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Brain network dynamics following induced acute stress: a neural marker of psychological vulnerability to real-life chronic stress

Adva Segal[1,2,3], Marina Charquero-Ballester[1,2,3], Sharon Vaisvasser[4], Joana Cabral[1,5], Ziv Ben-Zion[6,7,8,9], Diego Vidaurre[10], Eloise Stark[1,2], Hugh McManners[3], Mark Woolrich[10], Anke Ehlers[11], Yair Bar-Haim[9,12], Talma Hendler[8] and Morten L. Kringelbach[1,2,3,13]

[1]Centre for Eudaimonia and Human Flourishing, Linacre College, University of Oxford, Oxford, UK; [2]Department of Psychiatry, University of Oxford, Oxford, UK; [3]Scars of War Foundation, The Queen's College, University of Oxford, Oxford, UK; [4]School of Society and the Arts, Ono Academic College, Kiryat Ono, Israel; [5]Life and Health Sciences Research Institute (ICVS), University of Minho, Braga, Portugal; [6]Yale School of Medicine, Yale University, New Haven, CT, USA; [7]US Department of Veterans Affairs National Center for PTSD, Clinical Neuroscience Division, VA Connecticut Healthcare System, West Haven, CT, USA; [8]Sagol Brain Institute Tel-Aviv, Wohl Institute for Advanced Imaging, Tel-Aviv Sourasky Medical Center, Tel-Aviv, Israel; [9]Sagol School of Neuroscience, Tel Aviv University, Tel Aviv, Israel; [10]Wellcome Trust Centre for Integrative NeuroImaging, Oxford Centre for Human Brain Activity (OHBA), University of Oxford, Oxford, UK; [11]Oxford Centre for Anxiety Disorders and Trauma, Department of Experimental Psychology, University of Oxford, Oxford, UK; [12]School of Psychological Sciences, Tel Aviv University, Tel Aviv, Israel and [13]Centre for Music in the Brain, Aarhus University, Aarhus, Denmark

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Corresponding author:
Adva Segal;
Email: advasegal15@gmail.com

A.S. and M.C.B. contributed equally to this work.

T.H. and M.L.K. contributed equally to this work.

Abstract

Background. Stress leads to neurobiological changes, and failure to regulate these can contribute to chronic psychiatric issues. Despite considerable research, the relationship between neural alterations in acute stress and coping with chronic stress is unclear. This longitudinal study examined whole-brain network dynamics following induced acute stress and their role in predicting chronic stress vulnerability.
Methods. Sixty military pre-deployment soldiers underwent a lab-induced stress task where subjective stress and resting-state functional magnetic resonance imaging were acquired repeatedly (before stress, after stress, and at recovery, 90 min later). Baseline depression and post-traumatic stress symptoms were assessed, and again a year later during military deployment. We used the Leading Eigenvector Dynamic Analysis framework to characterize changes in whole-brain dynamics over time. Time spent in each state was compared across acute stress conditions and correlated with psychological outcomes.
Results. Findings reveal significant changes at the network level from acute stress to recovery, where the frontoparietal and subcortical states decreased in dominance in favor of the default mode network, sensorimotor, and visual states. A significant normalization of the frontoparietal state activity was related to successful psychological recovery. Immediately after induced stress, a significant increase in the lifetimes of the frontoparietal state was associated with higher depression symptoms ($r = 0.49$, $p < .02$) and this association was also observed a year later following combat exposure ($r = 0.49$, $p < .009$).
Conclusions. This study revealed how acute stress-related neural alterations predict chronic stress vulnerability. Successful recovery from acute stress involves reducing cognitive–emotional states and enhancing self-awareness and sensory–perceptual states. Elevated frontoparietal activity is suggested as a neural marker of vulnerability to chronic stress.

Introduction

Stress triggers a chain of reactions in multiple neurobiological circuits, enabling us to cope with challenging demands. Acute stress refers to a short-term, high-intensity response to discrete events, whereas chronic stress is a prolonged condition often linked to ongoing environmental or life circumstances. Repeated exposure to stressors, such as military deployment, can transform an initially acute response into chronic stress over time. Despite extensive research on stress, the influence of acute stress responses on our ability to cope with chronic stress remains unclear. Therefore, it is important to better characterize the brain changes involved in acute stress reactivity and recovery, as well as to identify how these processes may relate to chronic stress. Here, we examined the unfolding brain process following lab-induced acute stress and its prediction of vulnerability to later real-life chronic stress. We identified the changes in brain

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network dynamics using the Leading Eigenvector Dynamic Analysis (LEiDA) framework, an advanced time-varying whole-brain network approach.

Neuroimaging studies initially focused on specific key brain regions involved in stress-related neurocircuitry processes, such as limbic regions (i.e. amygdala, insula, hypothalamus, and hippocampus) and cortical structures (i.e. the medial prefrontal cortex and the anterior cingulate cortex; e.g. Liberzon & Sripada, 2007; Rauch, Shin, & Phelps, 2006). It becomes evident that these regions systematically co-activate or co-deactivate across different demands as well as in rest (Akiki, Averill, & Abdallah, 2017; Henigsberg, Kalember, Petrović, & Šečić, 2019).

Improving upon this work, Sousa (2016) shifted the focus to larger network changes, proposing that repeated stress induces a transition from acute to chronic stress, characterized by time-dependent neural structural and functional reorganization. Specifically, Hermans, Henckens, Joëls, and Fernández (2014) described how acute stress hyperactivates the salience network (SN), a system involved in processing emotional and interoceptive information. This hyperactivation occurs at the expense of the executive control network, a frontoparietal system that supports higher cognitive functions. As the stressor subsides, this effect reverses, allowing for emotional regulation and cognitive processing (Hermans et al., 2014; Krystal & Neumeister, 2009; McEwen, 2007). While efficient recovery from acute stress is linked to resilience (Karatsoreos & McEwen, 2011), disruptions in recovery, such as prolonged SN activation at the expense of the default mode network (DMN) and executive control network, are associated with chronic stress (Akiki et al., 2017; Koch et al., 2016). However, this evidence relies primarily on cross-sectional designs, providing at best an account for stable factors for successful or unsuccessful recovery (Stark et al., 2015). The current longitudinal study aims to reveal how the brain changes over time from acute stress to recovery and how these brain patterns are associated with later psychological vulnerabilities.

Previous longitudinal functional magnetic resonance imaging (fMRI) studies have explored changes in resting-state functional connectivity (rsFC) following acute stress induction. For example, Vaisvaser et al. (2013) found that immediately after acute stress, changes in rsFC occurred, particularly in the DMN and the hippocampus and amygdala. After 2 h, the observed changes returned to pre-stress levels, except for the amygdala–hippocampal connectivity, which was sustained. Similarly, Maron-Katz et al. (2016) identified alterations in thalamo–cortical connectivity and interhemispheric connectivity in response to acute stress. Additionally, limbic neural activity following an anger-provoking event predicted stress-related symptoms a year later in the context of combat deployment (Gilam et al., 2017; Lin et al., 2017). Building on these findings, the present study hypothesizes that acute stress will be associated with distinct alterations in functional connectivity (FC) networks, particularly the frontoparietal network, DMN, and SN, which involve limbic areas (e.g. Charquero-Ballester et al., 2022). Furthermore, a failure to normalize network activation following acute stress may predict later vulnerability to chronic stress.

Crucially, however, these studies have not taken into account the whole-brain dynamics of the neuroimaging data. Instead, they have used time-averaged fMRI approaches, in which connectivity between regions within a network is based on fMRI signal averaged over several minutes. As such, these approaches may overlook a critical gap, namely the rapid changes occurring in whole-brain networks. A growing body of evidence has shown that brain connectivity is dynamic, even at rest, and shifts through recurring states of coupling among brain regions (Deco, Jirsa, & McIntosh, 2011; Hansen et al., 2015).

In the context of acute and chronic stress, it is even more crucial to identify neuronal changes over time. Therefore, rising to this challenge, the present study aims to reveal the dynamics between network connectivity during and after acute stress induction using the time-varying LEiDA framework. This method offers a proven way to analyze dynamic brain connectivity, focusing on moment-to-moment fluctuations rather than assuming stable patterns (Cabral, Kringelbach, & Deco, 2017; Vohryzek et al., 2020). It captures dynamic shifts in FC, revealing recurring states and transitions over time. Unlike sliding window techniques, it does not rely on fixed window lengths, ensuring robust estimations and the detection of short-lived neural events. By uncovering these temporal patterns, this approach provides a deeper understanding of how acute stress impacts brain networks in real time, shedding light on mechanisms like network instability or prolonged activation. One study indicated that Post-Traumatic Stress Disorder (PTSD) is related to abnormal activity of DMN sub-networks and SN, which can be normalized following therapy (Charquero-Ballester et al., 2022). Similarly, increased synchrony between the amygdala and frontal cortical regions is observed in individuals with higher perceived acute stress (Caetano et al., 2022). While there is preliminary evidence linking acute stress to whole-brain dynamics, the causal mechanism and its prediction of chronic stress remain unclear.

