM-5	✓	✓	✓	✓
4	Birkeland, 2017	Female ministerial employees present during the 2011 Oslo bombing attack (Norway)	1088.8	1035	PCL-S	DSM-IV	✓	✓	✓	✓
	Birkeland, 2017	Male ministerial employees present during the 2011 Oslo bombing attack (Norway)	804	770	PCL-S	DSM-IV	✓	✓	✓	✓
5	Choi, 2017	Trauma-exposed urban men who have sex with men (US)	286.3	281	DTS	DSM-IV	✓	✓	✓	✓
6	McNally, 2017	Adults who reported having been sexually abused during childhood (US)	177.1	165	PCL-C	DSM-IV	✓	✓	✓	✓
7	Mitchell, 2017	Iraqi veterans	674.2	627	PCL-5	DSM-5	✓	✓	✓	✓

8	Russell, 2017	Youth exposed to Hurricanes Katrina and Gustav	782	750	UCLA PTSD-RI	DSM-5	✓	✓	✓	✓
9	Spiller, 2017	Asylum seekers or refugees in treatment (Swiss)	146.4	136	PDS	DSM-IV	✓	✓	✓	✓
10	Epskamp, 2018	Women with post-traumatic stress disorder	358.9	358	PSS-SR	DSM-IV	✓	✓	✓	✓
11	Fried, 2018	Treatment-seeking patients	517	517	HTQ	DSM-IV	✓	✓	X	X
	Fried, 2018	Treatment-seeking patients	363	363	PSS-SR	DSM-IV	✓	✓	X	X
	Fried, 2018	Treatment-seeking soldiers	923	923	PCL-C	DSM-IV	✓	✓	X	X
	Fried, 2018	Treatment-seeking refugees	928	928	HTQ	DSM-IV	✓	✓	X	X
12	Malgaroli, 2018	Bereaved individuals who had recently lost a spouse	263	263	Interview	DSM-5	✓	✓	✓	✓
13	Moshier, 2018	Veterans	378	378	PCL-5	DSM-5	✓	✓	X	X
	Moshier, 2018	Veterans	378	378	CAPS-5	DSM-5	✓	✓	X	X

14	Phillips, 2018	US military veterans (clinical)	912	912	DTS	DSM-IV	✓	✓	✓	✓
	Phillips, 2018	US military veterans (subclinical)	138	138	DTS	DSM-IV	✓	✓	✓	✓
15	von Stockert, 2018	Trauma-exposed U.S. military veterans	1268	1268	PCL-5	DSM-5	✓	✓	✓	✓
	von Stockert, 2018	Trauma-exposed U.S. military veterans	611	611	PCL-5	DSM-5	✓	✓	✓	✓
16	Bartels, 2019	Children and adolescents exposed to at least one potentially traumatic event	475	475	CATS	DSM-5	✓	✓	✓	✓
17	Djelantik, 2019	Bereaved patients seeking treatment following psychological trauma	458	458	PCL-5	DSM-5	✓	✓	✓	✓
18	Ge, 2019	Youth survivors exposed to Lushan earthquake	1073.12	1010	CRIES	DSM-IV	✓	✓	✓	✓
		Youth survivors exposed to Lushan earthquake	1073.85	1014	CRIES	DSM-IV	✓	✓	✓	✓
		Youth survivors exposed to Lushan earthquake	1088	1088	CRIES	DSM-IV	✓	✓	✓	✓
19	Gilbar, 2019	Males from the Jewish population in Israel who received treatment for domestic violence	234	234	ITQ	ICD-11	✓	✓	X	X

20	de Haan, 2019	Children and adolescents exposed to trauma	1611	1429	Multiple	ICD-11	✓	✓	✓	✓
21	Knefel, 2019a	German general population	275.4	258	ITQ	ICD-11	✓	✓	✓	✓
	Knefel, 2019a	Israeli general population	336	336	ITQ	ICD-11	✓	✓	✓	✓
	Knefel, 2019a	UK general population	447	447	ITQ	ICD-11	✓	✓	✓	✓
	Knefel, 2019a	US general population	521.3	495	ITQ	ICD-11	✓	✓	✓	✓
22	Knefel, 2019b	Scottish trauma center patients	192	183	ITQ	ICD-11	✓	✓	✓	✓
	Knefel, 2019b	Lithuanian primary mental health care patients	280	280	ITQ	ICD-11	✓	✓	✓	✓
	Knefel, 2019b	Welsh primary and secondary mental health service users	184.7	175	ITQ	ICD-11	✓	✓	✓	✓
	Knefel, 2019b	Austrian survivors of child maltreatment	219	218	ITQ	ICD-11	✓	✓	✓	✓
23	Lazarov, 2019	Treatment-seeking veteran patients	1489	1489	CAPS-IV	DSM-IV	✓	✓	✓	✓

24	Mancini, 2019	Female students exposed to the 2007 Virginia Tech campus tragedy	296	296	PSS-SR	DSM-IV	✓	✓	✓	✓
		Female students exposed to the 2007 Virginia Tech campus tragedy	258	257	PSS-SR	DSM-IV	✓	✓	✓	✓
25	McElroy, 2019	Trauma-exposed Israeli adults	1003	1003	ITQ	ICD-11	X	X	✓	✓
	McElroy, 2019	Internally displaced persons Ukraine	2203	1790	ITQ	ICD-11	X	X	✓	✓
26	Papini, 2019	Women with full or subthreshold PTSD and substance use	306	306	MPSS-SR	DSM-IV	✓	✓	✓	✓
27	Park, 2019	Patients exposed to various traumatic events and who were beginning psychiatric treatment	249	249	CAPS	DSM-IV	✓	✓	X	X
28	Pfeiffer, 2019	Refugee resettled in a European country	419	419	CATS	DSM-5	✓	✓	✓	✓
29	Price, 2019	Individuals who endorsed a traumatic event that met Criterion A for a diagnosis of PTSD	1184	1184	PCL-5	DSM-5	✓	✓	✓	✓
30	Segal, 2019	Israel Defense Force infantry soldiers, pre-deployment	902.6	873	PCL-S	DSM-IV	✓	✓	✓	✓
	Segal, 2019	Israel Defense Force infantry soldiers, post-combat	719.3	693	PCL-S	DSM-IV	✓	✓	✓	✓

31	Simons, 2019	Iraqi veterans	273.53	269	PCL-M	DSM-IV	✓	✓	✓	✓
32	Vanzhula, 2019	Clinical sample: participants met criteria for a diagnosis of eating disorder	125.8	124	PCL-C	DSM-IV	✓	✓	✓	✓
	Vanzhula, 2019	Nonclinical sample: undergraduate students	297.8	296	PCL-C	DSM-IV	✓	✓	✓	✓
33	Armour, 2020	US general population	417	417	PCL-5	DSM-5	✓	✓	✓	✓

