nature medicine

Supplementary information

Article <https://doi.org/10.1038/s41591-024-03057-9>

Personalized brain circuit scores identify clinically distinct biotypes in depression and anxiety

In the format provided by the authors and unedited

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SUPPLEMENTARY METHODS

Experimental Conditions used to Probe Circuits of Interest

The six circuits of interest in this study were measured from functional magnetic resonance imaging (fMRI) data using a novel standardized image processing procedure called 'the Stanford Et Cere Image Processing System'. This system allows the quantification of task-free and task-evoked brain circuit function at the level of the individual participants. Default Mode, Salience and Attention circuits were derived from the task-free periods of the fMRI sequencing protocols using a previously established procedure ¹. Negative and Positive Affect circuits were engaged by a facial expressions task, and the Cognitive Control circuit was engaged by a Go-NoGo task, the design of which was as follows:

Facial Expressions of Emotion Task

A standardized set of 3D-evoked facial expression stimuli were presented in pseudorandom order, with five repeated blocks of eight stimuli per block for sad, threat evoked by fear, threat evoked by anger, and happy, relative to neutral blocks; duration of stimulus was 500ms and the interstimulus interval was 750ms². Participants were instructed to actively attend in order to answer post-scan questions about these faces, and we monitored alertness using an eye tracking system. We also presented the same stimuli nonconsciously in a backward-masking design to prevent awareness; face stimuli were presented for 10 ms followed immediately by a neutral face mask stimulus for 150 ms, and with a stimulus onset asynchrony of 1250 ms to match that of the conscious condition ³ .

Go-NoGo Task

'Go' trials (the word "press" in GREEN) required participants to respond as quickly as possible, while the 'NoGo' trials ("press" in RED) required participants to withhold responses. 180 Go and 60 NoGo stimuli were presented in pseudorandom order; stimulus duration was 500 ms each with an interstimulus interval of 750 ms⁴.

Imaging Acquisition

MRI data was collected using a 3.0 Tesla GE Signa HDx (Sydney), a 3.0 Tesla GE MR750 Discovery (Stanford) and a 3.0 Tesla GE UHP (Stanford) (GE Healthcare, Milwaukee, Wisconsin) using an 8-channel head coil (Sydney) and 32-channel head coil (Stanford). The two Stanford scanners used identical sequences. Head motion was restricted with foam pads and participant alertness was monitored using an eye-tracking system. Head motion was also recorded, which was later subject to quality control and potential data exclusion on the premise of excess motion.

Stanford Sequences (RAD, HCP-DES, ENGAGE)

In RAD and ENGAGE, a T1-weighted structural scan was acquired using a 3D spoiled gradient echo (SPGR) sequence normalization into standard space: TR=0.008; TE=0.003; voxel size=1x1x1mm; number of slices=176; FOV=256x256; flip angle=11^o. In HCP-DES, the T1 parameters were TE = 3.548 ms; MPRAGE TR = 2.84s; FA = 8, acquisition time = 8 min and 33 sec; field of view = 256×256 mm; 3D matrix size = $320 \times$ 320×230 ; slice orientation = sagittal; angulation to AC-PC line; receiver bandwidth = 31.25 kHz; fat suppression = no; motion correction = $PROMO$; voxel size = 0.8 mm isotropic. Blood oxygenation leveldependent contrast functional images were acquired using echo-planar T2*-weighted imaging. Each whole brain volume consisted of 45 interleaved 3mm thick axial/oblique slices (74 x 74 matrix; TR=2000ms; TE=27.5ms; voxel size=3x3x3mm; FOV=222mm; flip angle=77°). Each of the three tasks acquired 154 volumes over 5 minutes and 8 seconds.

Sydney Sequences (iSPOT-D)

The T1-weighted structural scan was acquired in the sagittal plane using a 3D spoiled gradient echo (SPGR) sequence (TR = 8.3 ms; TE = 3.2 ms; flip angle = 11 degrees; TI = 500 ms; NEX = 1; ASSSET = 1.5; matrix = 256 x 256). A total of 180 contiguous slices, each 1 mm thick, covered the whole brain with an in-plane resolution of 1 mm x 1 mm. The functional images for each task were acquired using echo planar imaging (TR $= 2500$ ms; TE $= 27.5$ ms; matrix $= 64$ x 64; FOV $= 24$ cm; flip angle $= 90$ degrees). Forty slices, each 3.5 mm thick, covered the whole brain in each volume. Each of the three tasks acquired 123 volumes over 5 minutes and 8 seconds.

Image Pre-processing

For functional images, the first three volumes were removed to account for magnetization transfer artifacts before pre-processing. Pre-processing was performed using fMRIPrep 20.2.1 (iSPOTD) and fMRIPrep 20.2.3 (HCP-DES, ENGAGE, RAD)⁵. For details, the standardized methodology outputs from fMRIPrep for each study can be found at the end of the Supplementary Material.

Quality Control

The quality control reports generated by fMRIPrep were visually inspected for abnormalities by an experienced rater (L.T.) and scans with incidental findings, major scanner artifacts, and signal dropouts were discarded. Scans with more than 25% of volumes that contained significant frame-wise displacement as defined by fMRIPrep were also discarded. This threshold was chosen to maximize applicability to real world, clinical settings and to be consistent with the original design of the iSPOT-D pragmatic biomarker trial.

Derivation of Regions of Interest

The derivation of regions of interest (ROIs) is described in detail in a previous publication ⁶.

In summary, an anatomical definition of subcortical nodes was combined with an automated meta-analysis approach to cortical nodes using neurosynth.org⁷. Neurosynth uniformity (previously called forward- inference) maps were used with a false detection rate (FDR) threshold of .01 for each circuit and defined our ROIs (see **Supplementary Table 18** for Neurosynth search terms). A set of peaks associated with each circuit's search term were then identified using AFNI's 3dExtrema function. Because some terms yielded maps with excessively large spatial extent, a restriction was imposed that each peak have a minimum z-score of 6 and each region extend no farther than 10mm from the peak. For subcortical regions, neurosynth maps were restricted by anatomically defined boundaries from the AAL atlas ⁸ plus an additional anatomical boundary defining the ventral striatum from the FSL atlas ⁹. The Talairach atlas was used to identify the anatomical location of the peak of each region, and visual inspection of masks confirmed or adjusted these automatically derived labels.

In order to refine and maximize the quality of circuit definitions, we implemented the following steps in two healthy reference samples (see ⁶ for details). In the first sample, each individual's gray matter was identified by warping the output of FSL's FMRIB's Automated Segmentation Tool (FAST) to the MNI template. Each ROI was limited to gray matter only using this procedure. Using the second reference sample, we excluded ROIs with less than 50% average overlap between the original ROI and gray matter.

Next, in the first reference sample, ROIs were excluded if 95% of subjects had a temporal signal to noise ratio (tSNR) two standard deviations above the mean tSNR of a gray matter region with considerable signal drop out (peak coordinates 2, 46, -16, mean tSNR=47.03).

To further establish the internal validity of circuit definitions, the internal consistency of functional connectivity between pairs of regions was assessed, excluding region pairs for which connectivity (both task and task-free) showed stronger associations with out-of-circuit region pairs than with within-circuit region pairs in a healthy sample (see ⁶ for details).

For the current study, we selected the subset of regions most strongly implicated in circuit dysfunction in depression and anxiety in our theoretical synthesis 10. These regions are the same that have been used for the derivation of circuit scores in ⁶.

Task-evoked activation analysis

The task-evoked analysis was conducted using SPM8 [\(https://www.fil.ion.ucl.ac.uk/spm/\)](https://www.fil.ion.ucl.ac.uk/spm/) and MATLAB version 2018b (MathWorks).

Task-evoked activation was quantified using a generalized linear model (GLM) in which task events were convolved with a canonical hemodynamic response function as implemented in SPM8. In this analysis, a 128s high pass filter was applied to the data, and six realignment parameters as well as white matter and cerebrospinal fluid signals derived by fMRIPrep were added to the design matrix as confounds. Residuals from these models were saved and used for the estimation of task-free connectivity (see below). Specific contrasts of interest were then computed for each circuit as follows: 1) negative affect circuit: sad > neutral conscious faces; 2) negative affect circuit: threat > neutral conscious faces; 3) negative affect circuit: threat > neutral nonconscious faces; 4) positive affect circuit: happy > neutral conscious faces; 5) cognitive control circuit: NoGo > Go trials. Measures of activation for each region of each circuit were obtained by extracting the average value of the contrast of interest.

To quantify task-based functional connectivity, we computed psychophysiological interactions (PPI) between pairs of regions belonging to the same circuit. For each region in each circuit (PPI seed), we calculated the first eigenvariate of that region's time series and fit a whole-brain first-level GLM as described above, which consisted of the psychological variable (task contrast of interest), physiological variable (region time course), and the interaction between psychological and physiological variables (PPI effect of interest). Then, we computed the average PPI effect of interest in specific regions belonging to the same circuit in accordance with our hypothesized model of circuit dysfunction (PPI targets) (**Figure 1**). To account for the fact that regions were used once as PPI targets and once as PPI seeds in this calculation, we averaged these results, yielding a single PPI value for each connection.

Task-free analysis

The task-free analysis was conducted using FSL version 5.0.10¹¹ and MATLAB version 2018b (MathWorks).

Task-free data were derived following an established procedure ¹. First, the residuals of the task effects were saved from the GLM analysis described above. Then, these residuals were band-pass filtered between 0.08 and 0.009 Hz using FSL and concatenated across tasks. We then calculated from these data the correlation coefficient of the timeseries of each region pair belonging to the default mode, attention, and salience circuits. Finally, these values were converted to Fisher z and used as measures of task-free functional connectivity.

SUPPLEMENTARY FIGURES

Supplementary Figure 1: Sum of distances between participants for different numbers of clusters.

The plot showed an elbow at 5 clusters and another, smaller one at 9, which suggests that the optimal solution could lie between these two values. We selected 6 as the optimal number of clusters using four convergent sources of evidence: the elbow method, permutation-based significance testing of the silhouette index, stability using cross-validation; and the match of the solution to a theoretical framework (circled in red).

Supplementary Figure 2: Simulation-based significance testing of the silhouette index.

For different numbers of clusters, we show the mean silhouette (a) and its p-value defined as the fraction of mean silhouettes greater than our result obtained by clustering 10,000 synthetic datasets from a multivariate normal distribution (b). We selected 6 as the optimal number of clusters using four convergent sources of evidence: the elbow method, permutation-based significance testing of the silhouette index, stability using cross-validation; and the match of the solution to a theoretical framework (circled in red). The plot showing the silhouette values for each participant for the 6-cluster solution is shown (c).

Supplementary Figure 3: Permutation-based significance testing of the silhouette index.

