**Supplement 1: Data analysis**

Using partial polychoric correlations, we investigated the connectivity of each symptom while controlling for all other associations in the network. To control for the possibility of false positive associations [1], we used glasso regularization and a tuning parameter gamma set to ·5 thereby setting small edges, which are likely due to noise, exactly to zero and regularizing the network [2].

Nodes with more and/or stronger connections were placed more closely together in the network graph [3]. The maximum edge value was set to the strongest edge identified in the network (·69) and the minimum edge value was set to ·03 to enhance interpretability. We set positive edges to be printed in solid green lines and negative ones in dashed red lines. Stronger connections are indicated by more saturated and thicker edges. Importantly, the visual display of the network does not allow for a meaningful interpretation of the distances between nodes.

We used four parameters to describe the connectedness of each node in the estimated network: predictability, the centrality indices of node strength and expected influence, and bridge expected influence. Predictability is a characterization of symptom networks that gives an absolute measure of the controllability of each node. It is defined as the proportion of explained variance of a node by all other nodes. It thus quantifies how well a given node can be predicted by all other nodes it is connected to in the network [4]. We estimated the overall predictability of the nodes in the network as well as the predictability of each node.

We used strength centrality to analyse the direct connections of nodes [5,6]. Reflecting the sum of all absolute edge weights a node is directly connected to, strength centrality quantifies the connectivity of a node to all other nodes in the network. To take the potential importance of negative edges in symptom networks into account, we also estimated expected influence as an additional centrality metric. In networks consisting of symptoms of different psychiatric disorders, it is also important to consider bridge centrality [7]. Bridge symptoms in a network are symptoms that work as a link between groups of disorder-specific symptoms and may therefore be helpful in explaining comorbidity. Bridge expected influence (1-step) was chosen as outcome parameter as recommended when negative edges are present. Bridge expected influence (1-step) is defined as the sum of the values of all edges between a node and all nodes from different communities. We calculated the mean of the absolute values of all edges that connect any two disorders to investigate the average connectedness between any two disorder-specific symptom communities. For this, we used Fisher’s z-transformation to average the edge weights. Finally, we used exploratory graph analysis [8] to detect communities of nodes in the network. Using the walktrap algorithm as implemented in the EGAnet package with 10,000 non-parametric bootstrap iterations [9], we identified clusters of nodes that are highly connected with one another, but only modestly connected to nodes from other clusters. The replication across bootstrap iterations is an estimation of the stability of the result. We expected a strong overlap between the EGA results and the diagnostic categories.

To assess accuracy of the edge weight estimates, we conducted the routine implemented in the bootnet package [5], using nonparametric bootstrapping based on 2,000 bootstrap samples to estimate 95% confidence intervals of all edge weights. To assess accuracy of the centrality estimates (strength and expected influence), we used the subsetting bootstrap function implemented in the bootnet package using 2,000 samples with dropped cases. High correlations of the original centrality metric with the estimates from re-estimated networks indicate high stability. We then applied a correlation stability analysis [10]. The correlation stability coefficient reflects the maximum number of dropped cases to retain a 95% probability of a correlation of at least *r* =·7 between the parameters of the original network and the parameters of the dropped cases networks and should not be below ·25.

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