SUPPLEMENTARY INFORMATION

Altered Brain Dynamics Across Bipolar Disorder and Schizophrenia During Rest and Task-switching Revealed by Overlapping Brain States

Ye *et al.*

Supplemental Methods and Materials:

Supplementary Table 1. Medication information for the CNP dataset

	Resting-state sample		Task-switching sample	
Medication type	BD	SCZ	BD	SCZ
Antipsychotic	28.57%	82.35%	28.21%	75%
Antidepressant	17.86%	8.82%	15.38%	13.64%
Mood stabilizer	46.43%	5.88%	46.15%	9.09%
Others	7.14%	2.94%	10.26%	2.27%

Medication information available from the patient groups in the CNP dataset. We categorized medications into four main groups: antipsychotic, antidepressant, mood stabilizer and others. BD, bipolar disorder; SCZ, schizophrenia.

Additional participant information:

In the CNP dataset, patient diagnoses were made by trained clinicians using DSM-IV criteria for BD and SCZ (1, 2). For the SRPBS dataset, the healthy control (HC) group was screened using the Mini-International Neuropsychiatric Interview. HCs with lifetime psychiatric disorder diagnoses were excluded from the CNP dataset.

Functional magnetic resonance imaging data acquisition and preprocessing:

For the SRPBS dataset, the first four volumes were removed to allow magnetic field stabilization. After brain extraction with OptiBet (3), structural data was nonlinearly registered to the standard MNI-152 space. For functional data, slice time and motion correction were performed using SPM8 before being linearly aligned to the structural data. Data cleaning for all datasets was performed with BioImage Suite. Regression of covariates of no interest, including linear and quadratic drift, a 24-parameter model of motion, and mean white matter, cerebrospinal fluid and gray matter signals, was performed. Timeseries data were temporally smoothed (cutoff frequency approximately ~0.12Hz) and then extracted using the Shen-268 atlas (4) from all resting state fMRI datasets for each participant. We applied the same preprocessing pipeline and quality control procedures to the task-based fMRI data used in our secondary analysis. Several brain nodes were excluded from resting-state (n=7) and task-based (n=5) brain dynamics analyses due to noise and/or incomplete coverage. One CNP participant was excluded due to an incomplete resting-state scan. Fourteen SRPBS participants were excluded from further analysis after not meeting preprocessing quality control benchmarks (i.e., issues with skull stripping, nonlinear or linear registration).

Discussion on number of brain states:

The question of "how many brain states are there" remains unresolved, with the answer likely depending on the experimental methods and theoretical models of the brain used in a given study. Here, we identified brain states following procedures and pipelines established by our previous work (5). The number of brain states was determined using the Calinski-Harabascz criterion (6). A range of potential state numbers were explored, with 4 showing the largest Calinsk-Harabasz value (i.e., ratio between within-cluster and between-cluster dispersion). While previous co-activation patterns (CAP) literature typically resolves around 20 brain states, these CAPs are often spatially overlapping and correlated (7,8,9). Many other studies have also focused on a relatively small number of brain states. For example, Shine et al. (10) found that 5 brain states explained the majority of a low-dimensional embedding of several tasks. Similarly, Venkatesh et al. (11) demonstrated that 5 states significantly classified task conditions. Finally, dynamic functional connectivity studies typically used between 4 to 7 brain states (12).

It is also important to note here that since we allow a weighted combination of four brain states to explain each time point, we can realistically come up with a nearly infinite number of possible brain states by weighting the four representative brain states differently. For this reason, our approach should allow us to capture brain states that were spatially distinct from the four primary ones identified from the HCP dataset.

Brain dynamic measures validations:

Brain dynamic measures were systematically tested to ensure that they were sensitive to changes in brain dynamics. We first compared brain dynamic measures during rest and task since we have some information about the differences between these two conditions. Relative state engagement and state engagement variability measures were extracted from 176 CNP participants with both data available. As participants were actively performing a task during the task-switching paradigm, they should recruit the high-cognition state more during task than rest. Since the default mode network showed high activation during the fixation state, we also hypothesized that individuals would recruit the fixation brain state more during rest than task given the close association between this network and rest (13). We might additionally expect state engagement variability to be lower during task than rest. The task condition is more constrained than rest (14). Participants might need to limit mind wandering in order to perform well in the task.

Indeed, we found that during task, participants showed more high-cognition and low-cognition relative state engagement than rest (high-cognition: $p=0.016$; low-cognition: $p<0.001$; **Supplementary Table 2**). The low-cognition state recruited a large number of motor regions. Participants likely engaged this network when making button presses during task. Participants also showed more fixation relative state engagement during rest than task ($p<0.001$; **Supplementary Table 2**). State engagement variability was lower during task-based fMRI as compared to rest across all four states (fixation: $p<0.001$; high-cognition: $p<0.001$; low-cognition: $p=0.017$; cue/transition: $p<0.001$). These results support our earlier hypothesis, suggesting that the brain dynamic measures used in this study captured useful information.