*PCL-C: PTSD CheckList – Civilian Version; IES-R: Impact of Event Scale-Revised; PCL-5: PTSD Checklist for DSM-5; DTS: Davidson Trauma Scale; UCLA PTSD-RI: University of California at Los Angeles Posttraumatic Stress Disorder Reaction Index; PDS: Posttraumatic Diagnostic Scale; PSS-SR: Post-traumatic Stress Disorder Symptom Scale Self Report; HTQ: Harvard Trauma Questionnaire; PCBD: Persistent Complex Bereavement Disorder; CAPS-5: Clinician-Administered PTSD Scale for DSM-5; CATS: Child and Adolescent Trauma Screen; CRIES: Child Revised Impact of Events Scale; ITQ: International Trauma Questionnaire; CPTCI: Child Posttraumatic Cognitions Inventory; MPSS-SR: Modified PTSD Symptom Scale Self Report; DSM-IV: Diagnostic and Statistical Manual of Mental Disorders, fourth edition; DSM-V: Diagnostic and Statistical Manual of Mental Disorders, fifth edition; ICD-11: International Classification of Diseases, eleventh revision.

Supplementary Online Content

Isvoranu, A.M., Epskamp, S., Cheung, M. Network Models of Post-traumatic Stress Disorder: A Meta-analysis

sAppendix 1. R-function.

sAppendix 2. Table of node descriptions

sAppendix 3. Table of numeric results.

sFigure 1. Overview of the cumulative number of articles, and overall number of articles published annually.

sFigure 2. Number of samples for each pair of variables for which different types of correlations were available.

sFigure 3. Estimated edge-weights and confidence regions.

sFigure 4. Multiverse plot displaying MAGNA results for distinct MAGNA estimation procedures.

sFigure 5. Centrality indices obtained through all analyses run in the multiverse analysis.

sFigure 6. Comparison of the pooled MAGNA network results of PTSD systematic review and a large sample PTSD symptom network.

sFigure 7. Comparison of centrality measures obtained through the pooled MAGNA network and a large sample PTSD symptom network.

This supplementary material has been provided by the authors to give readers additional information about their work.

sAppendix 1. R-function

```
# This function can be used to write the following files:
# - Pearson_listwise.csv - Listwise Pearson correlations
# - Pearson_pairwise.csv - Pairwise Pearson correlations
# - Spearman_listwise.csv - Listwise Spearman correlations
# - Spearman_pairwise.csv - Pairwise Spearman correlations
# - descriptives.txt - Some general descriptive measures

getCorrelations <- function(data){
  # Check if this is a matrix or data frame:
  if (!is.matrix(data) && !is.data.frame(data)){
    stop("Input is not a matrix or data frame.")
  }

  # If it is a matrix, make it a data frame:
  if (is.matrix(data)){
    data <- as.data.frame(data)
  }

  # Descriptives:
  nSample_listwise <-
sum(apply(data,1,function(x)all(!is.na(x))))
  nSample_full <- sum(apply(data,1,function(x)any(!is.na(x))))

  # Compute average sample size for pairwise correlations:
  nomisdata <- !is.na(as.matrix(data))
  nMat <- t(nomisdata) %*% nomisdata
  nSample_pairwise <-
mean(nMat[lower.tri(nMat,diag=FALSE)],na.omit=TRUE)


  # Means:
  means <- colMeans(data,na.rm = TRUE)

  # SDs:
  SDs <- sapply(data,sd,na.rm = TRUE)

  # Number of levels:
  nLevels <- sapply(data,
function(x)length(unique(x)[!is.na(unique(x))]))

  # Set names:
  if (is.null(colnames(data))){
    colnames(data) <- paste0("V",seq_len(ncol(data)))
  }
    # Write these to a file:
  descriptivesFile <- paste0(getwd(),"/descriptives.txt")
  write(paste0(
    "Sample size (full): ", nSample_full, "\n",
    "Sample size (listwise): ", nSample_listwise, "\n",
```

```
    "Sample size (pairwise average): ", nSample_pairwise,
"\n",
    "Name: ", paste0(colnames(data), collapse = "; "), "\n",
    "Means: ", paste0(means, collapse = "; "), "\n",
    "Standard deviations: ", paste0(SDs, collapse = "; "),
"\n",
    "Number of levels: ", paste0(nLevels, collapse = "; ")
  ), file = descriptivesFile)

  # Correlations:
  try({
    pearsonCorsFile_listwise <-
paste0(getwd(),"/Pearson_listwise.csv")
    write.csv(cor(data, use = "complete.obs"), file =
pearsonCorsFile_listwise)
  })

  try({
    pearsonCorsFile_pairwise <-
paste0(getwd(),"/Pearson_pairwise.csv")
    write.csv(cor(data, use = "pairwise.complete.obs"), file =
pearsonCorsFile_pairwise)
  })

  try({
    spearmanCorsFile_listwise <-
paste0(getwd(),"/Spearman_listwise.csv")
    write.csv(cor(data, use = "complete.obs", method =
"spearman"), file = spearmanCorsFile_listwise)
  })

  try({
    spearmanCorsFile_pairwise <-
paste0(getwd(),"/Spearman_pairwise.csv")
    write.csv(cor(data, use = "pairwise.complete.obs", method
= "spearman"), file = spearmanCorsFile_pairwise)
  })

  cat("Done! Please mail us the following files:\n\n1.
",pearsonCorsFile_listwise,
      "\n2. ",pearsonCorsFile_pairwise,
      "\n3. ",spearmanCorsFile_listwise,
      "\n4. ",spearmanCorsFile_pairwise,
      "\n5. ",descriptivesFile,"\n\nThank you for your
assistance!")
  }
```

sAppendix 2. Table of node descriptions and alternative descriptions mapped to the nodes included.