In the present study, we examined how the alterations of FC states in response to lab-induced stress predict vulnerability to real-life chronic stress a year later. To this end, 60 pre-deployed soldiers underwent a standardized acute stress induction task (i.e. the Trier Social Stress Test [TSST]; Kirschbaum, Pirke, & Hellhammer, 1993), in which their brain FC was recorded via resting-state functional magnetic resonance imaging (rsfMRI) at three different time points: before the acute stress induction, immediately afterward, and 90 min later (i.e. reflecting a recovery period). Moreover, to study individual differences in stress and recovery responses, participants repeatedly reported their subjective stress over the experiment. In addition, we followed up with depression and post-traumatic stress symptoms a year later, at combat deployment, a period characterized by high stress. During deployment, the participants were exposed to a wide array of real-life combat experiences (see below for description). This exploration tested whether the dynamic brain patterns that are prompted through experimental acute stress are also predictive of later vulnerability to real-life chronic stress.

We expected that the transition from acute stress to recovery would be associated with distinct alterations in FC networks. More specifically, cognitive and emotion-related networks would be deactivated at the expense of other network activation, such as the DMN (Charquero-Ballester et al., 2022; Gilam et al., 2017; Lin et al., 2017). Furthermore, we predict that an inability to normalize these brain alterations would be sensitive to inter-individual differences in psychological responses to real-life stress a year later.

Materials and methods

Participants

Participants were newly recruited combat-bound soldiers ($N = 60$, all male, $M_{\text{age}} = 18.92$; SD = 0.99, range 18–21). All participants were physically and mentally healthy and met the eligibility requirements for mandatory military service in the Israeli Defense Forces. The majority (97.9%) were born in Israel, with only one participant born in the United States. A total of 97.9% had completed 12 years of formal education, with 95.84% having matriculated. Only one participant had 18 years of formal education. All participants were fluent in Hebrew, Jewish, not religious, and unmarried. As can be seen, the sample was highly homogeneous in terms of gender, age, education, family status, birthplace, religion, language, and mental health. Given this uniformity, demographic covariates were not included in the analyses.

The inclusion criteria were (1) age between 18 and 30 years, (2) position in a military combat unit, and (3) normal or corrected-to-normal vision. All participants were involved in the same military training course. The exclusion criteria were (1) history of psychiatric or neurological disorders, (2) current use of psychoactive drugs or alcohol abuse, and (3) previous exposure to childhood abuse and/or potentially traumatic events prior to the study, assessed using a standard six-item questionnaire that inquired whether participants had been present and/or injured in a terrorist attack or a motor vehicle crash or exposed to sexual or physical assault (Wald et al., 2013). All participants were eligible based on the inclusion criteria and did not meet any of the exclusion criteria. This sample is similar to that reported by Maron-Katz et al. (2016) and Vaisvaser et al. (2013). However, due to preprocessing considerations, the present analysis includes a subgroup of 48 participants from the original 60. Specifically, six participants were excluded due to missing MRI data points, and six were excluded due to signal artifacts and limited field of view in the scanner. This resulted in a final sample of 48 participants. Self-reported depression and post-traumatic stress symptoms were available for 36 participants at the time of the MRI scan and for 40 participants a year later, at combat deployment.

During the combat training period and pre-deployment, soldiers were assigned to occasional guarding and patrol missions, typically in less challenging areas. At pre-deployment, the participants were not yet exposed to real combat. A year later, at combat deployment, participants were deployed to routine security missions in intensive conflict zones. Their activity during combat deployment included close-quarter arrests and takedowns, patrol, and riot containment (i.e. thrown stones, Molotov cocktail bombs, stabbing attempts, and occasionally receiving incoming rocket, mortar, or small-arms fire). Hence, these two time points involved a progressive increase in military-related stress, with lower stress at training, followed by much higher stress in deployment while performing combat missions on a daily basis.

Written informed consent was obtained from all participants. The study was approved by the Tel Aviv Sourasky Medical Center Ethics Committee and conformed to the Code of Ethics of the World Medical Association (Helsinki Declaration).

Stress induction task

Acute stress was induced using a component of the TSST (Kirschbaum et al., 1993) adapted for an fMRI setting (Wang et al., 2005). During the task, participants were asked to continuously subtract 13 starting from 1,022 and verbally communicate the results to an experimenter. The experimenter assessed the performance of each participant from outside of the scanner, constantly demanding faster and more accurate performance. The participants could monitor the progress of time through a timer appearing at the top-left corner of the screen. The acute stress task was preceded by a control task involving backward counting from 1,000 for 6 min, without external monitoring. Stress induction was successful as suggested by the effects on behavioral and physiological measures (e.g. heart rate and cortisol) shown in previous publications from these data (Maron-Katz et al., 2016; Vaisvaser et al., 2013).

Psychological measures

Acute stress

A subjective psychological stress rating scale was used to assess stress levels on a 9-point Likert scale. Participants were asked, ‘How stressed are you feeling right now?’ Scores ranged from 1 to 9, with higher scores indicating greater stress severity.

Depression

The Patient Health Questionnaire (PHQ-9; Kroenke, Spitzer, & Williams, 2001) is a self-report depression rating scale consisting of nine items on which the Diagnostic and Statistical Manual of Mental Disorders (DSM) diagnosis of major depression is based. Scores can range from 0 to 27, with higher scores reflecting greater depression. The PHQ-9 has good validity, test–retest reliability, and internal consistency (Kroenke et al., 2001). It has been shown to have high associations with mental health status and quality of life (Martin, Rief, Klaiberg, & Braehler, 2006). Cronbach’s α of depression symptoms in the current study was 0.81 at the time of the MRI scan and 0.86 a year later, during combat deployment.

Post-trauma

The PTSD Checklist (PCL; Weathers et al., 1993) is a 17-item self-report inventory assessing the severity of symptoms corresponding to the key symptoms of PTSD. Scores can range from 17 to 85, with higher scores reflecting greater post-traumatic stress. Symptoms were assessed in relation to participants’ exposure to combat experiences (in the wording of the ‘specific stressor’ version of the checklist). The PCL has good test–retest reliability, as well as convergent and discriminant validity (Blanchard, Jones-Alexander, Buckley, & Forneris, 1996; Norris & Hamblen, 2004). Cronbach’s α for post-traumatic stress symptoms in the current study was 0.89 both at the time of the MRI scan and a year later, during combat deployment.

Study design

The study consisted of four phases: acclimation (15 min), a first session in the MRI scanner (55 min), intermission (90 min), and a second session in the MRI scanner (30 min). In the acclimation phase, participants were given a 15-min resting period, signed the informed consent forms, and were introduced to the experimental procedure. Then, each participant underwent the first session in the MRI scanner. This scan included an anatomical scan (15 min), a baseline rsfMRI condition (‘before stress’), a control task (6 min), an acute stress induction task (6 min; described above), a second rsfMRI condition (‘after stress’), and another anatomical scan (15 min). During the intermission phase outside the scanner, participants completed questionnaires and were given a light meal. Following a 90-min rest outside the scanner, a second scanning session was conducted, including a third rsfMRI (‘recovery’ condition). Each resting scan lasted 5 min, and participants were instructed to keep their eyes open and stare at a fixation point in the center of a screen. Psychological subjective stress was evaluated at four time points: (1) after the first resting scan, (2) after the control task (both before stress induction), (3) after the acute stress task, and (4) 20 min after the stress task, following the second anatomical scan (Figure 1). The depression and post-trauma questionnaires (PHQ-9 and PCL, respectively) were administered, as well as a year later, during a combat deployment, in which soldiers were faced with protracted and repeated stressful situations.