We shuffled each brain circuit score across subjects 10,000 times, then repeated the hierarchical clustering procedure and calculated the average silhouette index. Thus, we obtained null distributions for these average silhouette indexes, comprising 10,000 observations. We computed a p-value defined as the fraction of average silhouette indexes in this null distribution greater than our result. We selected 6 as the optimal number of clusters using six convergent sources of evidence: the elbow method, simulation-based significance testing of the silhouette index, permutation-based significance testing of the silhouette index, split-half reliability of the cluster profiles, stability using cross-validation; and the match of the solution to a theoretical framework (circled in red).

Supplementary Figure 4: Assessment of cluster stability using cross-validation.

To evaluate whether the clustering assignment was stable under small perturbations to the data, we repeated the clustering procedure 801 times, each time with one participant left out (leave-one-out cross-validation, left). We also repeated the clustering procedure 801 times, each time with 20% of participants left out (leave-20%-out cross-validation, right). For each run and for each solution between 2 and 15 clusters, we calculated the similarity of the new cluster assignments to those from the original analysis using the adjusted Rand index. We selected 6 as the optimal number of clusters using six convergent sources of evidence: the elbow method, simulationbased significance testing of the silhouette index, permutation-based significance testing of the silhouette index, split-half reliability of the cluster profiles, stability using cross-validation; and the match of the solution to a theoretical framework (circled in red).

Supplementary Figure 5: Biotypes identified by hierarchical clustering.

At the top, we show the regions of interest used to calculate regional circuit scores (see Supplementary Table 18 for details). Then, we show the average and standard error of regional circuit scores across participants. Colors correspond to each circuit. Measures are abbreviated as per Figure 1 in the main text. The size of spheres representing each circuit denotes an absolute activation difference of >0.50 SD compared to a healthy norm (small spheres=decreased activation, large spheres=increased activation). The thickness of lines between the spheres denotes an absolute connectivity difference of >0.50 SD compared to a healthy norm (dashed lines=decreased connectivity, thick lines=increased connectivity). We named each biotype according to the circuits and circuit features that specifically differentiated each relative to other biotypes and to the healthy reference. We used the following

nomenclature: each circuit is indicated with a letter ($D =$ default mode, $S =$ salience, $A =$ attention, $NS =$ negative affect circuit evoked by sad stimuli, NTC = negative affect circuit evoked by conscious threat stimuli, NTN = negative affect circuit evoked by nonconscious threat stimuli, P = positive circuit, C = cognitive circuit), the distinguishing circuit feature is indicated as a subscript ($C =$ connectivity or $A =$ activity) and the direction of dysfunction is indicated by + or -. The subscript x indicates that the sixth biotype is not differentiated by a prominent circuit dysfunction relative to other biotypes. Besides this nomenclature, we suggest a short plain-English description for each biotype (in quotes), that connects them with our theoretically synthesized biotypes: $D_{C}+S_{C}+A_{C}$ = 'Default with salience and attention hyperconnectivity' (N=169 participants); A_C- = 'Attention hypoconnectivity' (N=161 participants); NS_A+P_{A+} = 'Sad-elicited negative affect with positive affect hyperactivation'(N=154 participants); C_{A+} = 'Cognitive control hyperactivation'($N=258$ participants); NTC_C-C_A = 'Cognitive control hypoactivation with conscious threat-elicited negative affect hypoconnectivity'(N=15 participants); $D_XS_XA_XN_XP_XC_X =$ 'Intact activation and connectivity' (N=44 participants). *Abbreviations:* AG=angular gyrus; aI=anterior insula; aIPL=anterior inferior parietal lobule, amPFC=anterior medial prefrontal cortex; Amy=amygdala; dACC=dorsal anterior cingulate cortex; DLPFC=dorsolateral prefrontal cortex; LPFC=lateral prefrontal cortex; msPFC=medial superior prefrontal cortex; PCC=posterior cingulate cortex; PCU=precuneus; pgACC=pregenual anterior cingulate cortex; sgACC=subgenual anterior cingulate cortex; vmPFC=ventero-medial prefrontal cortex.

Supplementary Figure 6: Split-half reliability of the biotype profiles.

First, we split our dataset into two random samples of equal size. Then, we ran our clustering procedure on the first half-split. Then, we assigned each participant in the second split to one of the clusters obtained in the first half-split. To do so, we computed the mean circuit scores across all participants belonging to each cluster in the first half-split. Then, we calculated the Pearson correlation coefficient between each participant's brain circuit scores and these averaged scores. Each participant was assigned to the cluster for

which this correlation was highest. Finally, we identified the primary circuit dysfunctions of each cluster in each split as described above (>0.5 SD absolute mean difference compared to the healthy norm) and checked whether they replicated the ones found in the whole sample. We show the average and standard error of regional circuit scores across participants in the whole sample and in each of two random splits. All correlations of mean circuit profiles for each cluster between the two splits were significant $(Dc+Sc+Ac+CD)$ r=0.95, two-sided p=1.72e-21; AC- : r=0.97, two-sided p=7.08e-25; NSA+PA+ : r=0.93, two-sided p=1.10e-18; CA+ : r=0.96, two-sided $p=2.21e-23$; NTCc-C_A-: $r=0.79$, two-sided $p=1.15e-09$; $D_XS_XA_XN_XP_XC_X$: $r=0.86$, two-sided $p=4.44e-13$). We highlight with colored bands the primary circuit dysfunctions of the whole sample that replicated in the two half-splits (all but one). Colors correspond to each circuit. Measures are abbreviated as per Figure 1 in the main text. The size of spheres representing each circuit denotes an absolute activation difference of >0.50 SD compared to a healthy norm (small spheres=decreased activation, large spheres=increased activation). The thickness of lines between the spheres denotes an absolute connectivity difference of >0.50 SD compared to a healthy norm (dashed lines=decreased connectivity, thick lines=increased connectivity). We named each biotype according to the circuits and circuit features that specifically differentiated each relative to other biotypes and to the healthy reference. We used the following nomenclature: each circuit is indicated with a letter ($D =$ default mode, $S =$ salience, $A =$ attention, $NS =$ negative affect circuit evoked by sad stimuli, NTC = negative affect circuit evoked by conscious threat stimuli, NTN = negative affect circuit evoked by nonconscious threat stimuli, P = positive circuit, C = cognitive circuit), the distinguishing circuit feature is indicated as a subscript (C = connectivity or $A =$ activity) and the direction of dysfunction is indicated by + or -. The subscript x indicates that the sixth biotype is not differentiated by a prominent circuit dysfunction relative to other biotypes. Besides this nomenclature, we suggest a short plain-English description for each biotype (in quotes), that connects them with our theoretically synthesized biotypes: $D_{C+}S_{C+}A_{C+}$ = 'Default with salience and attention hyperconnectivity' (N=169 participants); A_c. = 'Attention hypoconnectivity' (N=161 participants); NS_A+P_{A+} = 'Sad-elicited negative affect with positive affect hyperactivation'(N=154 participants); C_{A+} = 'Cognitive control hyperactivation'(N=258 participants); NTC_C-C_A-= 'Cognitive control hypoactivation with conscious threat-elicited negative affect hypoconnectivity'(N=15 participants); $D_XS_XA_XN_XP_XC_X =$ 'Intact activation and connectivity' (N=44 participants).

Supplementary Figure 7: Correlation between symptoms and regional circuit scores.

Across all clinical participants, we calculated a Spearman correlation between regional circuit scores and symptoms and show the resulting Spearman rho values as a heatmap, unthresholded (a), thresholded at two-sided p<0.05 (b) and thresholded with FDR correction at two-sided pFDR<0.05 (c). When thresholded at two-sided p<0.05, 127 (31%) correlations were significant and when thresholded with FDR correction, 86 (21%) correlations were significant. Of the correlations significant when thresholded with FDR correction 10 (2 %) correlations were of absolute magnitude rho>0.10 and the remaining 76 (19%) were of absolute magnitude rho<0.10. *Abbreviation:* FDR=false discovery rate.

Supplementary Figure 8: Correlation between behavioral performance and regional circuit scores.

Across all clinical participants, we calculated a Spearman correlation between regional circuit scores and behavioral performance and show the resulting Spearman rho values as a heatmap, unthresholded (a), thresholded at two-sided p<0.05 (b) and thresholded with FDR correction at two-sided pFDR<0.05 (c). When thresholded at two-sided p<0.05, 131 (20%) correlations were significant and when thresholded with FDR correction, 66 (10%) correlations were significant. Of the correlations significant when thresholded with FDR correction 1 (0.15 %) correlation was of absolute magnitude rho>0.10 and the remaining 65 (10%) were of absolute magnitude rho<0.10. *Abbreviation:* FDR=false discovery rate.

Supplementary Figure 9: Correlation between treatment response and regional circuit scores.

Across all clinical participants, we calculated a Spearman correlation between between regional circuit scores and treatment response and show the resulting Spearman rho values as a heatmap, unthresholded (a), thresholded at two-sided p<0.05 (b) and thresholded with FDR correction at two-sided pFDR<0.05 (c). When thresholded at two-sided p<0.05, 79 (39%) correlations were significant and when thresholded with FDR correction, 63 (31%) correlations were significant. Of the correlations significant when thresholded with FDR correction 15 (7%) correlations were of absolute magnitude rho>0.10 and the remaining 48 (23%) were of absolute magnitude rho<0.10. *Abbreviation:* FDR=false discovery rate.

Supplementary Figure 10: Between biotype comparisons for each symptom domain.

Plots comparing the severity of our symptoms of interest for participants in each biotype to that of participants not in the biotype. The dots show individual data points for individuals in the biotype. The median of participants in the biotype is shown as a red diamond, the median of participants not in the biotype is shown as a black line. To enable comparison across symptoms, all symptoms were scaled between 0 and 1 based on the minimum and maximum of the corresponding scales. We named each biotype according to the circuits and circuit features that specifically differentiated relative to each other biotypes and to the healthy reference. We used the following nomenclature: each circuit is indicated with a letter $(D = \text{default mode}, S = \text{salience}, A = \text{attention}, NS = \text{negative affect})$ circuit evoked by sad stimuli, NTC = negative affect circuit evoked by conscious threat stimuli, NTN = negative affect circuit evoked by nonconscious threat stimuli, $P =$ positive circuit, $C =$ cognitive circuit), the distinguishing circuit feature is indicated as a subscript $(C =$ connectivity or A = activity) and the direction of dysfunction is indicated by + or -. The subscript x indicates that the sixth biotype is not differentiated by a prominent circuit dysfunction relative to other biotypes. Besides this nomenclature, we suggest a short plain-English description for each biotype (in quotes), that connects them with our theoretically synthesized biotypes: $D_{C+}S_{C+}A_{C+}$ $=$ 'Default with salience and attention hyperconnectivity' (N=169 participants); Ac- $=$ 'Attention hypoconnectivity' (N=161) participants); $NS_{A+}P_{A+}$ = 'Sad-elicited negative affect with positive affect hyperactivation'(N=154 participants); C_{A+} = 'Cognitive control hyperactivation'($N=258$ participants); NTC_C.C_A $=$ 'Cognitive control hypoactivation with conscious threat-elicited negative affect hypoconnectivity'(N=15 participants); $D_XS_XA_XN_XP_XC_X =$ 'Intact activation and connectivity' (N=44 participants).

