**Supplementary Material S2**

We estimated *partial correlation networks* [1] in the student and clinical samples using the Fused Graphical Lasso (FGL; Danaher, Wang, & Witten, 2014) implemented in the R package *EstimateGroupNetwork* [3]. In the following, we introduce FGL and we provide a detailed explanation of the steps that we followed for estimating the networks, to ensure exact reproducibility of our analysis.

**Introduction to the Fused Graphical Lasso**

In psychological networks, edges typically represent estimates of partial correlations [1]. Due to sampling error, maximum likelihood (or ordinary least squares) estimates of partial correlations are never exactly zero, even when two symptoms are actually independent; furthermore estimates can be often affected by overfitting, especially with a large number of covariates [4]. Regularization through the least absolute shrinkage and selection operator (*lasso*; [5]) assuages both these issues [6], therefore methods for estimating psychological networks typically rely on this type of regularization [1,7–9]. Among lasso regularization methods, the graphical lasso is the most widespread for estimating networks on normally distributed data [1,10,11]. Instead of maximizing the log-likelihood function to yield maximum likelihood estimates, this method maximizes a *penalized* log-likelihood, a log-likelihood function plus a term that depends on network density (the number and the weights of edges). A tuning parameter (λ1) allows regulating the importance of the density penalty. Larger values of λ1 yield sparser networks (i.e., with fewer and weaker edges), whereas smaller values yield denser networks. If λ1 is set equal to zero, the penalty becomes null and the graphical lasso simply returns maximum likelihood estimates.

Sometimes it is necessary to estimate networks on the same variables measured in different classes of observations (in our case, students and patients). If the true networks were similar enough, it would be possible to improve estimates by pooling all samples together and estimating a single network. However, this strategy would also overlook any difference among classes. Conversely, estimating networks individually would allow detecting such differences, but edges would be computed separately in each sample. If the true networks were similar, using this second strategy would result in poorer estimates [2]. The FGL is a recently developed extension of the Graphical Lasso aimed at solving this problem by *jointly* estimating networks in different classes [2,12]. Like the graphical lasso, FGL includes a penalty on density, regulated by the tuning parameter λ1. Unlike the graphical lasso, the FGL includes also a penalty on differences among networks, regulated by a tuning parameter λ2. Large value of λ2 yield very similar networks, in which edges are estimated by exploiting all samples together. Conversely, small values of λ2 allow network estimates to differ. If λ2 is equal to zero, the networks are estimated independently of each other.

For selecting the best values of λ1 and λ2, the Extended Bayesian Information Criterion can be used (EBIC; Chen & Chen, 2008; Foygel & Drton, 2010), which performs well in simulation studies [15]. It is important to notice that FGL does not assume that the true networks are similar, because the value of λ2 is selected empirically according to the EBIC. If the model fit did not improve by exploiting similarities among networks, the parameter λ2 would be selected to be very close to zero and the FGL would nearly reduce to estimating the networks independently, without masking their differences. Conversely, if a large value of λ2 were selected, edges would be estimated jointly, therefore exploiting similarities across networks to improve the estimates. Intermediate values of λ2 allow estimating networks by both exploiting their similarities, without masking their true differences.

**Network estimation procedure**

We used the following steps for estimating the two networks:

1. To relax the normality assumption, the nonparanormal transformation implemented in the R package *huge* [16,17], was applied to the data from each class (see also [1,18]).
2. One-hundred candidate values of λ1 and 100 values of λ2 were considered. The 100 values of λ1 were logarithmically spaced between two values, λ1min and λ1max. As λ1max we selected the value under which no edge was retained in at least one network; λ1min was defined as 0.01\* λ1max (see also [15]). For each value of λ1, 100 values of λ2 were selected, uniformly spaced between λ2min and λ2max. As λ2max we selected the value under which all edges were estimated to be identical in the two classes (the student and the clinical samples); λ2min was defined as 0.01\* λ2max. This tuning parameter selection strategy is implemented in function EstimateGroupNetwork within the homonymous package, by selecting setting parameter strategy = “simultaneous”.
3. Among the 10000 unique pairs of candidate λ1 and λ2 values, we selected those associated to the minimum value of EBIC, which is the default option in EstimateGroupNetwork. The values identified for the tuning parameters were λ1 = 0.024056083 and λ2 = 0.002908718 and were used for estimating the two networks. The values of the edges in the two networks are reported in Table S3, whereas centrality values are reported in Table S4.

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