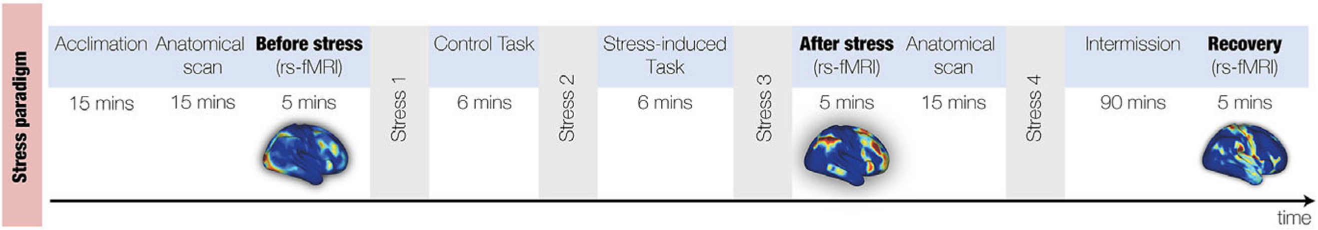

Figure 1. Overview of the study procedure. The figure shows all the parts of the experiment. For each participant, three resting-state functional resonance imaging scans (rsfMRI) were acquired during The Trier Social Stress Test: The first rsfMRI was taken before completion of any tasks ('Before stress'), a second one immediately after the stress-induced task ('After stress'), and a third and last one approximately 1 h 30 min after the stress task ('Recovery'). In addition, each participant gave four stress ratings during the study (indicated by the gray boxes).

fMRI data acquisition and preprocessing

Brain scanning was performed on a 3T (GE, HDXt) MRI scanner with an eight-channel head coil. Functional imaging was acquired with gradient echo-planar imaging sequence of T2*-weighted images (TR/TE/flip angle: 3,000/35/90; FOV: 20 cm× 20 cm; matrix size: 96 × 96) in 39 axial slices (thickness: 3 mm; gap: 0 mm), covering the whole cerebrum. Basic data preprocessing was performed using MELODIC (Beckmann & Smith, 2004) with the embedded tools MCFLIRT (Jenkinson, Bannister, Brady, & Smith, 2002) for motion correction and BET (Smith, 2002) for brain extraction, all parts of FMRIB's Software Library (http://www.fmrib.ox.ac.uk/fsl). The parameters used were defaulted, including spatial smoothing using a Gaussian kernel of FWHM 5 mm and high-pass temporal filtering with sigma = 50.0 s.

In order to make sure that we used the best possible quality neuroimaging data, we removed noise from the 4D FMRI data using FMRIB's ICA-Based Xnoiseifier (FIX; Griffanti et al., 2014; Salimi-Khorshidi et al., 2014). We followed the standard procedure where independent component analysis (ICA) components for 15 participants coming from the previous preprocessing MELODIC step and hand-labeled them according to 'signal', 'noise', or 'unknown' following the guidelines provided by Griffanti et al. (2017). The manual hand labeling on our dataset allowed for an optimized training of the FIX algorithm for this dataset. Subsequently, the classification of the components for each participant's ICA decomposition was done according to a range of thresholds (5, 10, and 15) to assess how much noise we could remove without affecting any signal components. Based on the results, a conservative threshold of 10 was chosen for this dataset.

Once the data were denoised, linear registration to their structural scans was applied followed by nonlinear registration to the MNI space. The mean Blood Oxygenation Level Dependent (BOLD) time series was then estimated on 90 brain areas of the Anatomical Automatic Labeling (AAL) atlas (Tzourio-Mazoyer et al., 2002) by averaging the BOLD signal over all voxels belonging to each brain area. Of these 90 brain regions, 4 were excluded due to signal artifacts in those regions, namely the left and right rectus (orbitofrontal cortex) and the left and right mid-temporal pole.

Dynamic functional connectivity

In order to characterize the FC between brain regions over time, we used the LEiDA framework (Cabral et al., 2017), which allows for the determination of the whole-brain dynamics in the neuroimaging data over time, but crucially without using windowing techniques. Overall, the LEiDA framework achieves this by first creating an FC map at each time point for each participant. Then we apply clustering to the leading eigenvectors of these matrices across participants and scans to find the optimum number of clusters. This is then used to characterize the whole-brain dynamics in terms of the probability of occurrence (i.e. fractional occupancy) and duration (i.e. lifetime).

More specifically, the signal of each brain region is transformed in polar coordinates as $x(t) = A(t) * \cos(\theta(n))$, and the phase, $\theta(n,t)$, is considered. Subsequently, the dynamic functional connectome $\mathrm{FC}_t(n,p)$, estimated as the phase coherence between brain areas n and p, at time t, is obtained using the following equation:

$$\mathrm{FC}_t(n,p) = \cos(\theta_t(n) - \theta_t(p)).$$

Therefore, for each time point t, the functional connectome FC_t is a matrix of phase coherence. It has been shown that the functional connectome is not static but evolves over time – therefore dynamic – and exhibits a repertoire of preferred patterns, or states, that relate to brain function. Each of these states can also be thought of as a network of brain regions that are bound to a given state. By quantifying, for each scan, the number of times these recurrent states are detected, it is possible to compare their occurrence between conditions and participants. We used a clustering algorithm (k-means) applied only to the leading eigenvector Vl_t of the matrix FC_t, to classify the states exhibited by the dynamic functional connectome into separate clusters and then quantify, for each participant, how often it 'visited' each state during the scan. Each FC state is represented by cluster centroid, which is the mean over time of all the patterns of FC_t that the clustering algorithm assigned to that state.

With this analysis, we leveraged the temporal information contained in the fMRI scans to look for modes appearing briefly and sporadically in brain activity (Vohryzek et al., 2020). It is important to note that the sign of each element in the mode is related to the separation of the system into two communities synchronized in anti-phase; therefore, when connectivity increases in one community, it decreases in the other and vice versa, and the relation of the sign with local activation/inhibition is unclear. When all elements have the same sign, it means that all elements within the system behave coherently. Moreover, the 'strength' with which brain areas belong to either of the communities is indicated through the magnitude of eigenvector elements (Newman, 2006), represented by the size of the spheres in the rendered brain plots.

Following the k-means clustering, we obtain a repertoire of K clusters/modes and information regarding the time points in which these K modes of connectivity occurred. Therefore, it is possible to calculate how often each participant spent in each of those K modes during the scan. Since we do not know a priori the level of granularity needed to detect the modes that are relevant for this study, we run the clustering into a range of K between 2 clusters (more coarse) and 20 clusters (more fine-grained).

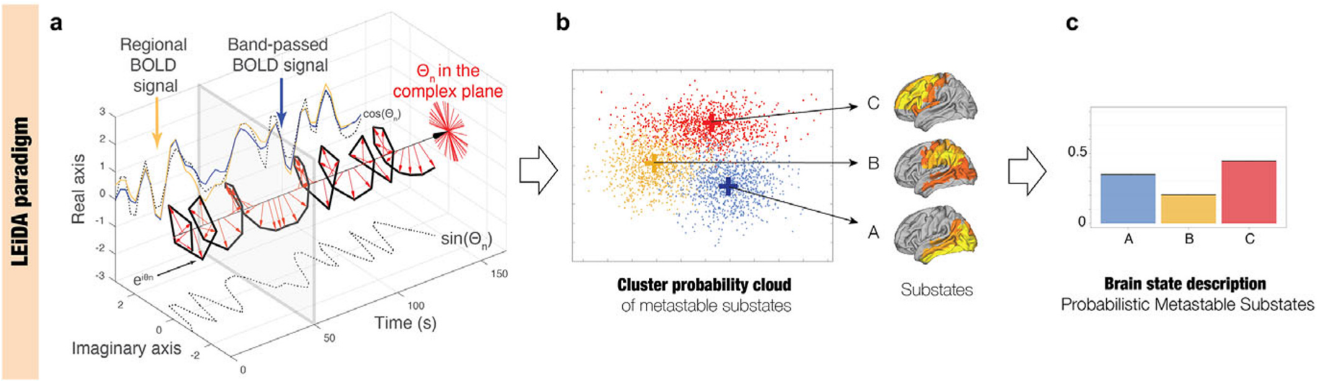

Figure 2. Time-varying characteristics of brain states. The figure shows the main component of the Leading Eigenvector Dynamic Analysis framework. (a) For every participant, we computed the phase of the BOLD signal for every timepoint for all brain regions in the Anatomical Automatic Labeling parcellation, which produces the BOLD phase coherence matrix between brain regions. (b) The leading eigenvectors for all phase coherence matrices in all participants are clustered in order to define the functional connectivity states in a given rsfMRI. (c) We compute the probabilistic metastable substate space, which captures the center of the clusters with their probability of occurrence and associated lifetimes. This framework allows for a given brain state to be accurately quantified.

Finally, each mode is characterized in terms of probability of occurrence (i.e. fractional occupancy) and duration (i.e. lifetime; see Figure 2 for an overview of the LEiDA analysis process).