Supplementary Figure 11: Between biotype comparisons for insomnia and suicidality.

Insomnia was measured by the QIDS-SR sum of items 1-3 and suicidality was measured by the QIDS-SR item 12. A participant was considered as endorsing the symptom if their score was >0. We named each biotype according to the circuits and circuit features that specifically differentiated relative to each other biotypes and to the healthy reference. We used the following nomenclature: each circuit is indicated with a letter ($D =$ default mode, $S =$ salience, $A =$ attention, $NS =$ negative affect circuit evoked by sad stimuli, NTC = negative affect circuit evoked by conscious threat stimuli, NTN = negative affect circuit evoked by nonconscious threat stimuli, $P =$ positive circuit, $C =$ cognitive circuit), the distinguishing circuit feature is indicated as a subscript ($C =$ connectivity or A $=$ activity) and the direction of dysfunction is indicated by $+$ or $-$. The subscript x indicates that the sixth biotype is not differentiated by a prominent circuit dysfunction relative to other biotypes. Besides this nomenclature, we suggest a short plain-English description for each biotype (in quotes), that connects them with our theoretically synthesized biotypes: $D_{C+}S_{C+}A_{C+}$ = 'Default with salience and attention hyperconnectivity'; Ac- = 'Attention hypoconnectivity'; NS_A+P_{A+} = 'Sad-elicited negative affect with positive affect hyperactivation'; C_{A+} = 'Cognitive control hyperactivation'; NTC_C-C_A- = 'Cognitive control hypoactivation with conscious threatelicited negative affect hypoconnectivity'; DXSXAXNXPXCX = 'Intact activation and connectivity'. *Abbreviation*: QIDS-SR= Quick Inventory of Depressive Symptomatology - Self-Report Revised.

Supplementary Figure 12: Between biotype comparisons of behavioral performance.

Plots comparing behavioral performance for participants in each biotype to that of participants not in the biotype. The dots show individual data points for individuals in the biotype. The median of participants in the biotype is shown as a red diamond, the median of participants not in the biotype is shown as a black line. Behavioral measures are adjusted for age and sex and are expressed relative to a healthy norm (Webneuro normed scores). We named each biotype according to the circuits and circuit features that specifically differentiated relative to each other biotypes and to the healthy reference. We used the following nomenclature: each circuit is indicated with a letter ($D =$ default mode, $S =$ salience, $A =$ attention, $NS =$ negative affect circuit evoked by sad stimuli, NTC = negative affect circuit evoked by conscious threat stimuli, NTN = negative affect circuit evoked by nonconscious threat stimuli, $P =$ positive circuit, $C =$ cognitive circuit), the distinguishing circuit feature is indicated as a subscript $(C =$ connectivity, $A =$ activity) and the direction of dysfunction is indicated by $+$ or $-$. The subscript x indicates that the sixth biotype is not differentiated by a prominent circuit dysfunction relative to other biotypes. Besides this nomenclature, we suggest a short plain-English description for each biotype (in quotes), that connects them with our theoretically synthesized biotypes: $D_{C+}S_{C+}A_{C+}$ = 'Default with salience and attention hyperconnectivity' (N=169 participants); Ac- = 'Attention hypoconnectivity' (N=161 participants); NS_{A+}P_{A+} = 'Sad-elicited negative affect with positive affect hyperactivation'(N=154 participants); C_{A+} = 'Cognitive control hyperactivation'(N=258 participants); NTC_CC_A = 'Cognitive control hypoactivation with conscious threat-elicited negative affect hypoconnectivity'(N=15 participants); DXSXAXNXPXCX = 'Intact activation and connectivity' (N=44 participants). *Abbreviation*: RT=reaction time.

Supplementary Figure 13: Between biotype comparisons of treatment outcomes.

Plots comparing clinical severity after treatment for participants in each biotype to that of participants not in the biotype. The dots show individual data points for individuals in the biotype. The median of participants in the biotype is shown as a red diamond, the median of participants not in the biotype is shown as a black line. Severity is scaled between 0 and 1 based on the minimum and maximum of the symptom scales used. We named each biotype according to the circuits and circuit features that specifically differentiated relative to each other biotypes and to the healthy reference. We used the following nomenclature: each circuit is indicated with a letter ($D =$ default mode, $S =$ salience, $A =$ attention, $NS =$ negative affect circuit evoked by sad stimuli, NTC = negative affect circuit evoked by conscious threat stimuli, $NTN =$ negative affect circuit evoked by non-conscious threat stimuli, $P =$ positive circuit, $C =$ cognitive circuit), the distinguishing circuit feature is indicated as a subscript ($C =$ connectivity, $A =$ activity) and the direction of dysfunction is indicated by $+$ or $-$. The subscript x indicates that the sixth biotype is not differentiated by a prominent circuit dysfunction relative to other biotypes. Besides this nomenclature, we suggest a short plain-English description for each biotype (in quotes), that connects them with our theoretically synthesized biotypes: $D_{C+}S_{C+}A_{C+}$ = 'Default with salience and attention hyperconnectivity' (N=169 participants); A_C- = 'Attention hypoconnectivity' (N=161 participants); NS_{A+}P_{A+} = 'Sad-elicited negative affect with positive affect hyperactivation'(N=154 participants); C_{A+} = 'Cognitive control hyperactivation'(N=258 participants); NTC_CC_A = 'Cognitive control hypoactivation with conscious threat-elicited negative affect hypoconnectivity'(N=15 participants); $D_XS_XA_XN_XP_XC_X =$ 'Intact activation and connectivity' (N=44 participants).

Supplementary Figure 14: Correlation between task-free and task regional circuit scores.

Across all clinical participants, we calculated a Spearman correlation between task-free and task regional circuit scores and show the resulting Spearman rho values as a heatmap, unthresholded (a), thresholded at two-sided p<0.05 (b) and thresholded with FDR correction at two-sided pFDR<0.05 (c). When thresholded at two-sided p<0.05, 110 (21%) correlations were significant and when thresholded with FDR correction, 53 (10%) correlations were significant. Of the correlations significant when thresholded with FDR correction 53 (10%) correlations were of absolute magnitude rho>0.10 and the remaining 0 (0%) were of absolute magnitude rho<0.10. *Abbreviation:* FDR=false discovery rate.

SUPPLEMENTARY TABLES

Supplementary Table 1: Demographics and diagnoses of the sample used in the cross-sectional analyses.

DSM-IV-TR (RAD), DSM-5 (HCP-DES), or DSM-IV (iSPOT-D) criteria for major depressive disorder, anxiety disorder, posttraumatic stress disorder or obsessive-compulsive disorder were ascertained by a psychiatrist, general practitioner or research personnel using the structured interview, Mini International Neuropsychiatric Interview (MINI) (Sheehan et al., 1998). In the ENGAGE sample, patients were considered eligible if they scored 10 or greater on PHQ-9, a threshold with 88% specificity for major depressive disorder (Kroenke et al., 2001), and had a qualifying BMI at study screening. Comorbidities were ascertained from electronic health records. *Abbreviations:* ENGAGE=Engaging self-regulation targets to understand the mechanisms of behavior change and improve mood and weight outcome; HCP-DES=Human Connectome Project for Disordered Emotional States; iSPOT-D=International Study to Predict Optimized Treatment in Depression; QIDS-SR=Quick Inventory of Depressive Symptomatology Self-Report Revised; RAD=Research on Anxiety and Depression study; SCL-20=Symptom Checklist 20 depression scale. A dash indicates that the information was not available in the dataset.

Supplementary Table 2: Demographics and diagnoses of the sample used in the treatment analyses.

Abbreviations: ENGAGE=Engaging self-regulation targets to understand the mechanisms of behavior change and improve mood and weight outcome; iSPOT-D=International Study to Predict Optimized Treatment in Depression; QIDS-SR=Quick Inventory of Depressive Symptomatology Self-Report Revised; SCL-20=Symptom Checklist 20 depression scale; I-CARE=active behavioral therapy; U-CARE=usual care. A dash indicates that the information was not available in the dataset.

Supplementary Table 3: Significant between biotype comparisons for each symptom domain.

For each symptom, the scores of participants in each biotype were compared to the median of participants not in the biotype using a Mann-Whitney U test. Here, we show the direction of the difference (\uparrow =symptom median was higher in the biotype, \downarrow =symptom median was lower in the biotype), number of participants used for this comparison in each biotype, the median, the two-sided p-value of the test, a measure of effect size r, calculated as the Z statistic divided by square root of the sample size and confidence interval (CI). We also show whether the finding replicates in split-half and leave-study-out procedures. We named each biotype according to the circuits and circuit features that specifically differentiated each relative to other biotypes and to the healthy reference. We used the following nomenclature: each circuit is indicated with a letter $(D = \text{default mode}, S = \text{salience}, A = \text{attention}, NS = \text{negative affect})$ circuit evoked by sad stimuli, NTC = negative affect circuit evoked by conscious threat stimuli, NTN = negative affect circuit evoked by non-conscious threat stimuli, $P =$ positive circuit, $C =$ cognitive circuit), the distinguishing circuit feature is indicated as a subscript $(C =$ connectivity or A = activity) and the direction of dysfunction is indicated by + or -. The subscript x indicates that the sixth biotype is not differentiated by a prominent circuit dysfunction relative to other biotypes. Besides this nomenclature, we suggest a short plain-English description for each biotype (in quotes), that connects them with our theoretically synthesized biotypes: D_{C+} S_{C+}A_{C+} $=$ 'Default with salience and attention hyperconnectivity'; A_C = 'Attention hypoconnectivity'; NS_{A+}P_{A+} = 'Sad-elicited negative affect with positive affect hyperactivation'; C_{A+} = 'Cognitive control hyperactivation'; NTC_C-C_A = 'Cognitive control hypoactivation with conscious threat-elicited negative affect hypoconnectivity'; $D_X S_X A_X N_X P_X C_X =$ 'Intact activation and connectivity'. *Abbreviation*: CI = confidence interval.

Supplementary Table 4: Between biotype comparisons for each symptom domain.