DSM-IV ID	Label	Examples of alternative descriptions	DSM-IV description
B1	Intrusive Thoughts	Intrusive recollections; Thought about it when didn't mean to	Recurrent and intrusive distressing recollections of the event, including images, thoughts, or perceptions. Note: In young children, repetitive play may occur in which themes or aspects of the trauma are expressed.
B2	Nightmares	Dreams, Traumatic dreams, Distressing dreams; Has upsetting dreams; Had dreams about it	Recurrent distressing dreams of the event.
B3	Flashbacks	Re-experiencing; Reminders brought back feelings; Pictures popped into mind	Acting or feeling as if the traumatic event were recurring (includes a sense of reliving the experience, illusions, hallucinations, and dissociative flashback episodes, including those that occur on awakening or when intoxicated). Note: In young children, trauma-specific re-enactment may occur.
B4	Psychological reactivity	Upset at reminder of trauma; Heightened emotional reactivity; Avoid letting themselves getting upset when thinking or being reminded of it	Intense psychological distress at exposure to the internal or external cues that symbolize or resemble an aspect of the traumatic event.
B5	Physiological reactivity	Physiological cue reactivity; Physiological reaction on exposure	Physiological reactivity on exposure to internal or external cues that symbolize or resemble an aspect of the traumatic event.
C1	Internal avoidance	Avoiding Thoughts/Feelings	Efforts to avoid thoughts, feelings, or conversations associated with the trauma.
C2	External avoidance	Avoidance of activities	Avoidance of or efforts to avoid external reminders (people, places, conversations, activities, objects, situations) that arouse distressing memories, thoughts, or feelings about or closely associated with the traumatic event(s).
C3	Amnesia	Inability remembering; felt as if it hadn't happened or wasn't real	Inability to recall important aspect of the trauma.
C4	Loss of interest	Anhedonia	Markedly diminished interest or participation in significant activities.
C5	Feeling detached	Feeling distant or cut off from others; Difficulties feeling close to others	Feelings of detachment or estrangement from others.
C6	Emotional numbing	Numbness Happiness/Love; Restricted Affect	Restricted range of affect (e.g., unable to have loving feelings).
D2	Irritability / anger	Anger; Irritability	Irritability or outbursts of anger
D4	Hypervigilant	Overly Alert; Watchful / On-guard	Hyper vigilance
D5	Easily startled	Exaggerated startle, Exaggerated startle response	Exaggerated startle response
D3	Difficulty concentrating	Concentration	Difficulty concentrating
D1	Sleep disturbance	difficulty falling or staying asleep; Trouble staying asleep; Trouble falling asleep	Difficulty falling or staying asleep
C7	Hopelessness	Future foreshortening; Feeling plans won't come true	Sense of a foreshortened future (e.g., does not expect to have a career, marriage, children, or a normal life span).

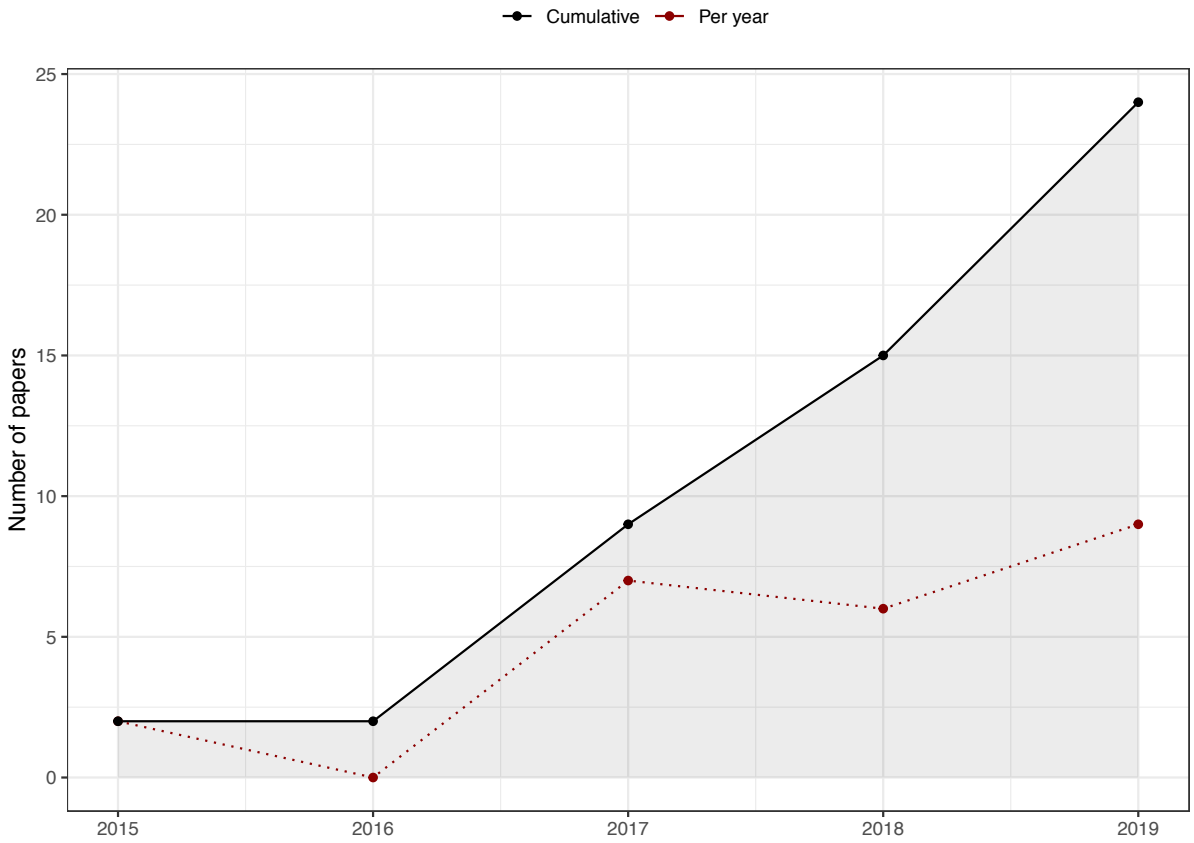
sAppendix 3. Table of numeric results.