The dynamic functional connectivity states

To optimize the number of FC states, we have two criteria: (1) inclusion of an FC state in which one of the two communities is dominated by regions of subcortical areas (such as limbic areas) and (2) high compactness of the set of clusters according to Dunn's Index. The first criterion guarantees the possibility of studying the role of the subcortical areas in relationship to stress from a time-varying FC perspective, complementing the results from previous studies (e.g. Charquero-Ballester et al., 2022). The second criterion optimizes the number of states according to their compactness so that each centroid is made based on the contribution of FC states that are similar between them and different from those of other clusters. Following this, the optimal compromise was estimated to be $k = 6$ states, which has the second-highest Dunn's index solution that also contained subcortical areas. Despite this one not being the clustering solution with the highest Dunn index, the algorithm was still able to reach the same index across different initializations, showing stability in the FC patterns. Of the six FC states, five resemble known resting-state networks, namely the default mode (DMN), sensorimotor, visual, frontoparietal, and subcortical networks, and a sixth state that is characterized by global covariance. Although there is no consensus on the number of FC states revealed by fMRI, the number reported in the literature generally ranges

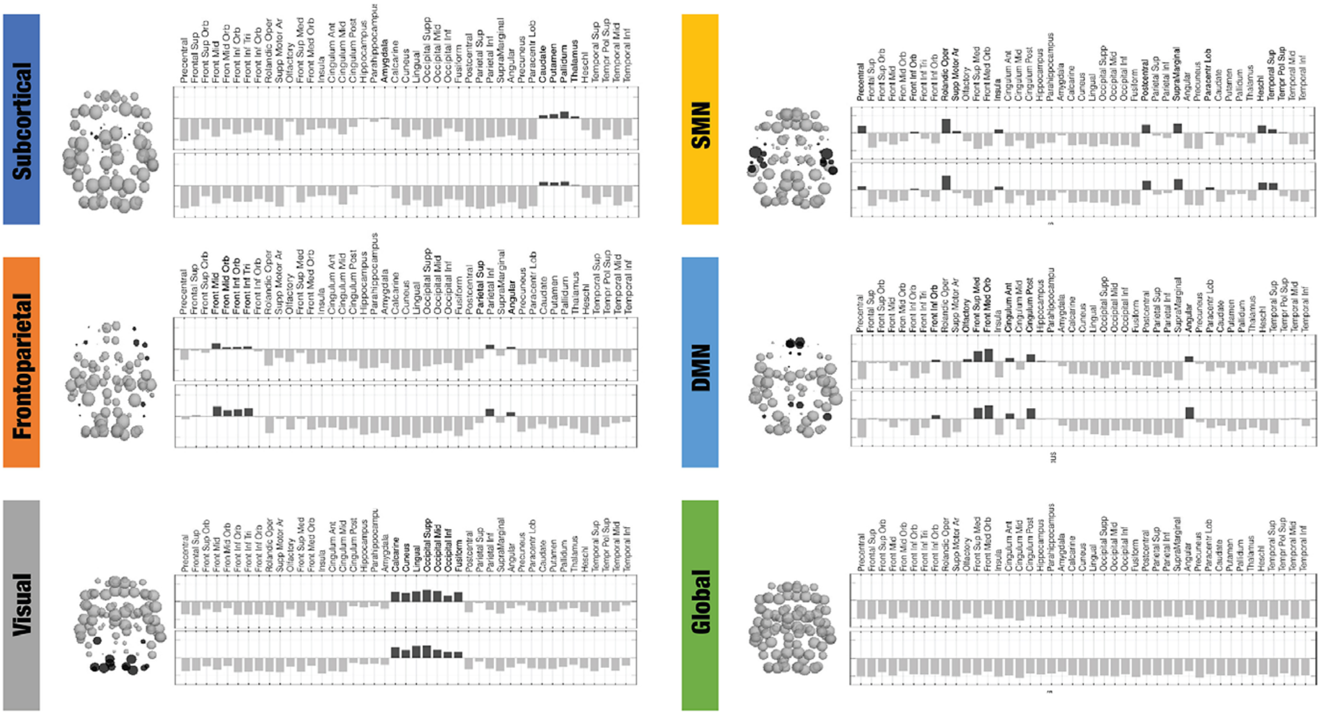

Figure 3. Functional connectivity (FC) states. The figure shows the regions involved in each of the six FC states; each brain region is illustrated by a sphere; Gray level of the sphere (light to dark) codes the community to which it belongs, while its size represents the strength with which it belongs to it. On the left, each of the brain regions is represented by a bar together with the corresponding Anatomical Automatic Labeling labels. The top bars represent the right hemisphere, and the bottom bars represent the left hemisphere.

between 5 and 20, depending on the selected criteria (Damoiseaux et al., 2006; Yeo et al., 2011). An illustration of each brain state together with its AAL labels is provided in Figure 3.

Statistical analysis

To examine how the FC states are characterized as a function of the acute stress induction, several dynamic measures were calculated for each participant across the three stress conditions (before stress, after stress, and recovery), as follows: (a) the mean duration of each FC state, referred to as *lifetime* (i.e. the mean number of consecutive epochs during which a given FC state was active) and (b) the probability of occurrence of each FC state, referred to as *fractional occupancy* (i.e. the number of epochs assigned to a specific FC state divided by the total number of epochs in each stress condition).

Repeated-measures analyses of variance (ANOVAs) were conducted to test the effect of acute stress induction on the FC and subjective stress measures (SPSS version 26). Follow-up analyses were corrected for multiple comparisons by Bonferroni correction. The Bonferroni-adjusted p-value thresholds were $p < .0033$ for FC (six levels) and $p < .0083$ for subjective stress (four levels), ensuring that the familywise error rate was controlled. In addition, to examine the relationship between the FC activity (i.e. lifetimes and fractional occupancies) and psychological vulnerability and resilience tendencies (i.e. subjective stress, depression, and post-trauma scores), simple correlations were used. These correlations were also corrected for multiple comparisons using the Bonferroni correction, with the threshold adjusted to $p < .0083$ (for six comparisons). Of note, the FC states were correlated with the changes of subjective stress from before to after stress (stress levels at time point 1 minus time point 3) and from after stress to recovery (time point 3 minus time point 4). For the LEiDA analysis, we used MATLAB version R-2017b.

Results

Psychological symptoms of stress vulnerability

ANOVA on the mean subjective stress scores yielded a main effect of time, $F(3,141) = 11.16, p < .0001, \eta_p^2 = .19$, indicating a difference between the stress conditions. Follow-up analysis revealed a significant increase in the mean stress scores from before (time point 1, Mean = 3.64, SD = 1.79; time point 2, Mean = 4.12, SD = 1.91) to after stress (time point 3, Mean = 5.23, SD = 1.94), $ps < .0001$ followed by a significant decrease in recovery (time point 4, Mean = 4.08, SD = 2.43), $p < .009$. No significant differences were found in stress scores between the two time points before the acute stress task, $p = 0.22$ (see Figure S1 in the Supplementary Material for a detailed view of the stress distribution). These findings converge with the physiological results (e.g. heart rate and cortisol) that have been reported in previous publications showing a successful stress induction (Maron-Katz et al., 2016; Vaisvaser et al., 2013).

Participants reported average depression and post-traumatic stress scores of 6.65 and 26.76 (SDs = 5.23 and 10.61, Range = 0–20 and 17–62, respectively) during lab testing, and 5.26 and 24 (SDs = 5.06 and 9.9, Range = 0–18 and 17–53, respectively) a year later, during combat deployment (see Figure S2 in the Supplementary Material for a detailed view of the depression and post-traumatic stress distributions). These relatively low symptom scores reflect the general mental health character of this sample, with only a small proportion of participants showing moderately severe to severe levels of depression (11% and 7.5% a year later; Kroenke et al., 2001), and only three participants who met the clinical cutoff in the post-traumatic stress scale (Norris & Hamblen, 2004) at both times.

The relation between FC states and subjective stress ratings

The results revealed a significant positive correlation between the lifetime of the frontoparietal state during recovery and the change in subjective stress rating from post-stress to recovery ($r = .39$, $p < .04$). This indicates that during recovery, a shorter lifetime rate of the frontoparietal state was related to a greater decrease in the subjective stress ratings from post-stress to recovery. In each of the stress conditions, neither lifetimes nor fractional occupancies of the other FC states were correlated with the subjective stress change from post-stress to recovery (all $ps > .7$). In addition, nonsignificant correlations were found between the FC states and the subjective stress change from before to after stress (all $ps > .07$).

The dynamic functional connectivity sequence of stress and recovery

Before conducting the repeated-measures ANOVA, we assessed the data to ensure compliance with the required assumptions. Outliers were evaluated using visual inspection of box plots and standardized z-scores (±3 SD), and no extreme outliers were identified. The normality of the data was tested using the Shapiro–Wilk test, which indicated that all variables were normally distributed ($ps > .05$). Based on these findings, no transformations or exclusions were necessary.