For each symptom, the scores of participants in each biotype were compared to the median of participants not in the biotype using a Mann-Whitney U test. Here, we show the direction of the difference (\uparrow =symptom median was higher in the biotype, \downarrow =symptom median was lower in the biotype), number of participants used for this comparison in each biotype, the median, the two-sided p-value of the test, a measure of effect size r, calculated as the Z statistic divided by square root of the sample size and confidence interval (CI). We named each biotype according to the circuits and circuit features that specifically differentiated each relative to other biotypes and to the healthy reference. We used the following nomenclature: each circuit is indicated with a letter $(D = \text{default mode}, S)$ $=$ salience, A $=$ attention, NS $=$ negative affect circuit evoked by sad stimuli, NTC $=$ negative affect circuit evoked by conscious threat stimuli, NTN = negative affect circuit evoked by non-conscious threat stimuli, $P =$ positive circuit, $C =$ cognitive circuit), the distinguishing circuit feature is indicated as a subscript $(C =$ connectivity or $A =$ activity) and the direction of dysfunction is indicated by + or -. The subscript x indicates that the sixth biotype is not differentiated by a prominent circuit dysfunction relative to other biotypes. Besides this nomenclature, we suggest a short plain-English description for each biotype (in quotes), that connects them with our theoretically synthesized biotypes: $D_{C+}S_{C+}A_{C+}$ = 'Default with salience and attention hyperconnectivity'; A $c =$ 'Attention hypoconnectivity'; NS_A+P_{A+} = 'Sad-elicited negative affect with positive affect hyperactivation'; C_{A+} = 'Cognitive control hyperactivation'; NTC_C-C_A- "Cognitive control hypoactivation with conscious threat-elicited negative affect hypoconnectivity'; $D_XS_XA_XN_XP_XC_X =$ 'Intact activation and connectivity'. *Abbreviation*: CI = confidence interval.

Supplementary Table 5: Between biotype comparisons for insomnia and suicidality.

Since insomnia and suicidality were assessed using only three and one item on the QIDS-SR respectively, we instead used a chisquare test comparing the fraction of participants in the biotype endorsing any of the items (total value >0) compared to those not in the biotype. Here we show number of participants used for this comparison in each biotype, the percentage of participants reporting the symptom in the biotype and in other biotypes, the value and two-sided p-value of the test. We named each biotype according to the circuits and circuit features that specifically differentiated each relative to other biotypes and to the healthy reference. We used the following nomenclature: each circuit is indicated with a letter $(D = \text{default mode}, S = \text{salience}, A = \text{attention}, NS = \text{negative affect}$ circuit evoked by sad stimuli, NTC = negative affect circuit evoked by conscious threat stimuli, NTN = negative affect circuit evoked by non-conscious threat stimuli, $P =$ positive circuit, $C =$ cognitive circuit), the distinguishing circuit feature is indicated as a subscript (C = connectivity or $A =$ activity) and the direction of dysfunction is indicated by + or -. The subscript x indicates that the sixth biotype is not differentiated by a prominent circuit dysfunction relative to other biotypes. Besides this nomenclature, we suggest a short plain-English description for each biotype (in quotes), that connects them with our theoretically synthesized biotypes: $D_{C+}S_{C+}A_{C+}$ $=$ 'Default with salience and attention hyperconnectivity'; Ac. $=$ 'Attention hypoconnectivity'; NS_{A+PA+} = 'Sad-elicited negative affect with positive affect hyperactivation'; C_{A+} = 'Cognitive control hyperactivation'; NTC_C-C_A = 'Cognitive control hypoactivation with conscious threat-elicited negative affect hypoconnectivity'; $D_XS_XA_XN_XP_XC_X = 'In fact$ activation and connectivity'.

Supplementary Table 6: Significant between biotype comparisons of behavioral performance.

For each behavioral measure, the scores of participants in each biotype were compared to the median of participants not in the biotype using a Mann-Whitney U test. Here, we show the direction of the difference (↑ =symptom median was higher in the biotype, ↓ =symptom median was lower in the biotype), number of participants used for this comparison in each biotype, the median, the twosided p-value of the test, a measure of effect size r, calculated as the Z statistic divided by square root of the sample size and confidence interval (CI). We also show whether the finding replicates in split-half and leave-study-out procedures. We named each biotype according to the circuits and circuit features that specifically differentiated each relative to other biotypes and to the healthy reference. We used the following nomenclature: each circuit is indicated with a letter ($D =$ default mode, $S =$ salience, $A =$ attention, NS = negative affect circuit evoked by sad stimuli, NTC = negative affect circuit evoked by conscious threat stimuli, NTN = negative affect circuit evoked by non-conscious threat stimuli, $P =$ positive circuit, $C =$ cognitive circuit), the distinguishing circuit feature is indicated as a subscript (C = connectivity or A = activity) and the direction of dysfunction is indicated by + or -. The subscript x indicates that the sixth biotype is not differentiated by a prominent circuit dysfunction relative to other biotypes. Besides this nomenclature, we suggest a short plain-English description for each biotype (in quotes), that connects them with our theoretically synthesized biotypes: $D_{C+}S_{C+}A_{C+}$ = 'Default with salience and attention hyperconnectivity'; A_C = 'Attention hypoconnectivity'; NS_A+P_{A+} = 'Sad-elicited negative affect with positive affect hyperactivation'; C_{A+} = 'Cognitive control hyperactivation'; NTCc-C_A = 'Cognitive control hypoactivation with conscious threat-elicited negative affect hypoconnectivity'; $D_xS_xA_xN_xP_xC_x =$ 'Intact activation and connectivity'. *Abbreviations*: CI = confidence interval, RT = reaction time.

Supplementary Table 7: Between biotype comparisons of behavioral performance.

For each behavioral measure, the scores of participants in each biotype were compared to the median of participants not in the biotype using a Mann-Whitney U test. Here, we show the direction of the difference (↑ =symptom median was higher in the biotype, ↓ =symptom median was lower in the biotype), number of participants used for this comparison in each biotype, the median, the twosided p-value of the test, a measure of effect size r, calculated as the Z statistic divided by square root of the sample size and confidence interval (CI). We named each biotype according to the circuits and circuit features that specifically differentiated each relative to the healthy reference. We used the following nomenclature: each circuit is indicated with a letter $(D = \text{default mode}, S =$ salience, $A =$ attention, $NS =$ negative affect circuit evoked by sad stimuli, $NTC =$ negative affect circuit evoked by conscious threat stimuli, NTN = negative affect circuit evoked by non-conscious threat stimuli, P = positive circuit, C = cognitive circuit), the distinguishing circuit feature is indicated as a subscript $(C =$ connectivity or $A =$ activity) and the direction of dysfunction is indicated by + or -. The subscript x indicates that the sixth biotype is not differentiated by a prominent circuit dysfunction relative to other biotypes. Besides this nomenclature, we suggest a short plain-English description for each biotype (in quotes), that connects them with our theoretically synthesized biotypes: $D_{C+}S_{C+}A_{C+}$ = 'Default with salience and attention hyperconnectivity'; A $c =$ 'Attention hypoconnectivity'; NS_A+P_{A+} = 'Sad-elicited negative affect with positive affect hyperactivation'; C_{A+} = 'Cognitive control hyperactivation'; NTC_C-C_A- 'Cognitive control hypoactivation with conscious threat-elicited negative affect hypoconnectivity'; \sum_{x}^{1} \sum_{x}^{1} \sum_{y}^{1} \sum_{z}^{1} \sum_{z}^{1} \sum_{z}^{1} \sum_{z}^{1} \sum_{z}^{1} \sum_{z}^{1} \sum_{z}^{2} \sum_{z}^{2}

Supplementary Table 8: Biotype distributions for number of participants receiving each treatment.

We report how many participants of each biotype received each treatment in the randomized clinical trial dataset. For comparisons of post-treatment severity, we chose to exclude combinations of treatment and biotype that had ≤5 participants. We named each biotype according to the circuits and circuit features that specifically differentiated each relative to other biotypes and to the healthy reference. We used the following nomenclature: each circuit is indicated with a letter ($D =$ default mode, $S =$ salience, $A =$ attention, $NS =$ negative affect circuit evoked by sad stimuli, NTC = negative affect circuit evoked by conscious threat stimuli, NTN = negative affect circuit evoked by non-conscious threat stimuli, $P =$ positive circuit, $C =$ cognitive circuit), the distinguishing circuit feature is indicated as a subscript (C = connectivity or A = activity) and the direction of dysfunction is indicated by + or -. The subscript x indicates that the sixth biotype is not differentiated by a prominent circuit dysfunction relative to other biotypes. Besides this nomenclature, we suggest a short plain-English description for each biotype (in quotes), that connects them with our theoretically synthesized biotypes: $D_{C+}S_{C+}A_{C+}$ = 'Default with salience and attention hyperconnectivity'; $Ac =$ 'Attention hypoconnectivity'; $NS_{A+}P_{A+}$ = 'Sad-elicited negative affect with positive affect hyperactivation'; C_{A+} = 'Cognitive control hyperactivation'; NTC_C-C_A = 'Cognitive control hypoactivation with conscious threat-elicited negative affect hypoconnectivity'; $DxSxAxNxPxCx = 'Intact$ activation and connectivity'. ¹. Biotype-treatment combinations for which the comparison of post-treatment severity with other biotypes was not conducted because of too small sample size (N≤5).

Supplementary Table 9: Between biotype comparisons of treatment outcomes.

The severity after treatment of participants in each biotype was compared to the median of participants not in the biotype using a Mann-Whitney U test for each treatment separately. Here, we show the direction of the difference (↑ =symptom median was higher in the biotype, ↓ =symptom median was lower in the biotype), number of participants used for this comparison in each biotype, the median, the two-sided p-value of the test, a measure of effect size r, calculated as the Z statistic divided by square root of the sample size and confidence interval (CI). Comparisons with $N \le 6$ were discarded. Significant comparisons ($p \le 0.05$) are bolded. We named each biotype according to the circuits and circuit features that specifically differentiated each relative to other biotypes and to the healthy reference. We used the following nomenclature: each circuit is indicated with a letter ($D =$ default mode, $S =$ salience, $A =$ attention, NS = negative affect circuit evoked by sad stimuli, NTC = negative affect circuit evoked by conscious threat stimuli, NTN = negative affect circuit evoked by non-conscious threat stimuli, $P =$ positive circuit, $C =$ cognitive circuit), the distinguishing circuit feature is indicated as a subscript (C = connectivity or $A =$ activity) and the direction of dysfunction is indicated by + or -. The subscript x indicates that the sixth biotype is not differentiated by a prominent circuit dysfunction relative to other biotypes. Besides this nomenclature, we suggest a short plain-English description for each biotype (in quotes), that connects them with our theoretically synthesized biotypes: $D_{C+}S_{C+}A_{C+}$ = 'Default with salience and attention hyperconnectivity'; A_{C-} = 'Attention hypoconnectivity'; NS_A+P_{A+} = 'Sad-elicited negative affect with positive affect hyperactivation'; C_{A+} = 'Cognitive control hyperactivation'; NTCc-C_A = 'Cognitive control hypoactivation with conscious threat-elicited negative affect hypoconnectivity'; $D_xS_xA_xN_xP_xC_x =$ 'Intact activation and connectivity'. *Abbreviations*: CI = confidence interval, I-CARE=active behavioral therapy, U-CARE=usual care.