We further investigated whether our brain dynamic measures can capture task performance information. We correlated relative state engagement during task-switching with mean response time (RT) from all available task-switching trials (N=96). Participants were excluded if more than 10% of their trials were missing RT data (likely due to not making a response press within the allotted time; final group included in the analysis: N=193). Decreased mean RT correlated significantly with increased

fixation (r=-0.173; p=0.016; **Supplementary Table 3**) but decreased low cognition (r=0.176; p=0.014; **Supplementary Table 3**) relative state engagement. These results provide preliminary evidence indicating that multiple brain states might be engaged simultaneously (and potentially in various ways) to support task performance. However, as the number of task trials was relatively low here, future study with data from more task trials should further investigate how state engagement supports sustained task performance.

When performing this analysis within patient participants (i.e., individuals with either bipolar disorder or schizophrenia) and HCs separately, we observed indications of group differences in the brain-behavior relationships. While there was no significant association between relative state engagement and mean RT in HC, higher fixation relative state engagement and lower low-cognition relative state engagement was associated with lower mean RT in patients. It is important to note here that patients also showed significantly higher mean RT than HC ($p<0.001$; HC: mean RT: 0.788, RT SD: 0.161; patients: mean RT: 0.926, RT SD: 0.182). It is possible that the lack of significant associations between mean RT and relative state engagement in HC was due to a ceiling effect. If the HC group already performed at an optimal level, we might not observe many mean RT differences across individuals. It might then become challenging to investigate whether differences in relative state engagement contribute to variations in mean RT. However, as patients had poorer task performance (as indicated by the higher mean RT), we might have more individual variations in this group to study how state engagement supported task performance.

Supplementary Table 2. Comparing brain dynamic measures between conditions.

Brain state measure	Rest M±SD	Task M±SD	T-stat	P-value
Fixation relative state engagement	0.4031±0.0027	0.4010±0.0027	7.690	<0.001
High-cognition relative state engagement	0.2306±0.0029	0.2313±0.0032	-2.4311	0.016
Low-cognition relative state engagement	0.0836±0.0032	0.0851±0.0033	-4.557	<0.001
Cue/transition relative state engagement	0.2826±0.0026	0.2826±0.0025	-0.1173	0.907
Fixation state engagement variability	1.1488±0.2171	1.0224±0.171	7.605	<0.001
High-cognition state engagement variability	0.7229±0.1341	0.6800±0.1243	4.115	<0.001
Low-cognition state engagement variability	0.2490±0.0393	0.2410±0.0316	2.405	0.017
Cue/transition state engagement variability	0.6953±0.1307	0.6464±0.1068	4.896	<0.001