ANOVA on the mean lifetimes (i.e. the time spent in an FC state) revealed significant differences between the brain states in the three stress conditions (before stress, after stress, and recovery), indicated by the main effects of brain states ($Fs(5, 235) = 75.15, 72$, and 101.83, $ps < .0001$, $\eta_p^2s = .62, .61$ and $.68$, respectively). Follow-up analysis indicated that the global state had significantly higher lifetimes relative to the other FC states ($ps < .0001$). Moreover, in the recovery phase, the subcortical state (i.e. caudate, putamen, pallidum, thalamus, and amygdala; see **Figure 3**) had significantly lower lifetimes than the DMN and sensorimotor states ($ps < .03$ and $.01$, respectively; Figure 4a).

ANOVA on the mean fractional occupancies (i.e. the dominance of activity of an FC state) yielded significant differences between the brain states in all stress conditions ($Fs(5, 235) = 93.02, 154.61$, and 168.03, $ps < .0001$, $\eta_p^2s = .66, .77$, and $.78$, respectively). Follow-up analysis indicated that in all stress conditions, the global state had significantly higher fractional occupancies than the other FC states ($ps < .001$). Furthermore, in the recovery condition, the subcortical state had significantly lower fractional occupancies than the visual state ($p < .02$). Lastly, the frontoparietal state had significantly lower fractional occupancies than the DMN, sensorimotor, and visual states ($ps < .04, .05$, and $.006$, respectively; Figure 4b). This means that during recovery, the subcortical and the frontoparietal states are less dominant in activity.

The relation between FC states and depression scores

The findings indicated that immediately after induced stress, an increase in lifetimes of the frontoparietal state was significantly related to higher depression symptoms ($r = .49, p < .02$; Figure 5a) and a year later, following combat exposure ($r = .49$, $p < .009$; Figure 5b). Before stress, an increase in both lifetimes and fractional occupancies of the subcortical state was significantly related to higher depression ($rs = .49$, $ps < .01$ and $.02$, respectively; Figure 5c,d). However, these associations were not significant a year later, during

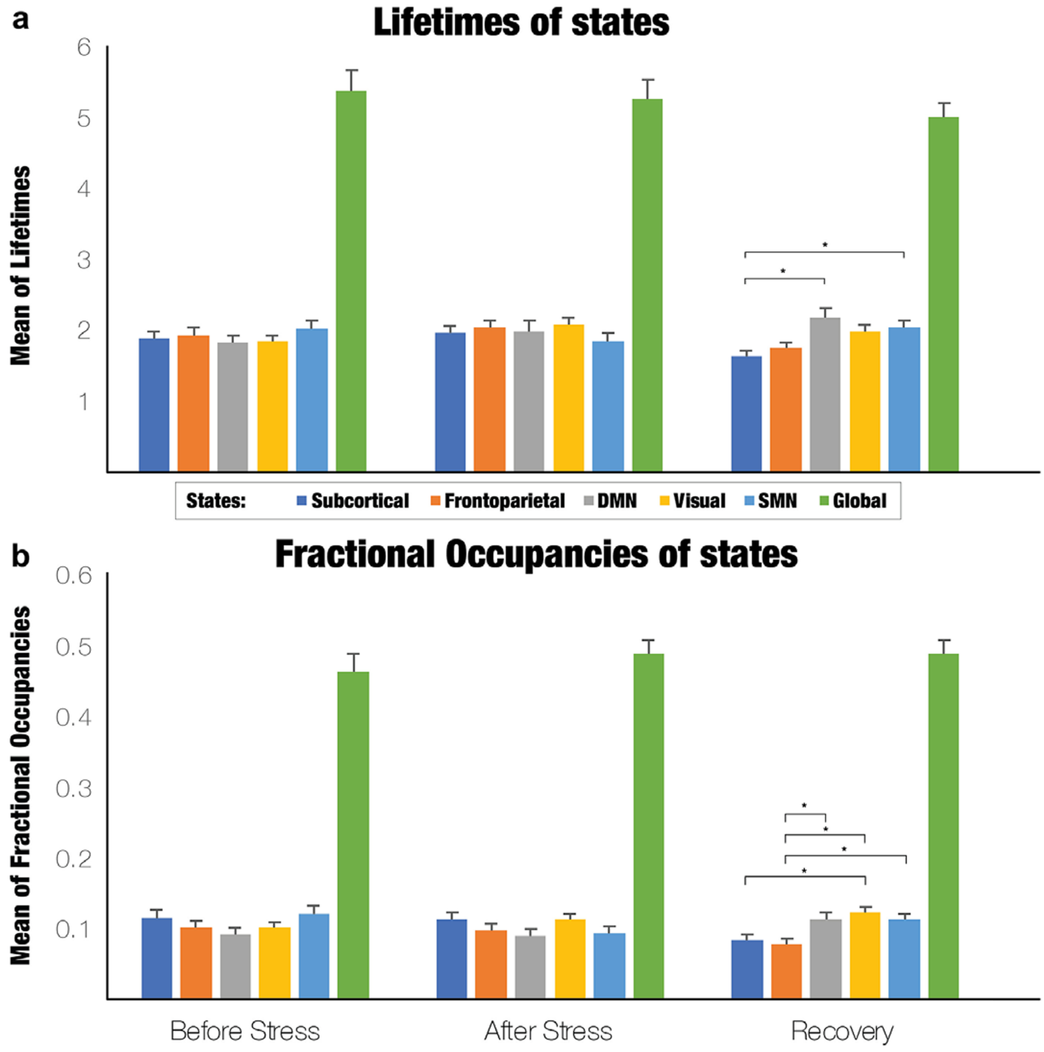

Figure 4. The recovery phase is characterized by significant differences in lifetime and fractional occupancy between the states. (a) The figure shows a plot of the duration (lifetimes) for each of the states as a function of the acute stress induction (before and after stress as well as recovery). (b) Similarly, the probabilities (fractional occupancy) are shown for each state. The stars indicate $p < 0.05$ after the Bonferroni correction. Abbreviations: DMN, default mode network; SMN, sensorimotor network.

combat deployment (*r*s = .39 and .35, *p*s > .08, respectively). Finally, during recovery, no significant correlations were found between the dynamic activation of the FC states (i.e. lifetimes and fractional occupancies) and depression symptoms (all *p*s > .18), neither a year later (all *p*s > .10).

In addition, no significant correlations were found between the dynamic activation of the FC states (i.e. lifetimes and fractional occupancies) and post-traumatic stress symptoms (all *p*s > .06), neither a year later (all *p*s > .19).

Discussion

Advanced time-varying analyses of rsfMRI during lab-induced acute stress reveal that (1) the normalization of the frontoparietal state activity is related to successful psychological recovery. (2) Overall, an investigation of the FC dynamics from acute stress to recovery (resting state measured at TP3 after 90 min) shows that frontoparietal and subcortical states decrease in dominance in favor of the DMN, sensorimotor, and visual states. (3) Lastly, elevated FC of the frontoparietal state is a risk for vulnerability to real-life chronic stress as indicated by depressive symptoms, suggesting its potential value as a biomarker for stress vulnerability.

An overall examination of the FC alterations during the stress manipulation indicates that the recovery phase involves a down-regulation of cognitive–emotional functioning states (i.e. the frontoparietal as well as the subcortical states) and an enhancement of self-awareness and sensory-perception states (i.e. DMN visual and sensorimotor states, respectively). The frontoparietal system is known to be involved with top-down emotional regulation, anchored in the medial prefrontal cortex and the orbitofrontal cortex (Cole, Repovš, & Anticevic, 2014; Habas et al., 2009; Seeley et al., 2007; Vittengl, 2017). Together, it can be assumed that a decrease in the frontoparietal state following the stressor's subsidence is an adaptive recovery mechanism, stemming from the deduction of the extensive emotional–cognitive demands. This might not coincide with Hermans et al.'s (2014) model, which postulated that the CEN, mainly comprised of frontoparietal areas, is expected to get upregulated in recovery from acute stress. The apparent contradiction can be explained by previous research showing that acute stress may have both facilitating and impairing influences on cognitive functioning. It depends on the context and