Supplementary Table 10: Biotype distribution of treatment response and remission rates.

Response was defined as a 50% reduction in symptoms at follow-up, and remission was defined as a follow-up Hamilton Depression Rating Scale score ≤7 (collected in iSPOT-D) and Symptom Checklist 20 Depression Scale score ≤0.5 (collected in ENGAGE). We named each biotype according to the circuits and circuit features that specifically differentiated each relative to other biotypes and to the healthy reference. We used the following nomenclature: each circuit is indicated with a letter $(D = \text{default mode}, S = \text{salience}, A =$ attention, NS = negative affect circuit evoked by sad stimuli, NTC = negative affect circuit evoked by conscious threat stimuli, NTN = negative affect circuit evoked by non-conscious threat stimuli, $P =$ positive circuit, $C =$ cognitive circuit), the distinguishing circuit feature is indicated as a subscript (C = connectivity or $A =$ activity) and the direction of dysfunction is indicated by + or -. The subscript x indicates that the sixth biotype is not differentiated by a prominent circuit dysfunction relative to other biotypes. Besides this nomenclature, we suggest a short plain-English description for each biotype (in quotes), that connects them with our theoretically synthesized biotypes: $D_{C+}S_{C+}A_{C+}$ = 'Default with salience and attention hyperconnectivity'; A_{C-} = 'Attention hypoconnectivity'; $NS_{A+}P_{A+}$ = 'Sad-elicited negative affect with positive affect hyperactivation'; C_{A+} = 'Cognitive control hyperactivation'; NTC_{C-}C_A = 'Cognitive control hypoactivation with conscious threat-elicited negative affect hypoconnectivity'; $DxSxAxNxPxCx = 'Intact$ activation and connectivity'. *Abbreviations:* I-CARE=active behavioral therapy; U-CARE=usual care.

Supplementary Table 11: Biotype distribution of number of participants by dataset.

We show how many participants belonged to each biotype in each dataset. Biotypes were represented differently between datasets (chi-square $= 161.37$, two-sided p=2.2e-16). We named each biotype according to the circuits and circuit features that specifically differentiated each relative to other biotypes and to the healthy reference. We used the following nomenclature: each circuit is indicated with a letter ($D =$ default mode, $S =$ salience, $A =$ attention, $NS =$ negative affect circuit evoked by sad stimuli, NTC = negative affect circuit evoked by conscious threat stimuli, $NTN =$ negative affect circuit evoked by non-conscious threat stimuli, $P =$ positive circuit, $C =$ cognitive circuit), the distinguishing circuit feature is indicated as a subscript $(C =$ connectivity or $A =$ activity) and the direction of dysfunction is indicated by $+$ or $-$. The subscript x indicates that the sixth biotype is not differentiated by a prominent circuit dysfunction relative to other biotypes. Besides this nomenclature, we suggest a short plain-English description for each biotype (in quotes), that connects them with our theoretically synthesized biotypes: $D_{C+}S_{C+}A_{C+}$ = 'Default with salience and attention hyperconnectivity'; Ac- = 'Attention hypoconnectivity'; $NS_{A+}P_{A+}$ = 'Sad-elicited negative affect with positive affect hyperactivation'; C_{A+} = 'Cognitive control hyperactivation'; NTC_C-C_A = 'Cognitive control hypoactivation with conscious threatelicited negative affect hypoconnectivity'; $DxSxAxNxPxCx = 'Intact$ activation and connectivity'. *Abbreviations:* ENGAGE=Engaging self-regulation targets to understand the mechanisms of behavior change and improve mood and weight outcome; HCP-DES=Human Connectome Project for Disordered Emotional States; iSPOT-D=International Study to Predict Optimized Treatment in Depression; RAD=Research on Anxiety and Depression study.

Supplementary Table 12: Biotype overlap with diagnoses.

Number and proportion of participants in each biotype that meet diagnostic criteria for major depressive disorder, generalized anxiety disorder, panic disorder, social anxiety disorder and obsessive-compulsive disorder. We named each biotype according to the circuits and circuit features that specifically differentiated each relative to other biotypes and to the healthy reference. We used the following nomenclature: each circuit is indicated with a letter ($D =$ default mode, $S =$ salience, $A =$ attention, $NS =$ negative affect circuit evoked by sad stimuli, NTC = negative affect circuit evoked by conscious threat stimuli, NTN = negative affect circuit evoked by nonconscious threat stimuli, P = positive circuit, C = cognitive circuit), the distinguishing circuit feature is indicated as a subscript (C = connectivity or $A =$ activity) and the direction of dysfunction is indicated by + or -. The subscript x indicates that the sixth biotype is not differentiated by a prominent circuit dysfunction relative to other biotypes. Besides this nomenclature, we suggest a short plain-English description for each biotype (in quotes), that connects them with our theoretically synthesized biotypes: $D_{C}+S_{C}+A_{C}$ = 'Default with salience and attention hyperconnectivity'; Ac- = 'Attention hypoconnectivity'; NS_{A+PA+} = 'Sad-elicited negative affect with positive affect hyperactivation'; C_{A+} = 'Cognitive control hyperactivation'; NTC_C-C_A- = 'Cognitive control hypoactivation with conscious threat-elicited negative affect hypoconnectivity'; $D_XS_XA_XN_XP_XC_X = 'In fact$ activation and connectivity'.

Supplementary Table 13: Comparison of the performance of our brain circuit features to other features.

We selected three competing alternative feature sets, each used in a recent paper reporting the identification of biotypes of depression using resting state fMRI $12-I4$. We did not replicate the entire analysis workflow used in these studies. Rather, we used them to derive alternative imaging feature sets supported by previous evidence that we then entered in our own analysis pipeline, validating the results with the same criteria and procedures we used for our own features. For each of these alternative sets, we tested the number of clusters reported in the original paper. We named each biotype according to the circuits and circuit features that specifically differentiated each relative to other biotypes and to the healthy reference. We used the following nomenclature: each circuit is indicated with a letter ($D =$ default mode, $S =$ salience, $A =$ attention, $NS =$ negative affect circuit evoked by sad stimuli, NTC = negative affect circuit evoked by conscious threat stimuli, NTN = negative affect circuit evoked by non-conscious threat stimuli, $P =$ positive circuit, $C =$ cognitive circuit), the distinguishing circuit feature is indicated as a subscript ($C =$ connectivity or $A =$ activity) and the direction of dysfunction is indicated by $+$ or $-$. The subscript x indicates that the sixth biotype is not differentiated by a prominent circuit dysfunction relative to other biotypes. Besides this nomenclature, we suggest a short plain-English description for each biotype (in quotes), that connects them with our theoretically synthesized biotypes: $D_{C+}S_{C+}A_{C+}$ = 'Default with salience and attention hyperconnectivity'; A_{C-} = 'Attention hypoconnectivity'; $NS_{A+}P_{A+}$ = 'Sad-elicited negative affect with positive affect hyperactivation'; C_{A+} = 'Cognitive control hyperactivation'; NTC_{C-CA}- $=$ 'Cognitive control hypoactivation with conscious threat-elicited negative affect hypoconnectivity'; $DxSxAxNxPxCx = 'Intact activation and connectivity'. We highlight in red tests for which the alternative biotyping strategy did not$ outperform the strategy presented in the current work and in green tests for which the alternative biotyping strategy outperformed the strategy presented in the current work. ¹Excluding features with bad coverage for $>5\%$ of participants. ^{2.} Too many features to compute a covariance matrix for the simulation. Abbreviations: AAL = automatic atlas labeling, Clu = cluster, Δ = difference, sil = silhouette index.

Supplementary Table 14. Comparison of our brain circuit features to other features using six clusters.

We selected three competing alternative feature sets, each used in a recent paper reporting the identification of biotypes of depression using resting state fMRI $12-i4$. We did not replicate the entire analysis workflow used in these studies. Rather, we used them to derive alternative imaging feature sets supported by previous evidence that we then entered in our own analysis pipeline, validating the results with the same criteria and procedures we used for our own features. For each of these alternative sets, we tested the number of clusters we chose in our own analysis. We highlight in red tests for which the alternative biotyping strategy did not outperform the strategy presented in the current work and in green tests for which the alternative biotyping strategy outperformed the strategy presented in the current work. For the resampling test of the silhouette index, the p-value is defined as the fraction of mean silhouettes greater than our result obtained by clustering 10,000 synthetic datasets from a multivariate normal distribution. For the permutation test of the silhouette index, we shuffled each brain circuit score across subjects 10,000 times, then repeated the hierarchical clustering procedure and calculated the average silhouette index. Thus, we obtained null distributions for these average silhouette indexes, comprising 10,000 observations. We computed a p-value defined as the fraction of average silhouette indexes in this null distribution greater than our result. ^{1.}Excluding features with bad coverage for >5% of participants; ^{2.} Too many features to compute a covariance matrix for the simulation; ³ Too many features to visually assess if cluster profiles were comparable. *Ab* $sil = silhouette index.$

Supplementary Table 15. Comparison of our brain circuit features to resting state features only.

To assess the impact of including task fMRI measures in addition to task-free measures only, we compared our original results to results obtained using only our task-free brain circuit scores. We validated the results with the same criteria and procedures we used for our own features and chose as number of clusters 6 (the number we chose in our analysis using all features) or 2 (the number of clusters with task-free dysfunction identified in our analyses). We highlight in red tests for which the alternative biotyping strategy did not outperform the strategy presented in the current work and in green tests for which the alternative biotyping strategy outperformed the strategy presented in the current work. For the resampling test of the silhouette index, the p-value is defined as the fraction of mean silhouettes greater than our result obtained by clustering 10,000 synthetic datasets from a multivariate normal distribution. For the permutation test of the silhouette index, we shuffled each brain circuit score across subjects 10,000 times, then repeated the hierarchical clustering procedure and calculated the average silhouette index. Thus, we obtained null distributions for these average silhouette indexes, comprising 10,000 observations. We computed a p-value defined as the fraction of average silhouette indexes in this null distribution greater than our result. *Abbreviations:* Clu = cluster, sil = silhouette index.

Supplementary Table 16: Cluster-derived biotypes comparison with theoretically synthesized biotypes.