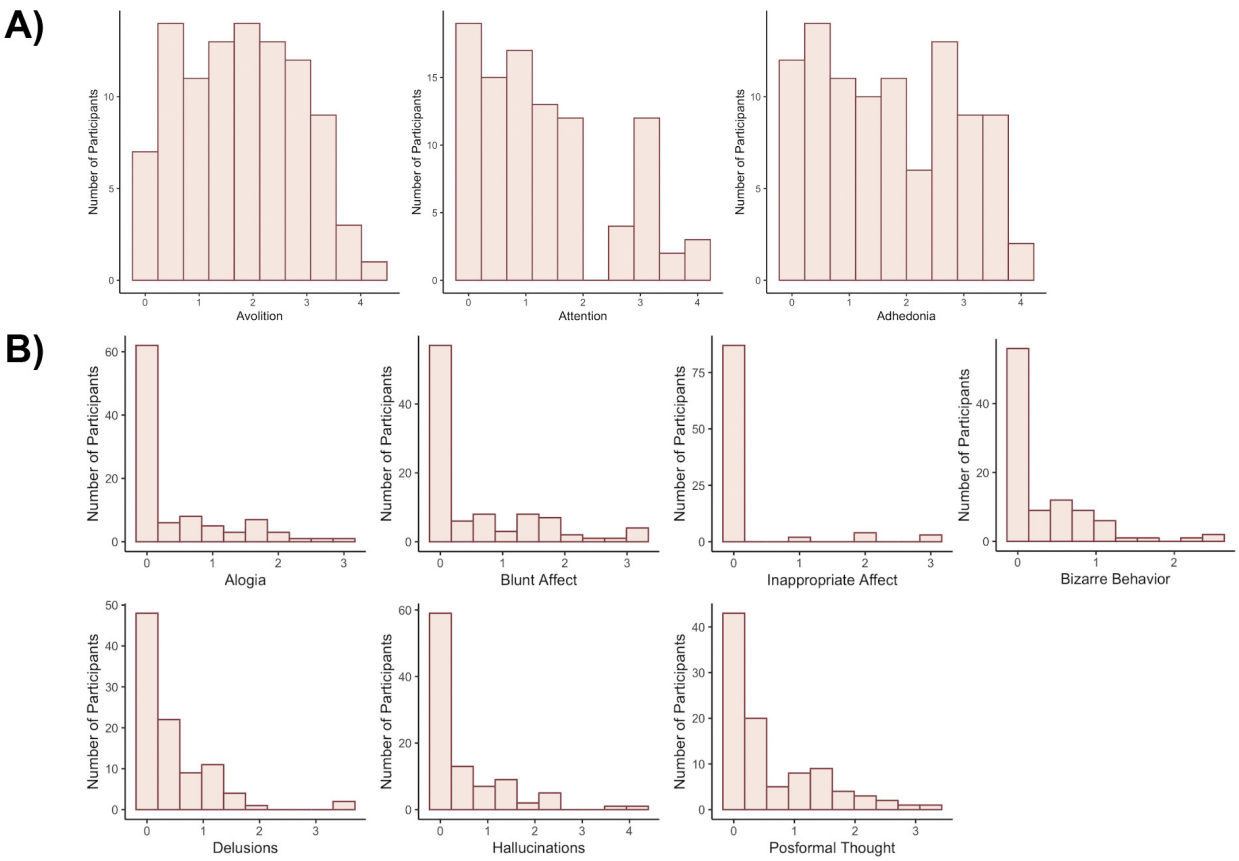
Note: We compared brain dynamic measures extracted from resting-state and task-based fMRI using paired t-tests. This analysis was done in CNP participants with both types of data available (N=176). Individuals showed higher fixation relative state engagement during rest than task. But compared to rest, participants demonstrated higher high-cognition and low-cognition relative state engagement during task. Cue/transition relative state engagement was not significantly different between the two conditions. Individuals additionally showed lower state engagement variability during task than rest across all four brain states.

Supplementary Table 3. Correlating relative state engagement with mean RT

	Fixation	High cognition	Low cognition	Cue/transition
All participants	r=-0.173; p=0.016	r=-0.126; p=0.08	r=0.176; p=0.014	r=0.116; p=0.109
BD or SCZ (N=82)	r=-0.312; p=0.004	r=-0.179; p=0.184	r=0.288; p=0.009	r=0.206; p=0.063
HC (N=111)	r=0.046; p=0.63	r=-0.011; p=0.912	r=0.006; p=0.951	r=-0.044; p=0.647

Comparison with a state discretization approach:

For our state discretization approach, each rest and task time point was first correlated with each state representative time point and then assigned to the state showing the highest correlation value. State transition was measured as the number of times there was a change in state assignment from one time point to the next, whereas dwell time was operationalized as the number of time points assigned to one state divided by the total number of time points. As the state transition measure here required a continuous assessment, we did not censor based on motion. But participants with excessive motion (i.e., more than 20% volumes showing over 0.45 framewise displacement) were excluded. We then compared dwell time and state transition across groups using ANCOVA, with site (when appropriate), medication, age and sex as covariates. ANCOVA was used here since the dwell time measures were not completely independent from each other, and there was only one state transition measure.



Supplementary Figure 1. *Distributions of clinical symptom scores.* **A)** showed the distribution of symptom scores used to correlate with combined state transition variability. We did not perform further analysis with the symptom scores shown in **B)** since the distribution was zero-inflated.

Supplementary Table 4. Number of volumes associated with each task condition for the identified four brain states

	Fixation	High-cognition	Low-cognition	Cue/Transition
Fixation	635	0	20	65
Cue	41	3	6	158
Working memory (0 back)	10	56	99	123
Working memory (2 back)	1	201	10	76
Emotion (Fear)	10	42	0	48
Emotion (Neutral)	23	12	99	16
Gambling (Win)	0	100	25	35
Gambling (Loss)	0	101	10	49
Motor (Tongue)	0	1	52	12
Motor (Left foot)	8	5	41	13
Motor (Left hand)	7	0	45	15
Motor (Right foot)	0	0	55	12
Motor (Right hand)	0	1	50	15
Social (Mental)	0	113	0	47
Social (Random)	0	111	0	109
Relational (Match)	3	9	17	40
Relational (Relation)	3	90	5	9

Note: This table shows the number of volumes associated with different task conditions for each state. The fixation state included predominantly fixation time points. The high-cognition state mainly contained time points from complex cognitive tasks including working memory, emotion, relational, gambling and social paradigms. The low-cognition state mostly contained time points from the motor tasks, as well as those from 0-back working memory and neutral emotion task conditions. The cue/transition state mostly consisted of time points from cue conditions across various tasks.