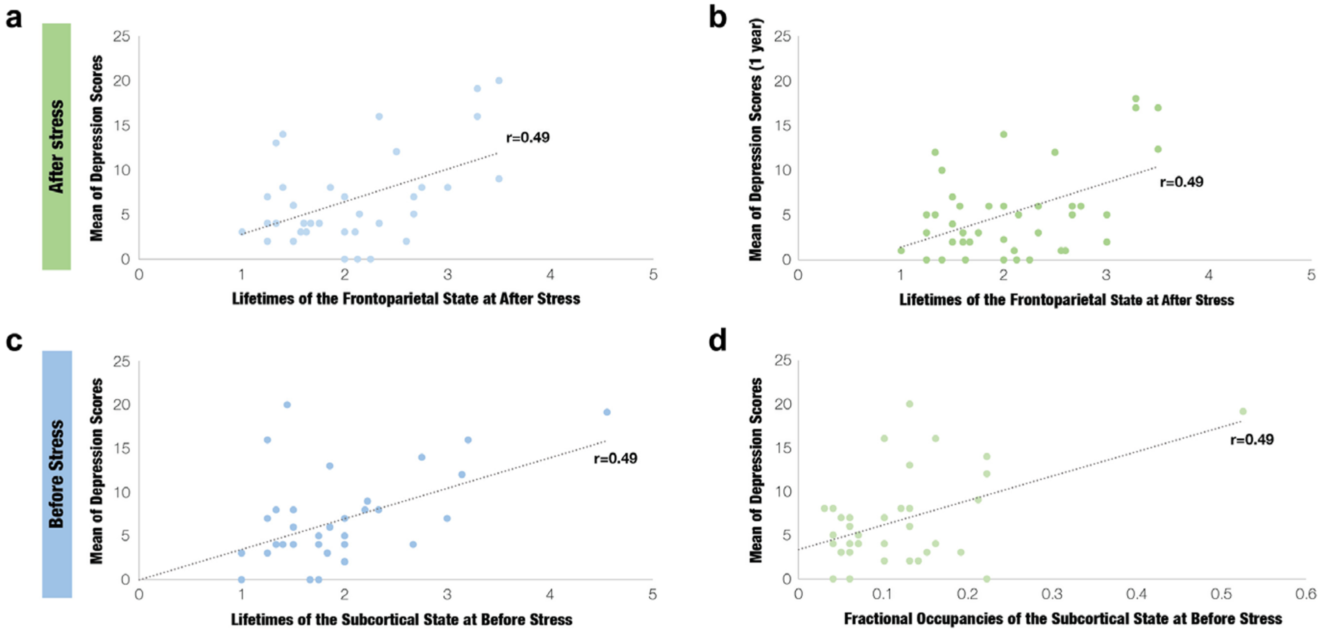

Figure 5. Significant correlations are found between dynamic state measures and mean depression scores, as well as subjective recovery changes. The figure shows the scatterplots and the slope line between the states following acute stress and psychological symptoms at different time points. (a,b) The correlation between the lifetimes of the frontoparietal state after stress and mean of depression scores, as well as a year later. (c,d) The correlation between the lifetimes and the fractional occupancies of the subcortical state at before stress and mean of depression scores.

nature of the stressor (Cole, Laurent, & Stocco, 2013; Joëls et al., 2006). Future studies could compare the dynamics of whole-brain networks under different types of stress.

The 1-year follow-up examination reveals that high activation of the frontoparietal state under induced lab stress predicts depression vulnerability when exposed to real-life chronic stressors. These findings are in line with previous research that shows that alterations in frontal cortical activity and structure immediately after exposure to severe stress are associated with the development of later chronic stress symptoms (Lyoo et al., 2011; Wang et al., 2016). Notably, our findings indicate that intense activation of the frontoparietal state in response to stress and inability to downregulate it during recovery is related to unsuccessful psychological recovery. This merges with research suggesting that the executive control system might be overloaded by the constant need to regulate elevated stress at the cost of responding to cognitive and external demands (Anticevic et al., 2012; Cole, Repovš, & Anticevic, 2014; Sato, Takenaka, & Kawahara, 2012). Hence, hyperactivation of the frontoparietal state following stress may reflect a compensatory mechanism that attempts to manage such an overload. Difficulties in normalizing this state may be a sign of a maladaptive neural process of recovery and an underlying mechanism for chronic stress maintenance (Krystal & Neumeister, 2009; McEwen, 2007; McEwen et al., 2015; Yehuda & LeDoux, 2007).

The current findings also suggest that the subcortical state, including the basal ganglia, thalamus, and amygdala, has a role in recovery following stressful manipulation. Although receiving less attention in the stress literature, the basal ganglia, together with limbic regions, comprise the SN that is responsible for vigilance-fear circuits of threats (Fragkaki, Thomaes, & Sijbrandij, 2016; Menon, 2011). Previous research suggested that the basal ganglia play a crucial role in survival-threatening situations, as it facilitates adaptive and fast responses to the stressor (Anderson & Adolphs, 2014; Berridge & Kringelbach, 2015; LeDoux, 2012; Panksepp, 2011). Moreover, it has been recently shown that the basal ganglia have an important involvement in stress-related psychopathology (Falconer et al., 2008; Krishnan et al., 2007; Linnman et al., 2011). A recent meta-analysis revealed that the regions of the basal ganglia (putamen and globus pallidum), as well as the fusiform gyrus, were at the core of the differences between PTSD and healthy trauma-exposed samples (Stark et al., 2015). The present results also indicate that increased activation of the subcortical state is linked to depression vulnerability, as observed before the stress manipulation. This is in line with previous animal and neuroimaging studies that show that elevated activity of these subcortical regions marks susceptibility to depression (Drysdale et al., 2017; Macpherson & Hikida, 2019; Russo et al., 2012).

Overall, the findings of this study highlight key aspects of emotional–cognitive models in acute and chronic stress. The observed dynamic neural process, characterized by the downregulation of cognitive–emotional states and the enhancement of self-awareness and sensory–perceptual states, reflects a recovery mechanism that could be targeted in therapeutic strategies. For instance, interventions could focus on enhancing time spent in adaptive neural states, as suggested by previous research that found that PTSD patients undergoing cognitive therapy spent more time in the DMN compared with those who did not (Charquero-Ballester et al., 2022). Furthermore, identifying individuals with persistent hyperactivation of the frontoparietal system after acute stress could inform targeted early interventions to prevent chronic stress and related mental health conditions. Future studies could further investigate how whole-brain neural dynamics differ in chronic stress-related conditions, potentially leading to the development of more precise and individualized interventions.

The present results should be considered in light of certain limitations. First, the study used a highly homogeneous and relatively resilient cohort (18-year-old male infantry soldiers), which may limit the generalizability of the findings. This homogeneity might also explain the relatively low levels of subjective stress observed during the stress induction task. These low symptom levels may have reduced the statistical power to detect significant associations with neural changes. Specifically, this could account for the lack of observed neural effects from before to after acute stress. Thus, it would be important in the future to test more divergent populations to better capture individual differences in neural reactivity to stress. Second, in the present study, we selected a solution of $k = 6$ for further analysis in detail, as this was the optimal solution with high stability of the FC patterns according to Dunn's index, and this solution comprises the subcortical FC pattern. It is still a possibility that evaluating further solutions will result in higher resolution of the states and more information. Importantly, however, a high-resolution approach involves multiple comparisons and limited statistical power. Besides, it may lead to difficulties in interpreting the meaning of the observed small FC states. As this time-varying data-driven approach is still in its infancy, it is important in the future to replicate and validate the core of our findings by conducting independent experiments using this analysis technique. Third, the sample of this study is a non-selected sample of young healthy soldiers who were exposed to ongoing combat stressors. Although highly stressful and entailing both combat situations and routine security missions, it does not reflect a specific clear-cut trauma experience as evaluated in the PCL, which is used to assess the severity of post-traumatic stress symptoms. As such, the PCL scores may lack the intensity of specific trauma, raising a question about the validity of the reported symptoms. For a better insight into the relationship between acute and post-traumatic stress, future research should test clinical populations with intense traumatic contexts. Finally, this study involved a team of experimenters conducting the performance assessment as part of the lab-induced acute stress task. While all experimenters received standardized training, variability in task delivery may have influenced participants' performance and outcome measures. Future research could explore alternative acute stress induction methods to enhance consistency and reliability.

In conclusion, the present study reveals that the frontoparietal state dynamics in response to acute stress is a precursor marker to vulnerability when coping with later chronic stress. In addition, the reduced ability of the frontoparietal state to normalize indicates unsuccessful psychological recovery. Further work is needed on the impaired dynamics of whole-brain networks in response to acute and chronic stress, as it may form potential targets for prevention and intervention solutions for stress-related disorders.

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Competing interests. The authors declare no competing interests exist.

Ethical standard. The authors assert that all procedures contributing to this work comply with the ethical standards of the relevant national and institutional committees on human experimentation and with the Helsinki Declaration of 1975, as revised in 2008.