In this table, we provide an interpretive synthesis of the cluster-derived biotypes from the clinical datasets in the present study and the theoretical taxonomy that informed this analysis. Cluster-derived biotypes from the present study are ordered to match the order of biotypes in the theoretical taxonomy based on a synthesis of extant knowledge in case-control studies (Williams, 2017, 2016). We named each biotype according to the circuits and circuit features that specifically differentiated each relative to other biotypes and to the healthy reference. We used the following nomenclature: each circuit is indicated with a letter $(D = \text{default mode}, S = \text{salience}, A =$ attention, NS = negative affect circuit evoked by sad stimuli, NTC = negative affect circuit evoked by conscious threat stimuli, NTN = negative affect circuit evoked by non-conscious threat stimuli, $P =$ positive circuit, $C =$ cognitive circuit), the distinguishing circuit feature is indicated as a subscript (C = connectivity or $A =$ activity) and the direction of dysfunction is indicated by + or -. The subscript x indicates that the sixth biotype is not differentiated by a prominent circuit dysfunction relative to other biotypes. Besides this nomenclature, we suggest a short plain-English description for each biotype (in quotes), that connects them with our theoretically synthesized biotypes. *Abbreviations*: ACC=anterior cingulate cortex; AG=angular gyrus; aI=anterior insula; aIPL=anterior inferior parietal lobule; amPFC=anterior medial prefrontal cortex; dACC=dorsal anterior cingulate cortex; DLPFC=dorsolateral prefrontal cortex; DPC=dorsal parietal cortex; LPFC=lateral prefrontal cortex; MPFC=medial prefrontal cortex; msPFC=medial superior prefrontal cortex; OFC=orbitofrontal cortex; PCC=posterior cingulate cortex; SLEA=sublenticular extended amygdala; TP=temporal pole; vmPFC=ventromedial prefrontal cortex.

Supplementary Table 17: Number of scans passing quality check and motion criteria before imputation.

Number of scans available by dataset passing quality check and motion criteria before multiple imputation. We show how many participants had scans available in each of the studies. *Abbreviations*: ENGAGE=Engaging self-regulation targets to understand the mechanisms of behavior change and improve mood and weight outcome; HCP-DES=Human Connectome Project for Disordered Emotional States; iSPOT-D=International Study to Predict Optimized Treatment in Depression; RAD=Research on Anxiety and Depression study.

Supplementary Table 18: Imaging features and brain regions.

We derived 41 measures of activation, task-based functional connectivity, and task-free connectivity from regions belonging to six brain circuits for which we have established relevance to depression and anxiety based on prior meta-analyses and rigorous empirical studies: a default mode circuit, a salience circuit, an attention circuit, a negative affect circuit elicited by sad and by threat, a positive affect circuit, and a cognitive control circuit. A source study established the image processing method for quantifying these circuit features and reported on the psychometric properties and reproducibility for 41 circuit features (6; Supplementary Tables S5A and S5B). Using this method, cortical regions of interest were defined from the meta-analytic database Neurosynth (search conducted on 06/04/2017) by identifying peak coordinates of a term search with a p_{FDR} threshold of .01 and identifying voxels at maximum 10 mm from the peak. Subcortical regions were derived from the Harvard-Oxford or AAL atlases. Regions were refined by removing those that did not pass quality control or for which circuit quantification did not meet a set of psychometric criteria, such as construct validity, internal consistency, and independence. Of the remaining regions, we only retained those which were also implicated in our theoretical synthesis of dysfunctions in depression and anxiety. From these regions we then extracted 41 features by computing intrinsic functional connectivity, task activation or task-based functional connectivity. *Abbreviations*: FDR=false discovery rate, MNI=Montreal neurological Institute, AAL=automatic labeling atlas, R=right, L=left.

Supplementary Table 19: Number of symptom and behavioral measures in the cross-sectional analyses.

We show how many participants had data available for each measure in each of the studies. The instrument from which each measure was derived is indicated in parentheses. Equivalent behavioral measures were derived from WebNeuro (RAD, HCP-DES, ENGAGE) and IntegNeuro (iSPOT-D). *Abbreviations*: SHAPS=Snaith-Hamilton Pleasure Scale, MASQ=Mood and Anxiety Questionnaire, BIS= Barratt Impulsiveness Scale, DASS=Depression Anxiety and Stress Scale, RRS=Ruminative Response Scale, PSWQ= Penn State Worry Questionnaire-Abbreviated, QIDS=Quick Inventory of Depressive Symptomatology Self-Report Revised, WN=WebNeuro, IN=IntegNeuro.

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iSPOT-D FMRIPREP PROCESSING DETAILS

Results included in this manuscript come from preprocessing performed using *fMRIPrep* 20.2.1 (Esteban, Markiewicz, et al. (2018); Esteban, Blair, et al. (2018); RRID:SCR_016216), which is based on *Nipype* 1.5.1 (Gorgolewski et al. (2011); Gorgolewski et al. (2018); RRID:SCR_002502).

Anatomical data preprocessing

A total of 1 T1-weighted (T1w) images were found within the input BIDS dataset.The T1-weighted (T1w) image was corrected for intensity non-uniformity (INU) with N4BiasFieldCorrection (Tustison et al. 2010), distributed with ANTs 2.3.3 (Avants et al. 2008, RRID: SCR 004757), and used as T1w-reference throughout the workflow. The T1w-reference was then skull-stripped with a *Nipype* implementation of the antsBrainExtraction.sh workflow (from ANTs), using OASIS30ANTs as target template. Brain tissue segmentation of cerebrospinal fluid (CSF), white-matter (WM) and gray-matter (GM) was performed on the brain-extracted T1w using fast (FSL 5.0.9, RRID:SCR_002823, Zhang, Brady, and Smith 2001). Brain surfaces were reconstructed using recon-all (FreeSurfer 6.0.1, RRID:SCR 001847, Dale, Fischl, and Sereno 1999), and the brain mask estimated previously was refined with a custom variation of the method to reconcile ANTsderived and FreeSurfer-derived segmentations of the cortical gray-matter of Mindboggle (RRID:SCR_002438, Klein et al. 2017). Volume-based spatial normalization to two standard spaces (MNI152NLin2009cAsym, MNI152NLin6Asym) was performed through nonlinear registration with antsRegistration (ANTs 2.3.3), using brain-extracted versions of both T1w reference and the T1w template. The following templates were selected for spatial normalization: *ICBM 152 Nonlinear Asymmetrical template version 2009c* [Fonov et al. (2009), RRID:SCR_008796; TemplateFlow ID: MNI152NLin2009cAsym], *FSL's MNI ICBM 152 non-linear 6th Generation Asymmetric Average Brain Stereotaxic Registration Model* [Evans et al. (2012), RRID:SCR_002823; TemplateFlow ID: MNI152NLin6Asym],

Functional data preprocessing

For each of the 10 BOLD runs found per subject (across all tasks and sessions), the following preprocessing was performed. First, a reference volume and its skull-stripped version were generated using a custom methodology of *fMRIPrep* . Susceptibility distortion correction (SDC) was omitted. The BOLD reference was then co-registered to the T1w reference using bbregister (FreeSurfer) which implements boundary-based registration (Greve and Fischl 2009). Co-registration was configured with six degrees of freedom. Head-motion parameters with respect to the BOLD reference (transformation matrices, and six corresponding rotation and translation parameters) are estimated before any spatiotemporal filtering using mcflirt (FSL 5.0.9, Jenkinson et al. 2002). BOLD runs were slice-time corrected using 3dTshift from AFNI 20160207 (Cox and Hyde 1997, RRID:SCR_005927). The BOLD time-series were resampled onto the following surfaces (FreeSurfer reconstruction nomenclature): *fsnative*, *fsaverage*. The BOLD time-series (including slice-timing correction when applied) were resampled onto their original, native space by applying the transforms to correct for headmotion. These resampled BOLD time-series will be referred to as *preprocessed BOLD in original space*, or just *preprocessed BOLD*. The BOLD time-series were resampled into standard space, generating a *preprocessed BOLD run in MNI152NLin2009cAsym space*. First, a reference volume and its skull-stripped version were generated using a custom methodology of *fMRIPrep* . *Grayordinates* files (Glasser et al. 2013) containing 91k samples were also generated using the highest-resolution fsaverage as intermediate standardized surface space. Automatic removal of motion artifacts using independent component analysis (ICA-AROMA, Pruim et al. 2015) was performed on the *preprocessed BOLD on MNI space* time-series after removal of non-steady state volumes and spatial smoothing with an isotropic, Gaussian kernel of 6mm FWHM (fullwidth half-maximum). Corresponding "non-aggresively" denoised runs were produced after such smoothing. Additionally, the "aggressive" noise-regressors were collected and placed in the corresponding confounds file. Several confounding time-series were calculated based on the *preprocessed BOLD*: framewise displacement (FD), DVARS and three region-wise global signals. FD was computed using two formulations following Power

(absolute sum of relative motions, Power et al. (2014)) and Jenkinson (relative root mean square displacement between affines, Jenkinson et al. (2002)). FD and DVARS are calculated for each functional run, both using their implementations in *Nipype* (following the definitions by Power et al. 2014). The three global signals are extracted within the CSF, the WM, and the whole-brain masks. Additionally, a set of physiological regressors were extracted to allow for component-based noise correction (*CompCor*, Behzadi et al. 2007). Principal components are estimated after high-pass filtering the *preprocessed BOLD* time-series (using a discrete cosine filter with 128s cut-off) for the two *CompCor* variants: temporal (tCompCor) and anatomical (aCompCor). tCompCor components are then calculated from the top 2% variable voxels within the brain mask. For aCompCor, three probabilistic masks (CSF, WM and combined CSF+WM) are generated in anatomical space. The implementation differs from that of Behzadi et al. in that instead of eroding the masks by 2 pixels on BOLD space, the aCompCor masks are subtracted a mask of pixels that likely contain a volume fraction of GM. This mask is obtained by dilating a GM mask extracted from the FreeSurfer's *aseg* segmentation, and it ensures components are not extracted from voxels containing a minimal fraction of GM. Finally, these masks are resampled into BOLD space and binarized by thresholding at 0.99 (as in the original implementation). Components are also calculated separately within the WM and CSF masks. For each CompCor decomposition, the *k* components with the largest singular values are retained, such that the retained components' time series are sufficient to explain 50 percent of variance across the nuisance mask (CSF, WM, combined, or temporal). The remaining components are dropped from consideration. The head-motion estimates calculated in the correction step were also placed within the corresponding confounds file. The confound time series derived from head motion estimates and global signals were expanded with the inclusion of temporal derivatives and quadratic terms for each (Satterthwaite et al. 2013). Frames that exceeded a threshold of 0.5 mm FD or 1.5 standardised DVARS were annotated as motion outliers. All resamplings can be performed with *a single interpolation step* by composing all the pertinent transformations (i.e. head-motion transform matrices, susceptibility distortion correction when available, and co-registrations to anatomical and output spaces). Gridded (volumetric) resamplings were performed using antsApplyTransforms (ANTs), configured with Lanczos interpolation to minimize the smoothing effects of other kernels (Lanczos 1964). Non-gridded (surface) resamplings were performed using mri_vol2surf (FreeSurfer).