Variable 1	Variable 12	Edge	SE	p	Implied Correlation	Random-effect SD
nightmares	intrusive thoughts	.229	0.016	<.001	.548	0.133
flashbacks	intrusive thoughts	.235	0.023	<.001	.550	0.133
psychological reactivity	intrusive thoughts	.174	0.025	<.001	.529	0.155
physiological reactivity	intrusive thoughts	.075	0.017	<.001	.505	0.099
internal avoidance	intrusive thoughts	.105	0.014	<.001	.448	0.117
external avoidance	intrusive thoughts	.023	0.012	.051	.413	0.118
amnesia	intrusive thoughts	-.014	0.014	.314	.256	0.129
loss of interest	intrusive thoughts	.016	0.013	.217	.354	0.124
feeling detached	intrusive thoughts	-.001	0.015	.948	.361	0.120
emotional numbing	intrusive thoughts	.025	0.015	.093	.346	0.118
irritability anger	intrusive thoughts	-.010	0.013	.437	.325	0.119
hypervigilant	intrusive thoughts	.043	0.012	<.001	.373	0.114
easily startled	intrusive thoughts	.009	0.013	.483	.388	0.113
difficulty concentrating	intrusive thoughts	.046	0.013	<.001	.390	0.099
sleep disturbance	intrusive thoughts	.027	0.017	.114	.394	0.109
hopelessness	intrusive thoughts	.061	0.019	.001	.368	0.108
flashbacks	nightmares	.211	0.020	<.001	.511	0.140
psychological reactivity	nightmares	-.009	0.023	0.694	.416	0.151
physiological reactivity	nightmares	.147	0.023	<.001	.493	0.134
internal avoidance	nightmares	.016	0.015	.260	.373	0.125
external avoidance	nightmares	.033	0.013	.010	.372	0.133
amnesia	nightmares	.003	0.017	.872	.233	0.142
loss of interest	nightmares	.021	0.016	.174	.320	0.139
feeling detached	nightmares	-.028	0.016	.080	.314	0.129
emotional numbing	nightmares	.009	0.014	.538	.302	0.115
irritability anger	nightmares	-.018	0.020	.362	.298	0.118
hypervigilant	nightmares	.023	0.011	.038	.341	0.108
easily startled	nightmares	.026	0.014	.069	.371	0.140
difficulty concentrating	nightmares	.006	0.018	.724	.352	0.120
sleep disturbance	nightmares	.234	0.025	<.001	.472	0.141
hopelessness	nightmares	.005	0.015	.749	.310	0.099
psychological reactivity	flashbacks	.118	0.021	<.001	.472	0.153
physiological reactivity	flashbacks	.088	0.031	.004	.470	0.144
internal avoidance	flashbacks	-.005	0.014	.739	.362	0.120
external avoidance	flashbacks	.038	0.011	.001	.372	0.135
amnesia	flashbacks	.063	0.014	<.001	.268	0.127
loss of interest	flashbacks	-.012	0.016	.452	.302	0.133

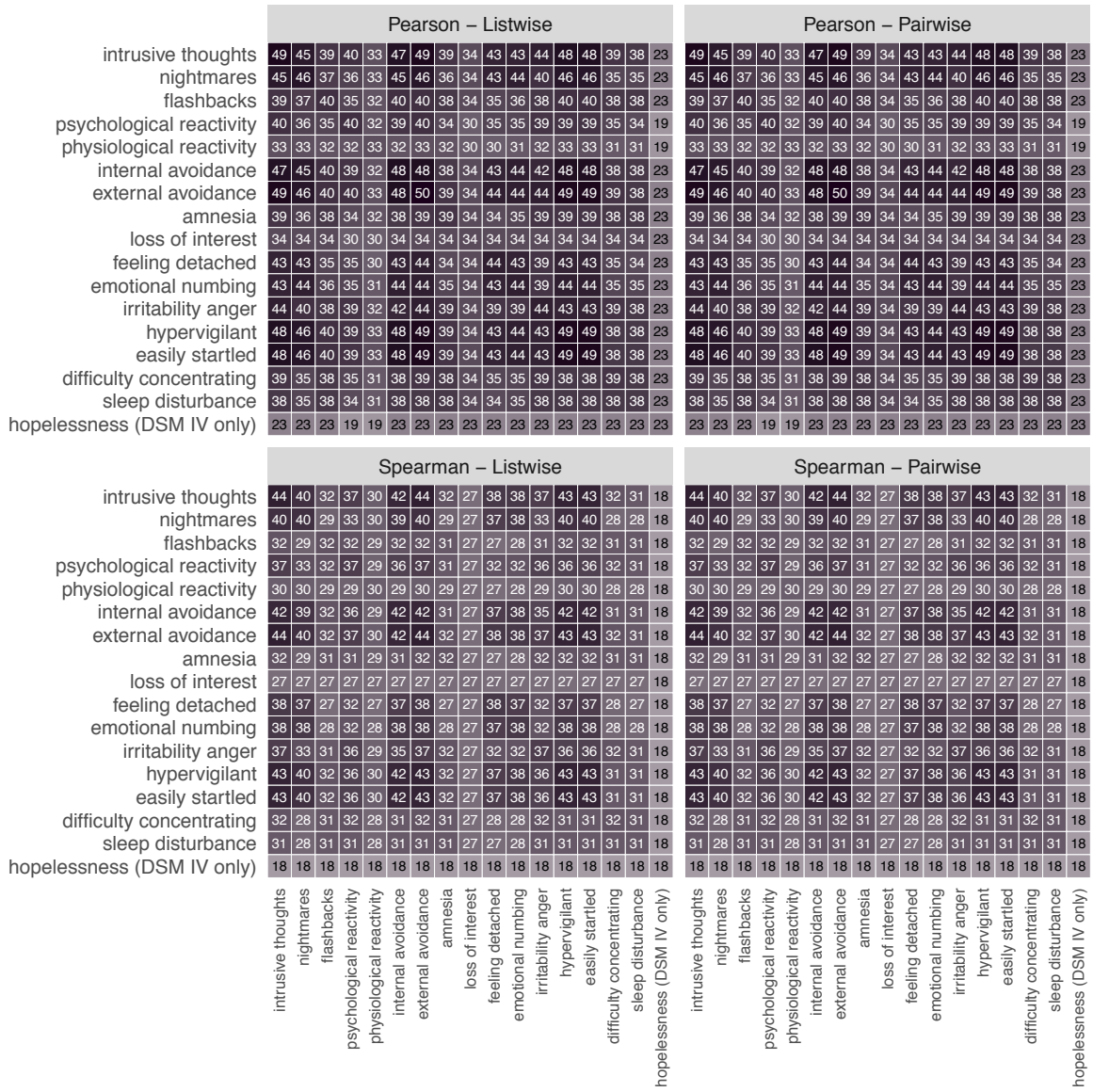
Variable 1	Variable 12	Edge	SE	p	Implied Correlation	Random-effect SD
feeling detached	flashbacks	-.000	0.018	.992	.318	0.130
emotional numbing	flashbacks	.016	0.014	.245	.307	0.115
irritability anger	flashbacks	.032	0.017	.070	.307	0.124
hypervigilant	flashbacks	.016	0.013	.227	.330	0.120
easily startled	flashbacks	.041	0.014	.002	.364	0.128
difficulty concentrating	flashbacks	-.007	0.016	.666	.327	0.114
sleep disturbance	flashbacks	-.018	0.014	.196	.336	0.129
hopelessness	flashbacks	.050	0.016	.002	.329	0.116
physiological reactivity	psychological reactivity	.249	0.025	<.001	.567	0.140
internal avoidance	psychological reactivity	.108	0.021	<.001	.461	0.148
external avoidance	psychological reactivity	.077	0.016	<.001	.446	0.149
amnesia	psychological reactivity	.035	0.015	.021	.286	0.130
loss of interest	psychological reactivity	.023	0.014	.109	.366	0.115
feeling detached	psychological reactivity	.041	0.020	.037	.388	0.120
emotional numbing	psychological reactivity	-.004	0.019	.831	.343	0.121
irritability anger	psychological reactivity	.065	0.016	<.001	.367	0.122
hypervigilant	psychological reactivity	.017	0.013	.208	.366	0.126
easily startled	psychological reactivity	.050	0.018	.006	.409	0.123
difficulty concentrating	psychological reactivity	.010	0.014	.468	.380	0.108
sleep disturbance	psychological reactivity	-.005	0.012	.682	.357	0.102
hopelessness	psychological reactivity	.035	0.017	.036	.354	0.103
internal avoidance	physiological reactivity	.056	0.018	.002	.444	0.123
external avoidance	physiological reactivity	.096	0.018	<.001	.455	0.135
amnesia	physiological reactivity	.025	0.019	.177	.283	0.125
loss of interest	physiological reactivity	.000	0.014	.990	.364	0.122
feeling detached	physiological reactivity	.032	0.026	.224	.391	0.123
emotional numbing	physiological reactivity	.011	0.021	.587	.351	0.133
irritability anger	physiological reactivity	.044	0.015	.003	.369	0.126
hypervigilant	physiological reactivity	.016	0.016	.309	.385	0.126
easily startled	physiological reactivity	.105	0.019	<.001	.450	0.128
difficulty concentrating	physiological reactivity	.048	0.018	.006	.408	0.124
sleep disturbance	physiological reactivity	.046	0.014	.001	.406	0.132
hopelessness	physiological reactivity	.008	0.018	.660	.346	0.115
external avoidance	internal avoidance	.332	0.027	<.001	.560	0.177
amnesia	internal avoidance	.079	0.016	<.001	.307	0.140
loss of interest	internal avoidance	.036	0.014	.011	.369	0.126
feeling detached	internal avoidance	.010	0.015	.513	.361	0.132
emotional numbing	internal avoidance	.037	0.013	.003	.339	0.119
irritability anger	internal avoidance	.011	0.013	.412	.318	0.121
hypervigilant	internal avoidance	.052	0.012	<.001	.362	0.107