References

Akiki, T. J., Averill, C. L., & Abdallah, C. G. (2017). A network-based neurobiological model of PTSD: Evidence from structural and functional neuroimaging studies. *Current Psychiatry Reports*, **19**, 1–10. https://doi.org/10.1007/s11920-017-0840-4

Anderson, D. J., & Adolphs, R. (2014). A framework for studying emotions across species. *Cell*, **157**, 187–200. https://doi.org/10.1016/j.cell.2014.03.003

Anticevic, A., Cole, M. W., Murray, J. D., Corlett, P. R., Wang, X. J., & Krystal, J. H. (2012). The role of default network deactivation in cognition and disease. *Trends in Cognitive Sciences*, **16**, 584–592. https://doi.org/10.1016/j.tics.2012.10.008

Beckmann, C. F., & Smith, S. M. (2004). Probabilistic independent component analysis for functional magnetic resonance imaging. *IEEE Transactions on Medical Imaging*, **23**, 137–152. https://doi.org/10.1109/TMI.2003.822821

Berridge, K. C., & Kringelbach, M. L. (2015). Pleasure systems in the brain. *Neuron*, **86**, 646–664. https://doi.org/10.1016/j.neuron.2015.02.018

Blanchard, E. B., Jones-Alexander, J., Buckley, T. C., & Forneris, C. A. (1996). Psychometric properties of the PTSD Checklist (PCL). *Behaviour Research and Therapy*, **34**, 669–673. https://doi.org/10.1016/0005-7967(96)00033-2

Cabral, J., Kringelbach, M. L., & Deco, G. (2017). Functional connectivity dynamically evolves on multiple time-scales over a static structural connectome: Models and mechanisms. *NeuroImage*, **160**, 84–96. https://doi.org/10.1016/j.neuroimage.2017.03.045

Caetano, I., Ferreira, S., Coelho, A., Amorim, L., Castanho, T. C., Portugal-Nunes, C., Miguel Soares, J., Gonçalves, N., Sousa, R., Reis, J., Lima, C., Marques, P., Silva Moreira, P., João Rodrigues, A., Correia Santos, N., Morgado, P., Magalhães, R., Picó-Pérez, M., Cabral, J., Sousa, N. (2022). Perceived stress modulates the activity between the amygdala and the cortex. *Molecular Psychiatry*, **27**, 4939–4947. https://doi.org/10.1038/s41380-022-01492-w

Charquero-Ballester, M., Kleim, B., Vidaurre, D., Ruff, C., Stark, E., Tuulari, J. J., … & Ehlers, A. (2022). Effective psychological therapy for PTSD changes the dynamics of specific large-scale brain networks. *Human Brain Mapping*, **43**, 3207–3220.

Cole, M. W., Laurent, P., & Stocco, A. (2013). Rapid instructed task learning: A new window into the human brain's unique capacity for flexible cognitive control. *Cognitive, Affective, & Behavioral Neuroscience*, **13**, 1–22. https://doi.org/10.3758/s13415-012-0125-7

Cole, M. W., Repovš, G., & Anticevic, A. (2014). The frontoparietal control system: A central role in mental health. *Neuroscientist*, **20**, 652–664. https://doi.org/10.1177/1073858414525995

Damoiseaux, J. S., Rombouts, S. A., Barkhof, F., Scheltens, P., Stam, C. J., Smith, S. M., & Beckmann, C. F. (2006). Consistent resting-state networks across healthy subjects. *Proceedings of the National Academy of Sciences of the United States of America*, **103**, 13848–13853. https://doi.org/10.1073/pnas.0601417103

Deco, G., Jirsa, V. K., & McIntosh, A. R. (2011). Emerging concepts for the dynamical organization of resting-state activity in the brain. *Nature Reviews Neuroscience*, **12**, 43–56. https://doi.org/10.1038/nrn2961

Drysdale, A. T., Grosenick, L., Downar, J., Dunlop, K., Mansouri, F., Meng, Y., et al. (2017). Resting-state connectivity biomarkers define neurophysiological subtypes of depression. *Nature Medicine*, **23**, 28–38. https://doi.org/10.1038/nm.4246

Falconer, E., Bryant, R., Felmingham, K. L., Kemp, A. H., Gordon, E., Peduto, A., et al. (2008). The neural networks of inhibitory control in posttraumatic stress disorder. *Journal of Psychiatry & Neuroscience*, **33**, 413–422. https://doi.org/10.1017/s0924270800032087

Fragkaki, I., Thomaes, K., & Sijbrandij, M. (2016). Posttraumatic stress disorder under ongoing threat: A review of neurobiological and neuroendocrine findings. *European Journal of Psychotraumatology*, **7**, Article 30915. https://doi.org/10.3402/ejpt.v7.30915

Gilam, G., Maron-Katz, A., Kliper, E., Lin, T., Fruchter, E., Shamir, R., et al. (2017). Tracing the neural carryover effects of interpersonal anger on resting-state fMRI in men and their relation to traumatic stress symptoms in a subsample of soldiers. *Frontiers in Behavioral Neuroscience*, **11**, Article 252.

Griffanti, L., Douaud, G., Bijsterbosch, J., Evangelisti, S., Alfaro-Almagro, F., Glasser, M. F., et al. (2017). Hand classification of fMRI ICA noise components. *NeuroImage*, **154**, 188–205. https://doi.org/10.1016/j.neuroimage.2016.12.036

Griffanti, L., Salimi-Khorshidi, G., Beckmann, C. F., Auerbach, E. J., Douaud, G., Sexton, C. E., et al. (2014). ICA-based artefact removal and accelerated fMRI acquisition for improved resting state network imaging. *NeuroImage*, **95**, 232–247. https://doi.org/10.1016/j.neuroimage.2014.03.034

Habas, C., Kamdar, N., Nguyen, D., Prater, K., Beckmann, C. F., Menon, V., et al. (2009). Distinct cerebellar contributions to intrinsic connectivity networks. *Journal of Neuroscience*, **29**, 8586–8594. https://doi.org/10.1523/JNEUROSCI.1868-09.2009

Hansen, E. C. A., Battaglia, D., Spiegler, A., Deco, G., & Jirsa, V. K. (2015). Functional connectivity dynamics: Modeling the switching behavior of the resting state. *NeuroImage*, **105**, 525–535. https://doi.org/10.1016/j.neuroimage.2014.11.001

Henigsberg, N., Kalember, P., Petrović, Z. K., & Šečić, A. (2019). Neuroimaging research in posttraumatic stress disorder – focus on amygdala, hippocampus and prefrontal cortex. *Progress in Neuro-Psychopharmacology and Biological Psychiatry*, **90**, 37–42. https://doi.org/10.1016/j.pnpbp.2018.11.003

Hermans, E. J., Henckens, M. J. A. G., Joëls, M., & Fernández, G. (2014). Dynamic adaptation of large-scale brain networks in response to acute stressors. *Trends in Neurosciences*, **37**, 304–314. https://doi.org/10.1016/j.tins.2014.03.006

Jenkinson, M., Bannister, P., Brady, M., & Smith, S. (2002). Improved optimization for the robust and accurate linear registration and motion correction of brain images. *Neuroimage*, **17**(2), 825–841.

Joëls, M., Pu, Z., Wiegert, O., Oitzl, M. S., & Krugers, H. J. (2006). Learning under stress: How does it work? *Trends in Cognitive Sciences*, **10**, 152–158. https://doi.org/10.1016/j.tics.2006.02.002

Karatsoreos, I. N., & McEwen, B. S. (2011). Psychobiological allostasis: Resistance, resilience and vulnerability. *Trends in Cognitive Sciences*, **15**, 576–584.

Kirschbaum, C., Pirke, K. M., & Hellhammer, D. H. (1993). The 'Trier Social Stress Test' – a tool for investigating psychobiological stress responses in a laboratory setting. *Neuropsychobiology*, **28**, 76–81. https://www.karger.com/Article/Abstract/119004

Koch, S. B. J., van Zuiden, M., Nawijn, L., Frijling, J. L., Veltman, D. J., & Olff, M. (2016). Aberrant resting-state brain activity in posttraumatic stress disorder: A meta-analysis and systematic review. *Depression and Anxiety*, **33**, 592–605. https://doi.org/10.1002/da.22478

Krishnan, V., Han, M. H., Graham, D. L., Berton, O., Renthal, W., Russo, S. J., et al. (2007). Molecular adaptations underlying susceptibility and resistance to social defeat in brain reward regions. *Cell*, **131**, 391–404. https://doi.org/10.1016/j.cell.2007.09.018

Kroenke, K., Spitzer, R. L., & Williams, J. B. W. (2001). The PHQ-9: Validity of a brief depression severity measure. *Journal of General Internal Medicine*, **16**, 606–613. https://doi.org/10.1046/j.1525-1497.2001.016009606.x

Krystal, J. H., & Neumeister, A. (2009). Noradrenergic and serotonergic mechanisms in the neurobiology of posttraumatic stress disorder and resilience. *Brain Research*, **1293**, 13–23. https://doi.org/10.1016/j.brainres.2009.03.044

LeDoux, J. (2012). Rethinking the emotional brain. *Neuron*, **73**, 653–676. https://doi.org/10.1016/j.neuron.2012.02.004

Liberzon, I., & Sripada, C. S. (2007). The functional neuroanatomy of PTSD: A critical review. *Progress in Brain Research*, **167**, 151–169. https://doi.org/10.1016/S0079-6123(07)67011-3

Lin, T., Gilam, G., Raz, G., Or-Borichev, A., Bar-Haim, Y., Fruchter, E., et al. (2017). Accessible neurobehavioral anger-related markers for vulnerability to post-traumatic stress symptoms in a population of male soldiers. *Frontiers in Behavioral Neuroscience*, **11**, Article 38.