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RAD fMRIPREP PROCESSING DETAILS

Results included in this manuscript come from preprocessing performed using *fMRIPrep* 20.2.3 (Esteban, Markiewicz, et al. (2018); Esteban, Blair, et al. (2018); RRID:SCR_016216), which is based on *Nipype* 1.6.1 (Gorgolewski et al. (2011); Gorgolewski et al. (2018); RRID:SCR_002502).

Anatomical data preprocessing

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Functional data preprocessing

For each of the 4 BOLD runs found per subject (across all tasks and sessions), the following preprocessing was performed. First, a reference volume and its skull-stripped version were generated using a custom methodology of *fMRIPrep* . Susceptibility distortion correction (SDC) was omitted. The BOLD reference was then coregistered to the T1w reference using bbregister (FreeSurfer) which implements boundary-based registration (Greve and Fischl 2009). Co-registration was configured with six degrees of freedom. Head-motion parameters with respect to the BOLD reference (transformation matrices, and six corresponding rotation and translation parameters) are estimated before any spatiotemporal filtering using mcflirt (FSL 5.0.9, Jenkinson et al. 2002). BOLD runs were slice-time corrected using 3dTshift from AFNI 20160207 (Cox and Hyde 1997, RRID:SCR_005927). The BOLD time-series were resampled onto the following surfaces (FreeSurfer reconstruction nomenclature): *fsnative*, *fsaverage*. The BOLD time-series (including slice-timing correction when applied) were resampled onto their original, native space by applying the transforms to correct for headmotion. These resampled BOLD time-series will be referred to as *preprocessed BOLD in original space*, or just *preprocessed BOLD*. The BOLD time-series were resampled into standard space, generating a *preprocessed BOLD run in MNI152NLin6Asym space*. First, a reference volume and its skull-stripped version were generated using a custom methodology of *fMRIPrep* . *Grayordinates* files (Glasser et al. 2013) containing 91k samples were also generated using the highest-resolution fsaverage as intermediate standardized surface space. Automatic removal of motion artifacts using independent component analysis (ICA-AROMA, Pruim et al. 2015) was performed on the *preprocessed BOLD on MNI space* time-series after removal of non-steady state volumes and spatial smoothing with an isotropic, Gaussian kernel of 6mm FWHM (full-width half-maximum). Corresponding "non-aggresively" denoised runs were produced after such smoothing. Additionally, the "aggressive" noise-regressors were collected and placed in the corresponding confounds file. Several confounding time-series were calculated based on the *preprocessed BOLD*: framewise displacement (FD), DVARS and three region-wise global signals. FD was computed using two formulations following Power

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ENGAGE fMRIPREP PROCESSING DETAILS

Results included in this manuscript come from preprocessing performed using *fMRIPrep* 20.2.3 (Esteban, Markiewicz, et al. (2018); Esteban, Blair, et al. (2018); RRID:SCR_016216), which is based on *Nipype* 1.6.1 (Gorgolewski et al. (2011); Gorgolewski et al. (2018); RRID:SCR_002502).

Anatomical data preprocessing

A total of 4 T1-weighted (T1w) images were found within the input BIDS dataset. All of them were corrected for intensity non-uniformity (INU) with N4BiasFieldCorrection (Tustison et al. 2010), distributed with ANTs 2.3.3 (Avants et al. 2008, RRID:SCR_004757). The T1w-reference was then skull-stripped with a *Nipype* implementation of the antsBrainExtraction.sh workflow (from ANTs), using OASIS30ANTs as target template. Brain tissue segmentation of cerebrospinal fluid (CSF), white-matter (WM) and gray-matter (GM) was performed on the brain-extracted T1w using fast (FSL 5.0.9, RRID:SCR 002823, Zhang, Brady, and Smith 2001). A T1w-reference map was computed after registration of 4 T1w images (after INU-correction) using mri robust template (FreeSurfer 6.0.1, Reuter, Rosas, and Fischl 2010). Brain surfaces were reconstructed using recon-all (FreeSurfer 6.0.1, RRID:SCR_001847, Dale, Fischl, and Sereno 1999), and the brain mask estimated previously was refined with a custom variation of the method to reconcile ANTs-derived and FreeSurfer-derived segmentations of the cortical gray-matter of Mindboggle (RRID:SCR_002438, Klein et al. 2017). Volume-based spatial normalization to two standard spaces (MNI152NLin2009cAsym, MNI152NLin6Asym) was performed through nonlinear registration with antsRegistration (ANTs 2.3.3), using brain-extracted versions of both T1w reference and the T1w template. The following templates were selected for spatial normalization: *ICBM 152 Nonlinear Asymmetrical template version 2009c* [Fonov et al. (2009), RRID:SCR_008796; TemplateFlow ID: MNI152NLin2009cAsym], *FSL's MNI ICBM 152 non-linear 6th Generation Asymmetric Average Brain Stereotaxic Registration Model* [Evans et al. (2012), RRID:SCR_002823; TemplateFlow ID: MNI152NLin6Asym],

Functional data preprocessing

For each of the 21 BOLD runs found per subject (across all tasks and sessions), the following preprocessing was performed. First, a reference volume and its skull-stripped version were generated using a custom methodology of *fMRIPrep* . Susceptibility distortion correction (SDC) was omitted. The BOLD reference was then co-registered to the T1w reference using bbregister (FreeSurfer) which implements boundary-based registration (Greve and Fischl 2009). Co-registration was configured with six degrees of freedom. Head-motion parameters with respect to the BOLD reference (transformation matrices, and six corresponding rotation and translation parameters) are estimated before any spatiotemporal filtering using mcflirt (FSL 5.0.9, Jenkinson et al. 2002). BOLD runs were slice-time corrected using 3dTshift from AFNI 20160207 (Cox and Hyde 1997, RRID:SCR_005927). The BOLD time-series were resampled onto the following surfaces (FreeSurfer reconstruction nomenclature): *fsnative*, *fsaverage*. The BOLD time-series (including slice-timing correction when applied) were resampled onto their original, native space by applying the transforms to correct for headmotion. These resampled BOLD time-series will be referred to as *preprocessed BOLD in original space*, or just *preprocessed BOLD*. The BOLD time-series were resampled into standard space, generating a *preprocessed BOLD run in MNI152NLin2009cAsym space*. First, a reference volume and its skull-stripped version were generated using a custom methodology of *fMRIPrep* . *Grayordinates* files (Glasser et al. 2013) containing 91k samples were also generated using the highest-resolution fsaverage as intermediate standardized surface space. Automatic removal of motion artifacts using independent component analysis (ICA-AROMA, Pruim et al. 2015) was performed on the *preprocessed BOLD on MNI space* time-series after removal of non-steady state volumes and spatial smoothing with an isotropic, Gaussian kernel of 6mm FWHM (fullwidth half-maximum). Corresponding "non-aggresively" denoised runs were produced after such smoothing. Additionally, the "aggressive" noise-regressors were collected and placed in the corresponding confounds file. Several confounding time-series were calculated based on the *preprocessed BOLD*: framewise displacement

(FD), DVARS and three region-wise global signals. FD was computed using two formulations following Power (absolute sum of relative motions, Power et al. (2014)) and Jenkinson (relative root mean square displacement between affines, Jenkinson et al. (2002)). FD and DVARS are calculated for each functional run, both using their implementations in *Nipype* (following the definitions by Power et al. 2014). The three global signals are extracted within the CSF, the WM, and the whole-brain masks. Additionally, a set of physiological regressors were extracted to allow for component-based noise correction (*CompCor*, Behzadi et al. 2007). Principal components are estimated after high-pass filtering the *preprocessed BOLD* time-series (using a discrete cosine filter with 128s cut-off) for the two *CompCor* variants: temporal (tCompCor) and anatomical (aCompCor). tCompCor components are then calculated from the top 2% variable voxels within the brain mask. For aCompCor, three probabilistic masks (CSF, WM and combined CSF+WM) are generated in anatomical space. The implementation differs from that of Behzadi et al. in that instead of eroding the masks by 2 pixels on BOLD space, the aCompCor masks are subtracted a mask of pixels that likely contain a volume fraction of GM. This mask is obtained by dilating a GM mask extracted from the FreeSurfer's *aseg* segmentation, and it ensures components are not extracted from voxels containing a minimal fraction of GM. Finally, these masks are resampled into BOLD space and binarized by thresholding at 0.99 (as in the original implementation). Components are also calculated separately within the WM and CSF masks. For each CompCor decomposition, the *k* components with the largest singular values are retained, such that the retained components' time series are sufficient to explain 50 percent of variance across the nuisance mask (CSF, WM, combined, or temporal). The remaining components are dropped from consideration. The head-motion estimates calculated in the correction step were also placed within the corresponding confounds file. The confound time series derived from head motion estimates and global signals were expanded with the inclusion of temporal derivatives and quadratic terms for each (Satterthwaite et al. 2013). Frames that exceeded a threshold of 0.5 mm FD or 1.5 standardised DVARS were annotated as motion outliers. All resamplings can be performed with *a single interpolation step* by composing all the pertinent transformations (i.e. head-motion transform matrices, susceptibility distortion correction when available, and co-registrations to anatomical and output spaces). Gridded (volumetric) resamplings were performed using antsApplyTransforms (ANTs), configured with Lanczos interpolation to minimize the smoothing effects of other kernels (Lanczos 1964). Non-gridded (surface) resamplings were performed using mri_vol2surf (FreeSurfer).

Many internal operations of *fMRIPrep* use *Nilearn* 0.6.2 (Abraham et al. 2014, RRID:SCR_001362), mostly within the functional processing workflow. For more details of the pipeline, see [the section corresponding to](https://fmriprep.readthedocs.io/en/latest/workflows.html) [workflows in](https://fmriprep.readthedocs.io/en/latest/workflows.html) *[fMRIPrep](https://fmriprep.readthedocs.io/en/latest/workflows.html)* ['s documentation.](https://fmriprep.readthedocs.io/en/latest/workflows.html)

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HCP-DES fMRIPREP PROCESSING DETAILS

Results included in this manuscript come from preprocessing performed using *fMRIPrep* 20.2.3 (Esteban, Markiewicz, et al. (2018); Esteban, Blair, et al. (2018); RRID:SCR_016216), which is based on *Nipype* 1.6.1 (Gorgolewski et al. (2011); Gorgolewski et al. (2018); RRID:SCR_002502).