Supplementary Table 5. Networks showing the highest activation and deactivation percentages for each state

	Fixation	High-cognition	Low-cognition	Cue/transition
Activation percentages	DMN (88.89%)	VAs (100%)	Motor network (100%)	Visual I (100%)
	Motor network (85.71%)	Visual II (88.87%)	MF (86.21%)	VAs (72.22%)
	MF (82.76%)	FP (82.35%)	Cerebellum (84%)	Visual II (66.67%)
Deactivation percentages	VAs (94.44%)	Motor network (87.76%)	Visual I (100%)	MF (89.66%)
	Visual I (66.67%)	DMN (83.33%)	Visual II, VAs, and DMN (66.67%)	DMN (88.87%)
	Visual II (66.67%)	Subcortical (79.31%)		Motor (83.67%)

Note: This table shows the canonical functional networks showing the three highest activation and deactivation percentages for each brain state. The actual activation and deactivation percentage values are denoted by parentheses. DMN, default mode network; MF, medial frontal network; VAs, visual association network; FP, frontoparietal network. Different brain networks were activated to different extent to support the cognitive processes associated with each brain state. For example, while the visual networks showed high activation percentages in the high-cognition brain state, they decreased their activation during fixation. This might be due to participants being shown much more complex visual stimuli during cognitively demanding tasks relative to periods of fixation. As participants were only presented with a white crosshair with a black background during fixation, we might expect activity to be limited to the primary visual cortex, with deactivation across the broader visual network. However, when performing a task, participants are presented with various visual stimuli with diverse characteristics (e.g., luminosity, color, orientation; 15). The richer visual information presented during tasks can then lead to elevated visual network activation during high-cognition state.

Investigations of model residuals and evaluations of model fit.

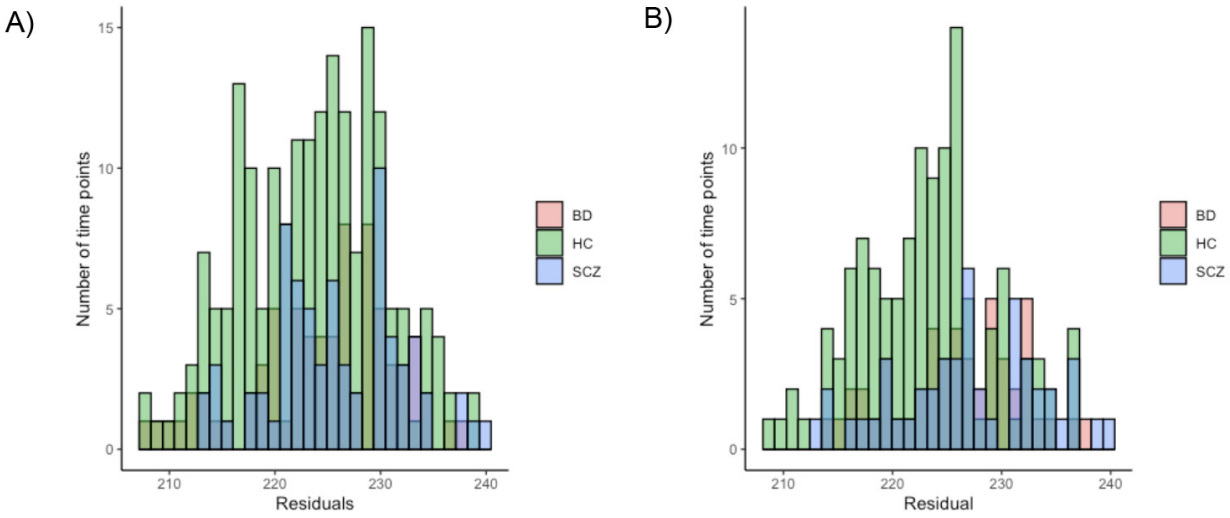
The main contribution of this study is to introduce a framework that can simultaneously track the engagement of multiple brain states in a continuous manner. We focused on four states identified using the HCP dataset here. It is not our intention to claim that these four states can fully account for the activation patterns in resting-state and task-based fMRI. However, we investigated whether the residuals from our model contained important clinical information and evaluated model fitting against a null model.

We first repeated the analysis we did with clinical measures by finding the mean of residuals across all time points. Mean residuals did not correlate significantly with any of the clinical measures (avolition: $r=0.197$, $p=0.053$; attention: $r=0.097$, $p=0.345$; anhedonia: $r=0.054$, $p=0.597$). The mean residual distributions are additionally plotted by groups below in **Supplementary Figure 2**.