Variable 1	Variable 12	Edge	SE	p	Implied Correlation	Random-effect SD
easily startled	internal avoidance	-.001	0.014	.949	.363	0.123
difficulty concentrating	internal avoidance	.057	0.017	.001	.376	0.129
sleep disturbance	internal avoidance	.043	0.014	.003	.355	0.120
hopelessness	internal avoidance	-.005	0.014	.709	.318	0.107
amnesia	external avoidance	.074	0.015	<.001	.303	0.130
loss of interest	external avoidance	.086	0.013	<.001	.380	0.122
feeling detached	external avoidance	.025	0.012	.046	.360	0.121
emotional numbing	external avoidance	-.021	0.015	.160	.313	0.139
irritability anger	external avoidance	.001	0.013	.948	.307	0.133
hypervigilant	external avoidance	.065	0.016	<.001	.373	0.123
easily startled	external avoidance	.062	0.021	.003	.388	0.128
difficulty concentrating	external avoidance	-.021	0.014	.127	.341	0.112
sleep disturbance	external avoidance	.011	0.014	.434	.335	0.121
hopelessness	external avoidance	.040	0.018	.024	.327	0.106
loss of interest	amnesia	.053	0.018	.003	.289	0.135
feeling detached	amnesia	.027	0.018	.125	.289	0.104
emotional numbing	amnesia	.065	0.016	<.001	.290	0.120
irritability anger	amnesia	.012	0.013	0.348	.233	0.134
hypervigilant	amnesia	-.000	0.014	.981	.224	0.122
easily startled	amnesia	.023	0.011	.042	.250	0.106
difficulty concentrating	amnesia	.036	0.014	.011	.273	0.127
sleep disturbance	amnesia	-.005	0.016	.772	.223	0.142
hopelessness	amnesia	.055	0.017	.001	.270	0.125
feeling detached	loss of interest	.243	0.023	<.001	.552	0.145
emotional numbing	loss of interest	.146	0.016	<.001	.489	0.125
irritability anger	loss of interest	.075	0.014	<.001	.396	0.127
hypervigilant	loss of interest	.017	0.017	.294	.328	0.125
easily startled	loss of interest	.003	0.013	.845	.347	0.131
difficulty concentrating	loss of interest	.129	0.018	<.001	.454	0.137
sleep disturbance	loss of interest	.032	0.017	.067	.363	0.119
hopelessness	loss of interest	.055	0.023	.016	.400	0.152
emotional numbing	feeling detached	.299	0.017	<.001	.580	0.120
irritability anger	feeling detached	.087	0.018	<.001	.427	0.139
hypervigilant	feeling detached	.011	0.015	.472	.345	0.137
easily startled	feeling detached	.045	0.016	.006	.379	0.132
difficulty concentrating	feeling detached	.076	0.013	<.001	.457	0.124
sleep disturbance	feeling detached	.071	0.018	<.001	.393	0.134
hopelessness	feeling detached	.137	0.017	<.001	.464	0.098
irritability anger	emotional numbing	.098	0.017	<.001	.402	0.142