Anatomical data preprocessing

A total of 1 T1-weighted (T1w) images were found within the input BIDS dataset.The T1-weighted (T1w) image was corrected for intensity non-uniformity (INU) with N4BiasFieldCorrection (Tustison et al. 2010), distributed with ANTs 2.3.3 (Avants et al. 2008, RRID:SCR_004757), and used as T1w-reference throughout the workflow. The T1w-reference was then skull-stripped with a *Nipype* implementation of the antsBrainExtraction.sh workflow (from ANTs), using OASIS30ANTs as target template. Brain tissue segmentation of cerebrospinal fluid (CSF), white-matter (WM) and gray-matter (GM) was performed on the brain-extracted T1w using fast (FSL 5.0.9, RRID:SCR_002823, Zhang, Brady, and Smith 2001). Brain surfaces were reconstructed using recon-all (FreeSurfer 6.0.1, RRID:SCR 001847, Dale, Fischl, and Sereno 1999), and the brain mask estimated previously was refined with a custom variation of the method to reconcile ANTsderived and FreeSurfer-derived segmentations of the cortical gray-matter of Mindboggle (RRID:SCR_002438, Klein et al. 2017). Volume-based spatial normalization to two standard spaces (MNI152NLin6Asym, MNI152NLin2009cAsym) was performed through nonlinear registration with antsRegistration (ANTs 2.3.3), using brain-extracted versions of both T1w reference and the T1w template. The following templates were selected for spatial normalization: *FSL's MNI ICBM 152 non-linear 6th Generation Asymmetric Average Brain Stereotaxic Registration Model* [Evans et al. (2012), RRID:SCR_002823; TemplateFlow ID: MNI152NLin6Asym], *ICBM 152 Nonlinear Asymmetrical template version 2009c* [Fonov et al. (2009), RRID:SCR_008796; TemplateFlow ID: MNI152NLin2009cAsym],

Functional data preprocessing

For each of the 6 BOLD runs found per subject (across all tasks and sessions), the following preprocessing was performed. First, a reference volume and its skull-stripped version were generated using a custom methodology of *fMRIPrep* . Susceptibility distortion correction (SDC) was omitted. The BOLD reference was then coregistered to the T1w reference using bbregister (FreeSurfer) which implements boundary-based registration (Greve and Fischl 2009). Co-registration was configured with six degrees of freedom. Head-motion parameters with respect to the BOLD reference (transformation matrices, and six corresponding rotation and translation parameters) are estimated before any spatiotemporal filtering using mcflirt (FSL 5.0.9, Jenkinson et al. 2002). BOLD runs were slice-time corrected using 3dTshift from AFNI 20160207 (Cox and Hyde 1997, RRID:SCR_005927). The BOLD time-series were resampled onto the following surfaces (FreeSurfer reconstruction nomenclature): *fsnative*, *fsaverage*. The BOLD time-series (including slice-timing correction when applied) were resampled onto their original, native space by applying the transforms to correct for headmotion. These resampled BOLD time-series will be referred to as *preprocessed BOLD in original space*, or just *preprocessed BOLD*. The BOLD time-series were resampled into standard space, generating a *preprocessed BOLD run in MNI152NLin6Asym space*. First, a reference volume and its skull-stripped version were generated using a custom methodology of *fMRIPrep* . *Grayordinates* files (Glasser et al. 2013) containing 91k samples were also generated using the highest-resolution fsaverage as intermediate standardized surface space. Automatic removal of motion artifacts using independent component analysis (ICA-AROMA, Pruim et al. 2015) was performed on the *preprocessed BOLD on MNI space* time-series after removal of non-steady state volumes and spatial smoothing with an isotropic, Gaussian kernel of 6mm FWHM (full-width half-maximum). Corresponding "non-aggresively" denoised runs were produced after such smoothing. Additionally, the "aggressive" noise-regressors were collected and placed in the corresponding confounds file. Several confounding time-series were calculated based on the *preprocessed BOLD*: framewise displacement (FD), DVARS and three region-wise global signals. FD was computed using two formulations following Power

(absolute sum of relative motions, Power et al. (2014)) and Jenkinson (relative root mean square displacement between affines, Jenkinson et al. (2002)). FD and DVARS are calculated for each functional run, both using their implementations in *Nipype* (following the definitions by Power et al. 2014). The three global signals are extracted within the CSF, the WM, and the whole-brain masks. Additionally, a set of physiological regressors were extracted to allow for component-based noise correction (*CompCor*, Behzadi et al. 2007). Principal components are estimated after high-pass filtering the *preprocessed BOLD* time-series (using a discrete cosine filter with 128s cut-off) for the two *CompCor* variants: temporal (tCompCor) and anatomical (aCompCor). tCompCor components are then calculated from the top 2% variable voxels within the brain mask. For aCompCor, three probabilistic masks (CSF, WM and combined CSF+WM) are generated in anatomical space. The implementation differs from that of Behzadi et al. in that instead of eroding the masks by 2 pixels on BOLD space, the aCompCor masks are subtracted a mask of pixels that likely contain a volume fraction of GM. This mask is obtained by dilating a GM mask extracted from the FreeSurfer's *aseg* segmentation, and it ensures components are not extracted from voxels containing a minimal fraction of GM. Finally, these masks are resampled into BOLD space and binarized by thresholding at 0.99 (as in the original implementation). Components are also calculated separately within the WM and CSF masks. For each CompCor decomposition, the *k* components with the largest singular values are retained, such that the retained components' time series are sufficient to explain 50 percent of variance across the nuisance mask (CSF, WM, combined, or temporal). The remaining components are dropped from consideration. The head-motion estimates calculated in the correction step were also placed within the corresponding confounds file. The confound time series derived from head motion estimates and global signals were expanded with the inclusion of temporal derivatives and quadratic terms for each (Satterthwaite et al. 2013). Frames that exceeded a threshold of 0.5 mm FD or 1.5 standardised DVARS were annotated as motion outliers. All resamplings can be performed with *a single interpolation step* by composing all the pertinent transformations (i.e. head-motion transform matrices, susceptibility distortion correction when available, and co-registrations to anatomical and output spaces). Gridded (volumetric) resamplings were performed using antsApplyTransforms (ANTs), configured with Lanczos interpolation to minimize the smoothing effects of other kernels (Lanczos 1964). Non-gridded (surface) resamplings were performed using mri_vol2surf (FreeSurfer). First, a reference volume and its skullstripped version were generated using a custom methodology of *fMRIPrep* . A B0-nonuniformity map (or *fieldmap*) was estimated based on two (or more) echo-planar imaging (EPI) references with opposing phaseencoding directions, with 3dQwarp Cox and Hyde (1997) (AFNI 20160207). Based on the estimated susceptibility distortion, a corrected EPI (echo-planar imaging) reference was calculated for a more accurate coregistration with the anatomical reference. The BOLD reference was then co-registered to the T1w reference using bbregister (FreeSurfer) which implements boundary-based registration (Greve and Fischl 2009). Coregistration was configured with six degrees of freedom. Head-motion parameters with respect to the BOLD reference (transformation matrices, and six corresponding rotation and translation parameters) are estimated before any spatiotemporal filtering using mcflirt (FSL 5.0.9, Jenkinson et al. 2002). BOLD runs were slice-time corrected using 3dTshift from AFNI 20160207 (Cox and Hyde 1997, RRID:SCR_005927). The BOLD timeseries were resampled onto the following surfaces (FreeSurfer reconstruction nomenclature): *fsnative*, *fsaverage*. The BOLD time-series (including slice-timing correction when applied) were resampled onto their original, native space by applying a single, composite transform to correct for headmotion and susceptibility distortions. These resampled BOLD time-series will be referred to as *preprocessed BOLD in original space*, or just *preprocessed BOLD*. The BOLD time-series were resampled into standard space, generating a *preprocessed BOLD run in MNI152NLin6Asym space*. First, a reference volume and its skull-stripped version were generated using a custom methodology of *fMRIPrep* . *Grayordinates* files (Glasser et al. 2013) containing 91k samples were also generated using the highest-resolution fsaverage as intermediate standardized surface space. Automatic removal of motion artifacts using independent component analysis (ICA-AROMA, Pruim et al. 2015) was performed on the *preprocessed BOLD on MNI space* time-series after removal of non-steady state volumes and spatial smoothing with an isotropic, Gaussian kernel of 6mm FWHM (fullwidth half-maximum). Corresponding "non-aggresively" denoised runs were produced after such smoothing.

Additionally, the "aggressive" noise-regressors were collected and placed in the corresponding confounds file.

Several confounding time-series were calculated based on the *preprocessed BOLD*: framewise displacement (FD), DVARS and three region-wise global signals. FD was computed using two formulations following Power (absolute sum of relative motions, Power et al. (2014)) and Jenkinson (relative root mean square displacement between affines, Jenkinson et al. (2002)). FD and DVARS are calculated for each functional run, both using their implementations in *Nipype* (following the definitions by Power et al. 2014). The three global signals are extracted within the CSF, the WM, and the whole-brain masks. Additionally, a set of physiological regressors were extracted to allow for component-based noise correction (*CompCor*, Behzadi et al. 2007). Principal components are estimated after high-pass filtering the *preprocessed BOLD* time-series (using a discrete cosine filter with 128s cut-off) for the two *CompCor* variants: temporal (tCompCor) and anatomical (aCompCor). tCompCor components are then calculated from the top 2% variable voxels within the brain mask. For aCompCor, three probabilistic masks (CSF, WM and combined CSF+WM) are generated in anatomical space. The implementation differs from that of Behzadi et al. in that instead of eroding the masks by 2 pixels on BOLD space, the aCompCor masks are subtracted a mask of pixels that likely contain a volume fraction of GM. This mask is obtained by dilating a GM mask extracted from the FreeSurfer's *aseg* segmentation, and it ensures components are not extracted from voxels containing a minimal fraction of GM. Finally, these masks are resampled into BOLD space and binarized by thresholding at 0.99 (as in the original implementation). Components are also calculated separately within the WM and CSF masks. For each CompCor decomposition, the *k* components with the largest singular values are retained, such that the retained components' time series are sufficient to explain 50 percent of variance across the nuisance mask (CSF, WM, combined, or temporal). The remaining components are dropped from consideration. The head-motion estimates calculated in the correction step were also placed within the corresponding confounds file. The confound time series derived from head motion estimates and global signals were expanded with the inclusion of temporal derivatives and quadratic terms for each (Satterthwaite et al. 2013). Frames that exceeded a threshold of 0.5 mm FD or 1.5 standardised DVARS were annotated as motion outliers. All resamplings can be performed with *a single interpolation step* by composing all the pertinent transformations (*i.e.* head-motion transform matrices, susceptibility distortion correction when available, and co-registrations to anatomical and output spaces). Gridded (volumetric) resamplings were performed using antsApplyTransforms (ANTs), configured with Lanczos interpolation to minimize the smoothing effects of other kernels (Lanczos 1964). Non-gridded (surface) resamplings were performed using mri_vol2surf (FreeSurfer).

Many internal operations of *fMRIPrep* use *Nilearn* 0.6.2 (Abraham et al. 2014, RRID:SCR_001362), mostly within the functional processing workflow. For more details of the pipeline, see the section corresponding to [workflows in](https://fmriprep.readthedocs.io/en/latest/workflows.html) *[fMRIPrep](https://fmriprep.readthedocs.io/en/latest/workflows.html)* ['s documentation.](https://fmriprep.readthedocs.io/en/latest/workflows.html)

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