We additionally compared our current model with a null model including only the mean activation level of each time point. The model with four brain states provided a significantly better fit for 82.40% and 86.02% of the time points during rest and task-switching, respectively (see **Supplementary Table 6** for the median and interquartile range within each group), indicating that our model was able to account for variance in brain activation.

Supplementary Table 6. Percentage of time points showing better fit than a null model during resting-state and task-switching paradigms

Resting-state		
Group	Median	Interquartile range
HC	89.4%	5.6%
BD	89.4%	7.6%
SCZ	87.4%	8.6%
Task-switching		
Group	Median	Interquartile range
HC	87.9%	6.3%
BD	85.5%	7.7%
SCZ	85.5%	11.7%



Supplementary Figure 2. *Mean residuals from resting-state and task-switching plotted by groups.* The mean residuals from resting-state fMRI is shown in A) (mean residual in healthy control: 223.467; mean residual in the bipolar disorder group: 224.633; mean residual in the schizophrenia group: 225.874) and the task-switching residuals are shown in B) (mean residual in healthy control: 223.224; mean residual in the bipolar disorder group: 226.01; mean residual in the schizophrenia group: 227.017).

Supplementary Table 7. Resting-state MANCOVA covariates

State engagement variability		
Predictor	F-stat	p
Site	F(4,323)=23.884	<0.001
Medication	F(16,1304)=1.078	0.371
Age	F(4,323)=8.749	<0.001
Sex	F(4,323)=1.337	0.256
Relative state engagement		
Site	F(4,323)=3.734	0.005
Medication	F(16,1304)=1.584	0.066
Age	F(4,323)=1.793	0.130
Sex	F(4,323)=0.857	0.490

Note: This table shows the covariate results from MANCOVA analysis using the resting-state data from both datasets. We further investigated whether there was a significant site-by-age or site-by-sex interaction. Neither site-by-sex (F(1,325)=1.202; p=0.31) nor site-by-age interaction effects (F(1,325)=1.125; p=0.036) was significantly related to state engagement variability. Site-by-sex (F(1,325)=1.534; p=0.192) and site-by-age (F(1,325)=0.739; p=0.567) interactions for relative state engagement were also not significant.

Supplementary Table 8. Resting-state state engagement variability T-squared covariates

HC vs. BD		
Predictor	F-stat	p
Site	F(4,253)=20.803	<0.001
Medication	F(16,1024)=1.232	0.236
Age	F(4,253)=6.070	<0.001
Sex	F(4,253)=1.745	0.141
HC vs. SCZ		
Site	F(4,249)=18.753	<0.001
Medication	F(16,1008)=1.264	0.213
Age	F(4,249)=6.084	<0.001
Sex	F(4,249)=1.130	0.343

Note: This table provides covariate results from T-squared analyses comparing state engagement variabilities during rest between each clinical group and healthy control. HC: healthy control; BD: bipolar disorder; SCZ: schizophrenia.

Supplementary Table 9. Resting-state state engagement variability effect sizes (Cohen's d)

State	HC vs. BD	HC vs. SCZ
Fixation	0.499	0.317
High cognition	0.524	0.382
Low cognition	0.213	0.233
Cue/transition	0.394	0.272

Note: This table provides the effect sizes of group differences in state engagement variability during rest for each brain state. The Cohen's d effect sizes here were computed using Matlab's computeCohen_d function (16). HC: healthy control; BD: bipolar disorder; SCZ: schizophrenia.

Supplementary Table 10. Task-switching MANCOVA covariates

State engagement variability		
Predictor	F-stat	p
Medication	F(16,832)=1.195	0.265
Age	F(4,205)=9.352	<0.001
Sex	F(4,205)=3.727	0.006
Relative state engagement		
Medication	F(16,832)=1.642	0.053
Age	F(4,205)=1.876	0.116
Sex	F(4,205)=1.424	0.227

Note: This table shows the covariate results from MANCOVA analysis using the task-switching dataset.

Supplementary Table 11. Task-switching state engagement variability T-squared covariates

HC vs. BD		
Predictor	F-stat	p
Medication	F(16,644)=1.588	0.067
Age	F(4,158)=6.582	<0.001
Sex	F(4,158)=4.422	0.002
HC vs. SCZ		
Medication	F(16,640)=0.573	0.905
Age	F(4,157)=6.464	<0.001
Sex	F(4,157)=1.872	0.118

Note: This table reports covariate results from T-squared analyses comparing state engagement variabilities during task-switching between each clinical group and healthy control. HC: healthy control; BD: bipolar disorder; SCZ: schizophrenia.