Linnman, C., Rougemont-Bücking, A., Beucke, J. C., Zeffiro, T. A., & Milad, M. R. (2011). Unconditioned responses and functional fear networks in human classical conditioning. *Behavioural Brain Research*, **221**, 237–245. https://doi.org/10.1016/j.bbr.2011.02.045

Lyoo, I. K., Kim, J. E., Yoon, S. J., Hwang, J., Bae, S., & Kim, D. J. (2011). The neurobiological role of the dorsolateral prefrontal cortex in recovery from trauma: Longitudinal brain imaging study among survivors of the South Korean subway disaster. *Archives of General Psychiatry*, **68**, 701–713. https://doi.org/10.1001/archgenpsychiatry.2011.70

Macpherson, T., & Hikida, T. (2019). Role of basal ganglia neurocircuitry in the pathology of psychiatric disorders. *Psychiatry and Clinical Neurosciences*, **73**, 289–301. https://doi.org/10.1111/pcn.12830

Maron-Katz, A., Vaisvaser, S., Lin, T., Hendler, T., & Shamir, R. (2016). A large-scale perspective on stress-induced alterations in resting-state networks. *Scientific Reports*, **6**, Article 21503. https://doi.org/10.1038/srep21503

Martin, A., Rief, W., Klaiberg, A., & Braehler, E. (2006). Validity of the Brief Patient Health Questionnaire Mood Scale (PHQ-9) in the general population. *General Hospital Psychiatry*, **28**, 71–77. https://doi.org/10.1016/j.genhosppsych.2005.07.003

McEwen, B. S. (2007). Physiology and neurobiology of stress and adaptation: Central role of the brain. *Physiological Reviews*, **87**, 873–904. https://doi.org/10.1152/physrev.00041.2006

McEwen, B. S., Bowles, N. P., Gray, J. D., Hill, M. N., Hunter, R. G., Karatsoreos, et al. (2015). Mechanisms of stress in the brain. *Nature Neuroscience*, **18**, 1353–1363. https://doi.org/10.1038/nn.4086

Menon, V. (2011). Large-scale brain networks and psychopathology: A unifying triple network model. *Trends in Cognitive Sciences*, **15**, 483–506. https://doi.org/10.1016/j.tics.2011.08.003

Newman, M. E. J. (2006). Finding community structure in networks using the eigenvectors of matrices. *Physical Review E*, **74**, Article 036104. https://doi.org/10.1103/PhysRevE.74.036104

Norris, F. H., & Hamblen, J. L. (2004). Standardized self-report measures of civilian trauma and PTSD. In J. P. Wilson & T. M. Keane (Eds.), *Assessing Psychological Trauma and PTSD* (pp. 63–102). The Guilford Press.

Panksepp, J. (2011). The basic emotional circuits of mammalian brains: Do animals have affective lives? *Neuroscience & Biobehavioral Reviews*, **35**, 1791–1804. https://doi.org/10.1016/j.neubiorev.2011.08.003

Rauch, S. L., Shin, L. M., & Phelps, E. A. (2006). Neurocircuitry models of posttraumatic stress disorder and extinction: Human neuroimaging research-past, present, and future. *Biological Psychiatry*, **60**, 376–382. https://doi.org/10.1016/j.biopsych.2006.06.004

Russo, S. J., Murrough, J. W., Han, M. H., Charney, D. S., & Nestler, E. J. (2012). Neurobiology of resilience. *Nature Neuroscience*, **15**, 1475–1484. https://doi.org/10.1038/nn.3234

Salimi-Khorshidi, G., Douaud, G., Beckmann, C. F., Glasser, M. F., Griffanti, L., & Smith, S. M. (2014). Automatic denoising of functional MRI data: Combining independent component analysis and hierarchical fusion of classifiers. *NeuroImage*, **90**, 449–468. https://doi.org/10.1016/j.neuroimage.2013.11.046

Sato, H., Takenaka, I., & Kawahara, J. I. (2012). The effects of acute stress and perceptual load on distractor interference. *The Quarterly Journal of Experimental Psychology*, **65**, 617–623. https://doi.org/10.1080/17470218.2011.648944

Seeley, W. W., Menon, V., Schatzberg, A. F., Keller, J., Glover, G. H., Kenna, H., et al. (2007). Dissociable intrinsic connectivity networks for salience processing and executive control. *Journal of Neuroscience*, **27**, 2349–2356. https://doi.org/10.1523/JNEUROSCI.5587-06.2007

Smith, S. M. (2002). Fast robust automated brain extraction. *Human Brain Mapping*, **17**, 143–155. https://doi.org/10.1002/hbm.10062

Sousa, N. (2016). The dynamics of the stress neuromatrix. *Molecular Psychiatry*, **21**, 302–312. https://doi.org/10.1038/mp.2015.196

Stark, E. A., Parsons, C. E., Van Hartevelt, T. J., Charquero-Ballester, M., McManners, H., Ehlers, A., et al. (2015). Post-traumatic stress influences the brain even in the absence of symptoms: A systematic, quantitative meta-analysis of neuroimaging studies. *Neuroscience & Biobehavioral Reviews*, **56**, 207–221. https://doi.org/10.1016/j.neubiorev.2015.07.007

Tzourio-Mazoyer, N., Landeau, B., Papathanassiou, D., Crivello, F., Etard, O., Delcroix, N., et al. (2002). Automated anatomical labeling of activations in SPM using a macroscopic anatomical parcellation of the MNI MRI single-subject brain. *NeuroImage*, **15**, 273–289. https://doi.org/10.1006/nimg.2001.0978

Vaisvaser, S., Lin, T., Admon, R., Podlipsky, I., Greenman, Y., Stern, N., et al. (2013). Neural traces of stress: Cortisol related sustained enhancement of amygdala–hippocampal functional connectivity. *Frontiers in Human Neuroscience*, **7**, Article 313. https://doi.org/10.3389/fnhum.2013.00313

Vittengl, J. R. (2017). Who pays the price for high neuroticism? Moderators of longitudinal risks for depression and anxiety. *Psychological Medicine*, **47**, 1794–1805. https://doi.org/10.1017/S0033291717000253

Vohryzek, J., Deco, G., Cessac, B., Kringelbach, M. L., & Cabral, J. (2020). Ghost attractors in spontaneous brain activity: Recurrent excursions into functionally relevant BOLD phase-locking states. *Frontiers in Systems Neuroscience*, **14**, Article 20.

Wald, I., Degnan, K. A., Gorodetsky, E., Charney, D. S., Fox, N. A., Fruchter, E., et al. (2013). Attention to threats and combat-related posttraumatic stress symptoms: prospective associations and moderation by the serotonin transporter gene. *JAMA Psychiatry*, **70**, 401–408.

Wang, J., Rao, H., Wetmore, G. S., Furlan, P. M., Korczykowski, M., Dinges, D. F., et al. (2005). Perfusion functional MRI reveals cerebral blood flow pattern under psychological stress. *Proceedings of the National Academy of Sciences of the United States of America*, **102**, 17804–17809. https://doi.org/10.1073/pnas.0503082102

Wang, X., Xie, H., Cotton, A. S., Duval, E. R., Tamburrino, M. B., Brickman, K. R., et al. (2016). Preliminary study of acute changes in emotion processing in trauma survivors with PTSD symptoms. *PLoS One*, **11**, Article e0159065. https://doi.org/10.1371/journal.pone.0159065

Weathers, F., Litz, B., Herman, D., Huska, J., & Keane, T. (1993). The PTSD Checklist (PCL): Reliability, validity, and diagnostic utility. In *Annual convention of the International Society for Traumatic Stress Studies*, San Antonio, TX.

Yehuda, R., & LeDoux, J. (2007). Response variation following trauma: A translational neuroscience approach to understanding PTSD. *Neuron*, **56**, 19–32. https://doi.org/10.1016/j.neuron.2007.09.006

Yeo, B. T., Krienen, F. M., Sepulcre, J., Sabuncu, M. R., Lashkari, D., Hollinshead, M., … Buckner, R. L. (2011). The organization of the human cerebral cortex estimated by intrinsic functional connectivity. *Journal of Neurophysiology*, **106**, 1125–1165. https://doi.org/10.1152/jn.00338.2011