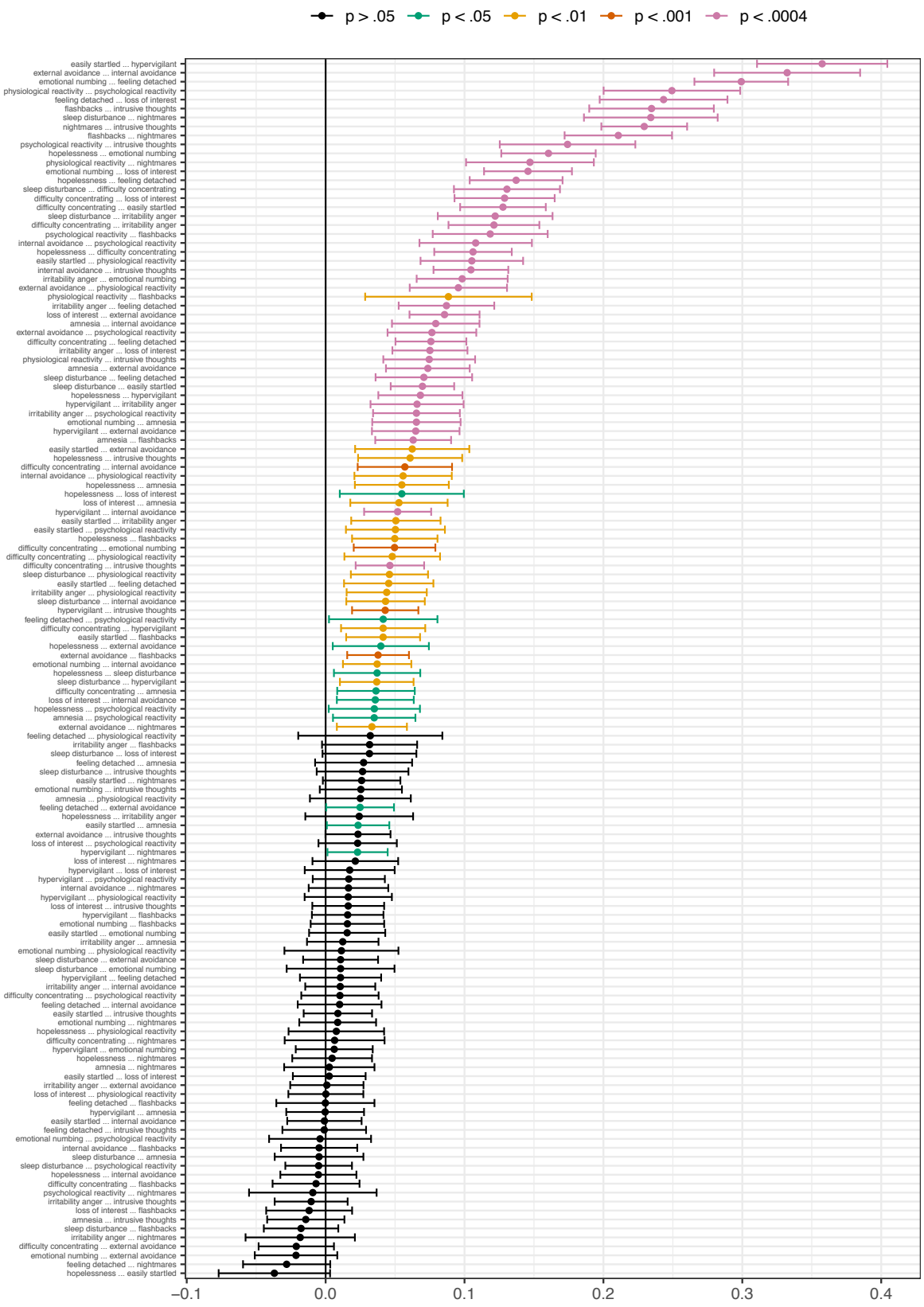
Variable 1	Variable 12	Edge	SE	p	Implied Correlation	Random-effect SD
hypervigilant	emotional numbing	.006	0.014	.661	.312	0.134
easily startled	emotional numbing	.016	0.014	.267	.334	0.121
difficulty concentrating	emotional numbing	.050	0.015	.001	.415	0.115
sleep disturbance	emotional numbing	.011	0.020	.586	.343	0.127
hopelessness	emotional numbing	.160	0.017	<.001	.454	0.115
hypervigilant	irritability anger	.066	0.017	<.001	.347	0.131
easily startled	irritability anger	.051	0.016	.002	.367	0.138
difficulty concentrating	irritability anger	.121	0.017	<.001	.425	0.155
sleep disturbance	irritability anger	.122	0.021	<.001	.391	0.147
hopelessness	irritability anger	.024	0.020	.222	.336	0.147
easily startled	hypervigilant	.357	0.024	<.001	.555	0.164
difficulty concentrating	hypervigilant	.041	0.015	.007	.380	0.130
sleep disturbance	hypervigilant	.037	0.014	.007	.351	0.108
hopelessness	hypervigilant	.068	0.015	<.001	.327	0.104
difficulty concentrating	easily startled	.128	0.016	<.001	.436	0.135
sleep disturbance	easily startled	.070	0.012	<.001	.390	0.119
hopelessness	easily startled	-.037	0.020	.071	.304	0.143
sleep disturbance	difficulty concentrating	.131	0.019	<.001	.433	0.128
hopelessness	difficulty concentrating	.106	0.014	<.001	.408	0.097
hopelessness	sleep disturbance	.037	0.016	.019	.335	0.110



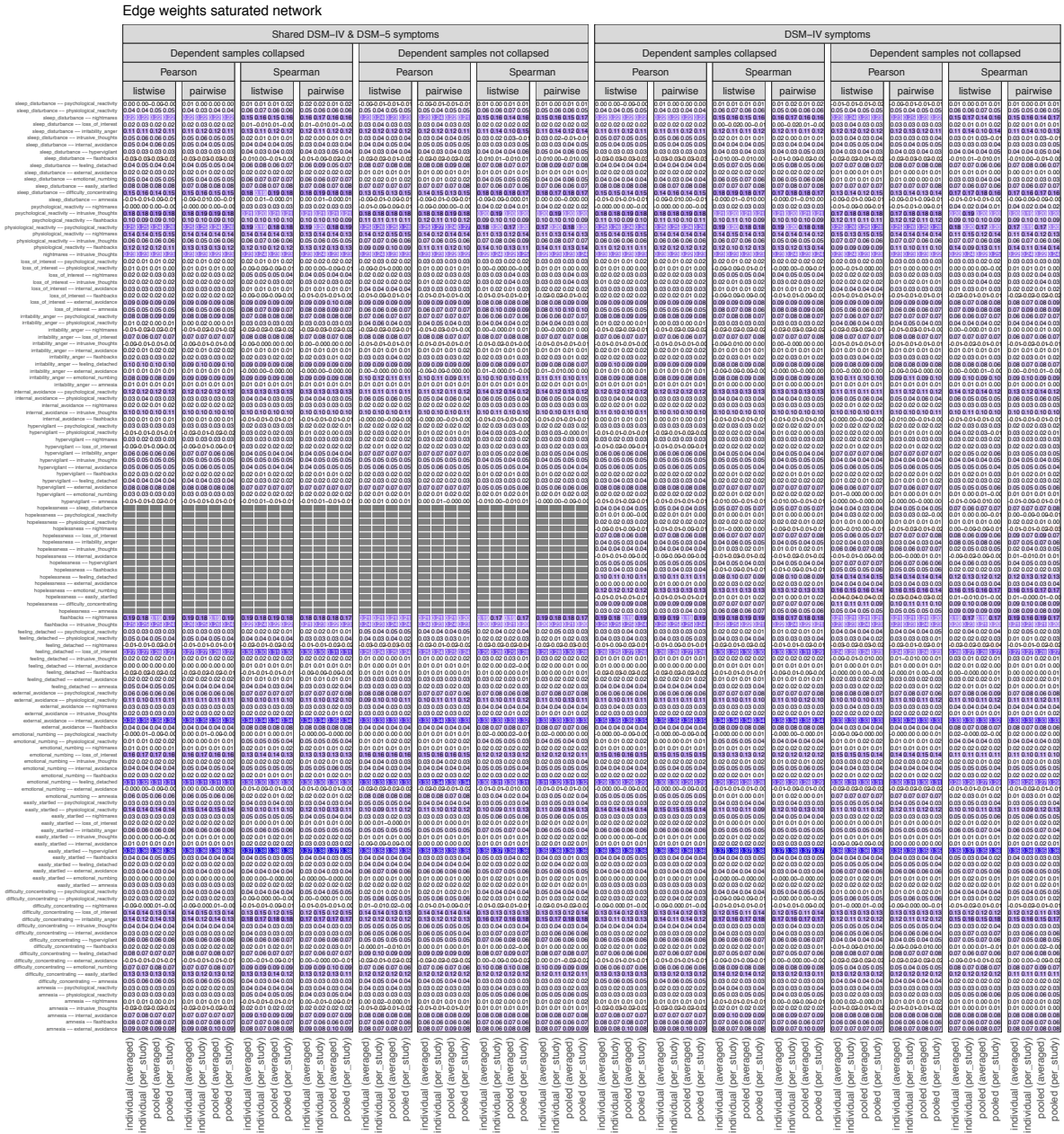
sFigure 1. Overview of the cumulative number of articles, and overall number of articles published per year.