Supplementary Table 12. Task-switching state engagement variability effect size (Cohen's d)

State	HC vs. BD	HC vs. SCZ
Fixation	0.420	0.245
High cognition	0.415	0.349
Low cognition	0.201	-0.129
Cue/transition	0.246	-0.011

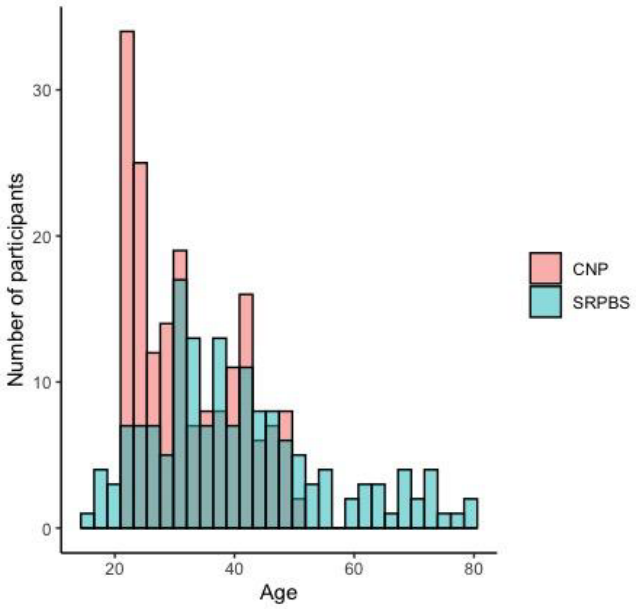
Note: This table reports the effect sizes of group differences in state engagement variability during task-switching for each brain state. The Cohen's d effect sizes here were computed using Matlab's computeCohen_d function (16). HC: healthy control; BD: bipolar disorder; SCZ: schizophrenia.

Investigations on site effects:

We performed follow-up analyses to understand the significant site effects on state engagement variability in both rest and task-based fMRI. The SRPBS dataset showed lower state engagement variability than the CNP dataset across all four states (two-sample t-tests; fixation: $p<0.001$; high-cognition: $p<0.001$; low-cognition: $p<0.001$; cue/transition: $p<0.001$; see **Supplementary Table 13**). While there are several plausible explanations for these site effects (including differences in participants' treatment history, scanner hardware, and geographic location), we believe that age differences between the cohorts may play a key role in the observed differences in state engagement variability. The two datasets were not age matched. The age range for the CNP dataset was between 21 and 50 years old, whereas the SRPBS participants were between 16 and 80 years old. The SRPBS dataset also included more older participants while the CNP recruited relatively younger individuals (see age distribution in Supplementary Figure 13). Given that our exploratory analyses indicated that overall state engagement variability decreases with age in the present cohorts, it is not too surprising that the SRPBS dataset would show lower state engagement variability than CNP due to the differences in age range and distribution. Importantly, we did not find a significant age-by-site interaction effect (MANOVA; $F(1,325)=1.125$; $p=0.325$; Supplementary Table 13), indicating that age has a similar effect on state engagement variability regardless of the study site.

Supplementary Table 13. The mean and standard deviation of state engagement variability by datasets

Brain state	CNP M±SD	SRPBS M±SD
Fixation state engagement variability	1.153±0.22	1.015±0.157
High-cognition state engagement variability	0.725±0.135	0.622±0.099
Low-cognition state engagement variability	0.25±0.04	0.229±0.030
Cue/transition state engagement variability	0.697±0.132	0.642±0.099



Supplementary Figure 3. *Age distribution by datasets*. CNP, the UCLA Consortium for Neuropsychiatric Phenomics dataset; SRPBS, the Japanese Strategic Research Program for the Promotion of Brain Sciences dataset.

Supplementary Table 14. Two-sample t-tests comparing state engagement variability between groups during resting-state and task-based fMRI

Resting-state fMRI								
	Fixation		High-cognition		Low-cognition		Cue/Transition	
Comparison	t(df)	*p*	t(df)	*p*	t(df)	*p*	t(df)	*p*
HC vs. BD	t(201.35) =4.329	<0.001	t(179.42) =4.344	<0.001	t(167.16) =1.717	0.088	t(201.65) =3.42	<0.001
HC vs. SCZ	t(132.67) =2.34	0.021	t(130.26) =2.8	0.006	t(136.8) =1.672	0.097	t(143.8) =2.09	0.038
Task-based fMRI								
	Fixation state		High-cognition		Low-cognition		Cue/Transition	
Comparison	t(df)	*p*	t(df)	*p*	t(df)	*p*	t(df)	*p*
HC vs. BD	t(83.92) =2.41	0.018	t(85.74) =2.402	0.018	t(1.164) =1.164;	0.248	t(1.455) =1.455	0.149
HC vs. SCZ	t(94.481) =1.491	0.139	t(2.127) =2.127	0.036	t(79.551) =-0.723	0.472	t(100.23) =-0.071	0.943

Supplementary Table 15. Discrete state approach results for resting-state data

Fixation dwell time		
Predictor	F-stat	p
Diagnosis	F(2,326)=2.830	0.060
Site	F(1,326)=0.012	0.913
Medication	F(4,326)=1.446	0.219
Age	F(1,326)=0.183	0.669
Sex	F(1,326)=1.569	0.211
High cognition dwell time		
Predictor	F-stat	p
Diagnosis	F(2,326)=0.866	0.422
Site	F(1,326)=1.767	0.185
Medication	F(4,326)=2.053	0.087
Age	F(1,326)=6.875	0.009
Sex	F(1,326)=0.069	0.792
Low cognition dwell time		
Predictor	F-stat	p
Diagnosis	F(2,326)=0.400	0.670
Site	F(1,326)=0.0002	0.990
Medication	F(4,326)=1.398	0.234
Age	F(1,326)=0.022	0.883
Sex	F(1,326)=2.844	0.093
Cue/transition dwell time		
Predictor	F-stat	p
Diagnosis	F(2,326)=1.973	0.141
Site	F(1,326)=2.214	0.138

Medication	F(4,326)=1.692	0.151
Age	F(1,326)=5.685	0.018
Sex	F(1,326)=0.018	0.895
State transition		
Predictor	F-stat	p
Diagnosis	F(2,326)=1.404	0.247
Site	F(1,326)=1480.383	<0.001
Medication	F(4,326)=0.990	0.413
Age	F(1,326)=0.296	0.587
Sex	F(1,326)=0.029	0.865

Note: This table shows the results from ANOVA analyses comparing dwell times and state transition during rest across groups using a state discretization approach.

Supplementary Table 16. Discrete state approach results for task-switching data

Fixation dwell time		
Predictor	F-stat	p
Diagnosis	F(2,208)=3.221	0.042
Medication	F(4,208)=0.304	0.875
Age	F(1,208)=1.921	0.167
Sex	F(1,208)=2.851	0.093
High cognition dwell time		
Predictor	F-stat	p
Diagnosis	F(2,208)=0.160	0.853
Medication	F(4,208)=0.419	0.795
Age	F(1,208)=0.852	0.357
Sex	F(1,208)=1.772	0.185
Low cognition dwell time		
Predictor	F-stat	p
Diagnosis	F(2,208)=0.491	0.613
Medication	F(4,208)=0.301	0.877
Age	F(1,208)=1.757	0.187
Sex	F(1,208)=0.132	0.717
Cue/transition dwell time		
Predictor	F-stat	p
Diagnosis	F(2,208)=1.829	0.163
Medication	F(4,208)=0.540	0.707
Age	F(1,208)=0.800	0.372
Sex	F(1,208)=0.047	0.828
State transition		

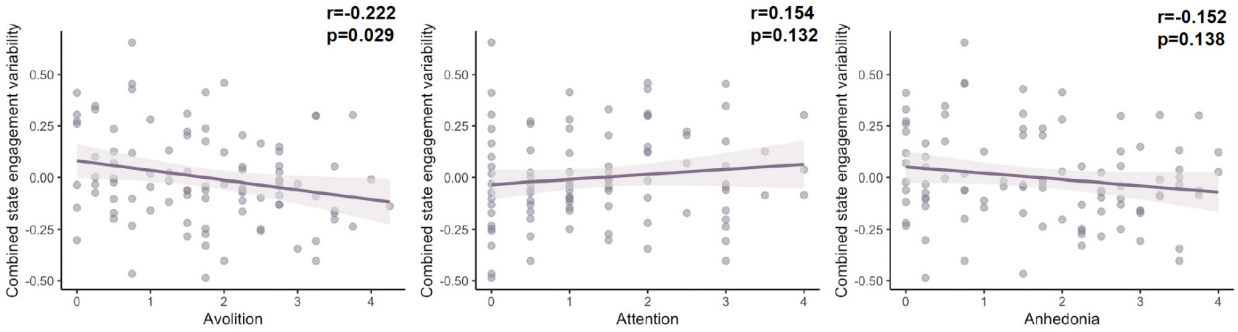
Predictor	F-stat	p
Diagnosis	F(2,208)=0.167	0.846
Medication	F(4,208)=0.678	0.608
Age	F(1,208)=0.154	0.695
Sex	F(1,208)=5.469	0.020

Note: This table shows the results from ANOVA analyses comparing dwell times and state transition during task-switching across groups using a state discretization approach.