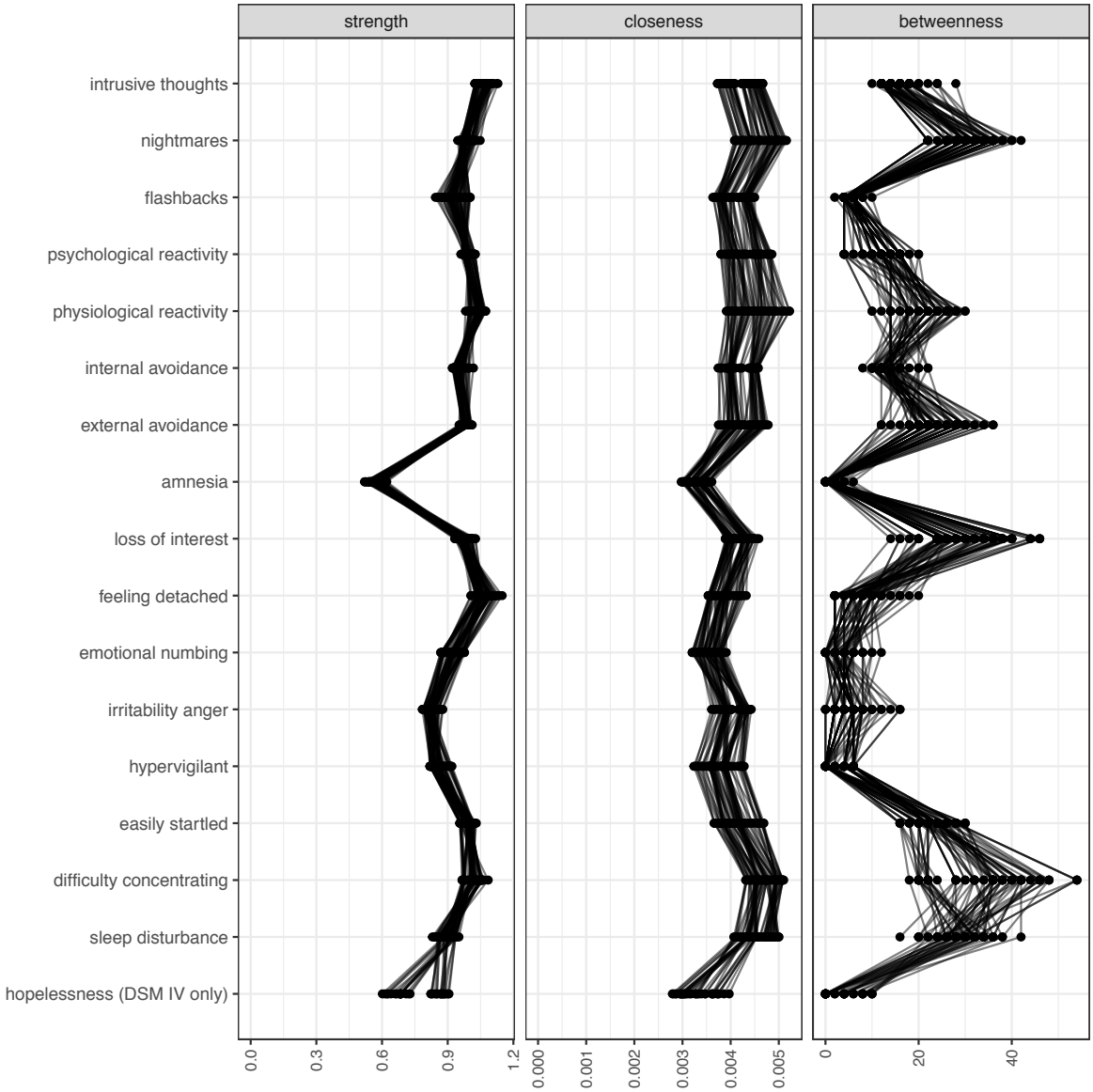
sFigure 2. Number of samples for each pair of variables for which different types of correlations were available.



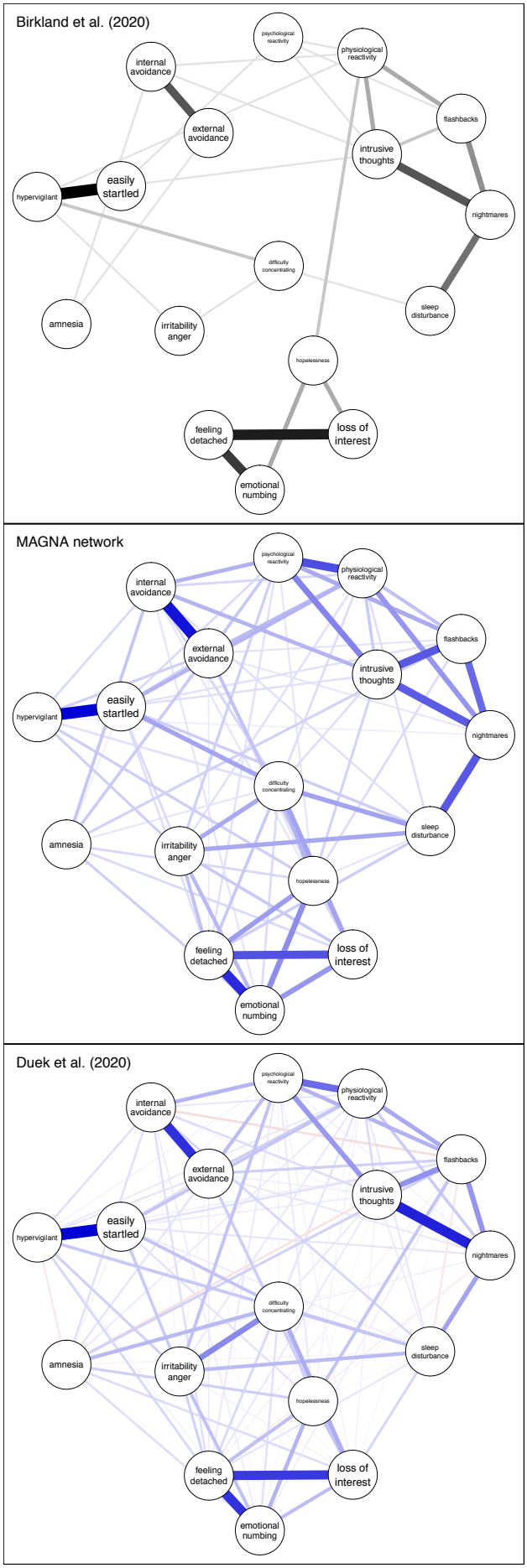
sFigure 3. Estimated edge weights in the pooled MAGNA and 95% confidence regions based on the estimated standard. The $\alpha = .0004$ level corresponds to a Bonferroni corrected α level of .05 rounded to four digits.