Supplementary Table 17. Variance explained by the first component from principal component analysis on state engagement variability measures

Post-hoc age analysis	
Resting-state state engagement variability measures	94.42%
Task-switching state engagement variability measures	95.26%
Exploratory age analysis	
Task-switching engagement variability measures	92.56%

Note: This table reports the variance accounted for by the combined state engagement variability measure. For post-hoc age analysis, PCA was applied to state engagement variabilities from all three groups using resting-state and task-switching data, separately. We focused on the task-switching engagement variability measures for our exploratory age analysis. As the symptom measures were only available in patient participants, PCA was performed using data from individuals with bipolar disorder or schizophrenia for this analysis.



Supplementary Figure 4. *Associations between combined state engagement variability and clinical symptoms.* Elevated avolition symptoms were associated with decreased combined state engagement variability. But state engagement variability was not correlated with attention or anhedonia.

Supplementary References

1. Poldrack, R. A., Congdon, E., Triplett, W., Gorgolewski, K. J., Karlsgodt, K. H., Mumford, J. A., *et al.* (2016). A phenome-wide examination of neural and cognitive function. *Scientific Data*, *3*(1), Article 1.
2. Tanaka, S. C., Yamashita, A., Yahata, N., Itahashi, T., Lisi, G., Yamada, T., *et al.* (2021). A multi-site, multi-disorder resting-state magnetic resonance image database. *Scientific Data*, *8*(1), Article 1.
3. Lutkenhoff, E. S., Rosenberg, M., Chiang, J., Zhang, K., Pickard, J. D., Owen, A. M., & Monti, M. M. (2014). Optimized Brain Extraction for Pathological Brains (optiBET). *PLOS ONE*, *9*(12), e115551.
4. Shen, X., Tokoglu, F., Papademetris, X., & Constable, R. T. (2013). Groupwise whole-brain parcellation from resting-state fMRI data for network node identification. *NeuroImage*, *82*, 403–415.
5. Gao, S., Mishne, G., & Scheinost, D. (2021). Nonlinear manifold learning in functional magnetic resonance imaging uncovers a low-dimensional space of brain dynamics. *Human Brain Mapping*, *42*(14), 4510–4524.
6. Caliński, T., & Harabasz, J. (1974). A dendrite method for cluster analysis. *Communications in Statistics*, *3*(1), 1–27.
7. Karahanoğlu, F. I., & Van De Ville, D. (2015). Transient brain activity disentangles fMRI resting-state dynamics in terms of spatially and temporally overlapping networks. *Nature Communications*, *6*, 7751.
8. Liu, X., Chang, C., & Duyn, J. (2013). Decomposition of Spontaneous Brain Activity into Distinct fMRI Co-activation Patterns. *Frontiers in Systems Neuroscience*, *7*.
9. Smith, S. M., Miller, K. L., Moeller, S., Xu, J., Auerbach, E. J., Woolrich, M. W., *et al.* (2012). Temporally-independent functional modes of spontaneous brain activity. *Proceedings of the National Academy of Sciences*, *109*(8), 3131–3136.
10. Shine, J. M., Breakspear, M., Bell, P. T., Ehgoetz Martens, K. A., Shine, R., Koyejo, O., *et al.* (2019). Human cognition involves the dynamic integration of neural activity and neuromodulatory systems. *Nature Neuroscience*, *22*(2), Article 2.
11. Venkatesh, M., Jaja, J., & Pessoa, L. (2019). Brain dynamics and temporal trajectories during task and naturalistic processing. *NeuroImage*, *186*, 410–423.
12. Allen, E. A., Damaraju, E., Plis, S. M., Erhardt, E. B., Eichele, T., & Calhoun, V. D. (2014). Tracking Whole-Brain Connectivity Dynamics in the Resting State. *Cerebral Cortex (New York, NY)*, *24*(3), 663–676.
13. Raichle, M. E. (2015). The Brain's Default Mode Network. *Annual Review of Neuroscience*, *38*(1), 433–447.
14. Finn, E. S. (2021). Is it time to put rest to rest? *Trends in Cognitive Sciences*, *25*(12), 1021–1032.
15. Van Essen, D. C., Smith, S. M., Barch, D. M., Behrens, T. E. J., Yacoub, E., & Ugurbil, K. (2013). The WU-Minn Human Connectome Project: An overview. *NeuroImage*, *80*, 62–79.
16. Bettinardi, R. G.(2022). computeCohen_d(x1, x2, varargin) (https://www.mathworks.com/matlabcentral/fileexchange/62957-computecohen_d-x1-x2-varargin), MATLAB Central File Exchange.