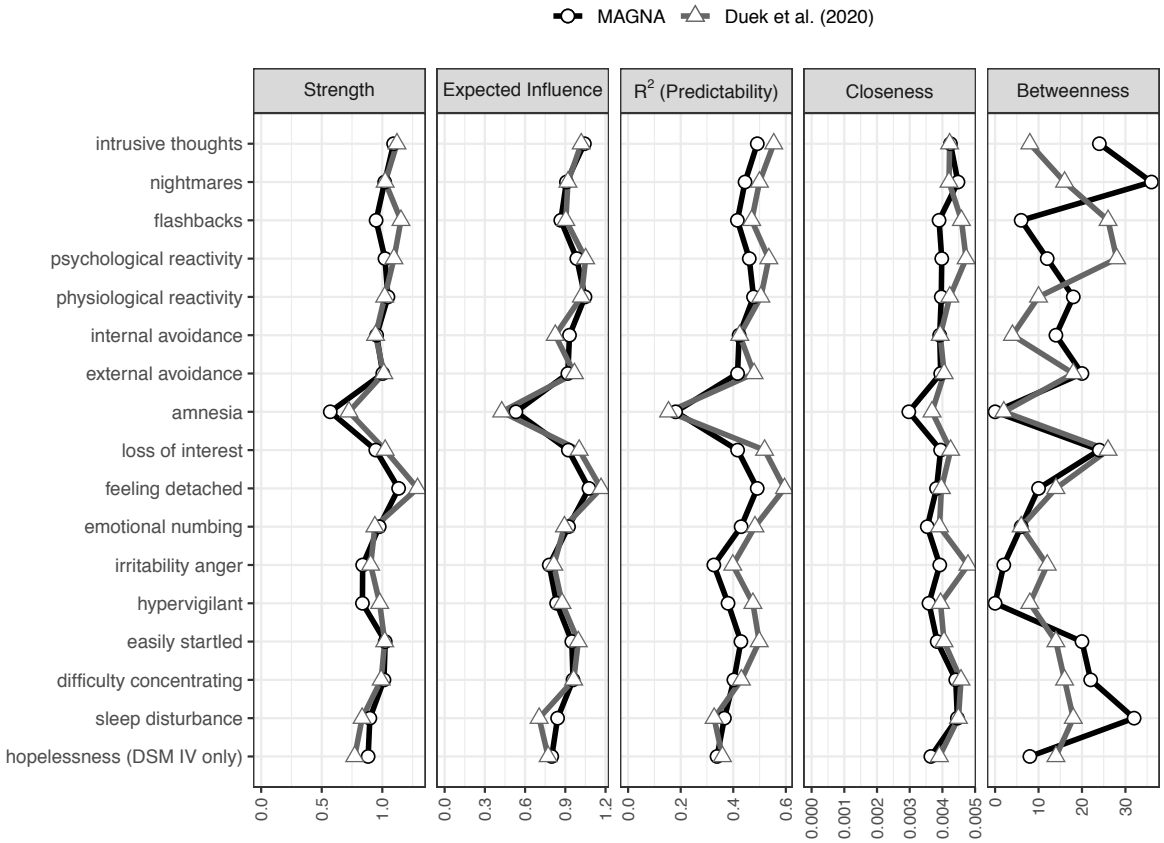
sFigure 4. Multiverse plot displaying results for distinct MAGNA estimation procedures and data variants. Each box shows the edge weight estimated using different settings and different data sources in MAGNA. To handle dependent samples (samples of the same participants), we *collapsed* samples by averaging correlations and by taking the largest sample size as input sample size. Of note, we made two simplifications to the optimization routine to make the multiverse analysis feasible (as the main analysis took over 5 hours to run and cannot be parallelized): we used a lower convergence tolerance level of 1×10^{-5} instead of the default of 1.5×10^{-8}, and we used the model estimates of Pearson (listwise) analyses using individual (averaged) estimation—which is the analysis shown in the paper—as starting values for the optimizer in other model evaluations to improve convergence time (the analysis is very slow without good starting values). This may inflate similarity, although there is no principle reason to believe these choises to have a substantial effect on the outcomes (all models converged adequately).



sFigure 5. Multiverse analysis of centrality indices. Each line corresponds to the centrality results of one of the variants reported in sFigure 4.



sFigure 6. This figure compares the pooled MAGNA network (middle panel) to results from the literature review presented by Birkland and colleagues (2020, top panel) and a recent large-scale PTSD symptom network estimated by Duek and colleagues (2020, bottom panel) on.a sample of 158,139 veterans with PTSD. The top panel is a visual representation of the table presented in Figure 3 of Birkeland et al. (2020), and shows how often edges were be stronger than two-thirds of the included edges of a given network.



sFigure 7. Centrality coefficients of the pooled MAGNA network compared to the results from Duek and colleagues (2020).

References

Birkeland, M. S., Greene, T., & Spiller, T. R. (2020). The network approach to posttraumatic stress disorder: a systematic review. *European Journal of Psychotraumatology*, *11*(1), 1700614. https://doi.org/10.1080/20008198.2019.1700614

Duek, O., Spiller, T. R., Pietrzak, R. H., Fried, E. I., & Harpaz-Rotem, I. (2020). Network analysis of PTSD and depressive symptoms in 158,139 treatment-seeking veterans with PTSD. *Depression and Anxiety*, 1–9. https://doi.org/10.1002/da.23112