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Differences in interference processing and frontal brain function with climate trauma from California's deadliest wildfire

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Abstract

As climate change accelerates extreme weather disasters, the mental health of the impacted communities is a rising concern. In a recent study of 725 Californians we showed that individuals that were directly exposed to California's deadliest wildfire, the Camp Fire of 2018, had significantly greater chronic symptoms of post-traumatic stress disorder, anxiety and depression than control individuals not exposed to the fires. Here, we study a subsample of these individuals: directly exposed (n = 27), indirectly exposed (who witnessed the fire but were not directly impacted, n = 21), versus age and gender-matched non-exposed controls (n = 27). All participants underwent cognitive testing with synchronized electroencephalography (EEG) brain recordings. In our sample, 67% of the individuals directly exposed to the fire reported having experienced recent trauma, while 14% of the indirectly exposed individuals and 0% of the non-exposed controls reported recent trauma exposure. Fire-exposed individuals showed significant cognitive deficits, particularly on the interference processing task and greater stimulus-evoked fronto-parietal activity as measured on this task. Across all subjects, we found that stimulus-evoked activity in left frontal cortex was associated with overall improved interference processing efficiency, suggesting the increased activity observed in fire exposed individuals may reflect a compensatory increase in cortical processes associated with cognitive control. To the best of our knowledge this is the first study to examine the cognitive and underlying neural impacts of recent climate trauma.

Introduction

As the temperature of the planet warms as a result of unchecked emissions, weather extremes and environmental disasters such as the wildfires are becoming increasingly more commonplace [1,2]. The annual western forest-fire area in the US has increased by ~1000% from 1984 to 2017, so much so that California now has a designated annual fire season [3,4].

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Climate change accelerated weather extremes and disasters such as the California wildfires are taking a huge toll on human health [5,6]. More recently, we have shown notable mental health sequelae of the wildfires, including significantly greater traumatic experience reports, and symptoms of anxiety and depression in communities impacted by California's deadliest wildfire, the Camp Fire of 2018 [7]. These findings dovetail with significant psychological impacts noted after extreme climate events [8–14]. Warming temperatures have been further linked to greater suicide rates [15].

In this context, while mental health self-reports provide one dimension of insight, it is not understood how objective cognitive performance and underlying brain function is impacted in climate-stressed communities. Cognitive performance assays measure the ability to pay selective attention to goal-relevant information as well as process and ignore irrelevant distractions [16–18]. Working memory builds upon these basic cognitive abilities, wherein attended information can be maintained and manipulated for brief periods of time [19]. Crucial to these cognitive abilities is brain activity in frontal and parietal brain regions that enables moment-to-moment cognitive control [20–23]. Investigation of post-climate disaster neuro-cognitive impacts can provide important mechanistic insights into rehabilitation priorities, yet has not been studied to-date.

Here, we use a standardized, validated, and rapidly deployable neuro-cognitive platform, the *BrainE* platform [24,25], to investigate several dimensions of cognitive performance in a community sample of individuals impacted by the 2018 Camp Fire. This neuro-cognitive platform was designed for user-friendly and feasible community-deployment and includes core cognitive tasks that can be sensitive to changes in mental health observed in a climate change affected community sample. Per our prior research, symptoms of post-traumatic stress disorder (PTSD), anxiety and depression are observed in the Camp Fire affected community [7]. Much cognitive research shows that these mental health problems can be associated with changes in selective attention [26,27], response inhibition [28,29], working memory [30–32], as well as processing of interference from either sensory [33,34] or emotional distractions [35–38]. Hence, the *BrainE* platform implements an assessment suite of these specific tasks, while also limiting the total number of tasks to this set to keep the overall participation burden low. All *BrainE* platform cognitive tasks are synchronized with simultaneous electroencephalography (EEG) readily allowing measurement of underlying neural function. Here, we hypothesized that chronic cognitive impacts would be observed in the wildfire exposed, potentially trauma-enriched individuals, i.e. impacts notable in assays 6–12 months after the fire experience. We further hypothesized that these cognitive impacts may be associated with underlying differences in brain function particularly in notable fronto-parietal brain regions that dictate cognitive control.

Materials and methods

Participants

This study included 75 participants (mean age: 24.57 ± 6.20 years, range: 18–47 years, 63 females), who provided cognitive and neural data and were a subset of participants sampled in our previous wildfire study [39]. All participants were sampled within 6–12 months after the 2018 Camp Fire in Northern California, i.e. all study data was collected prior to the COVID-19 pandemic period. This sample included three groups of participants: directly exposed to the wildfire (n = 27), indirectly exposed to the wildfire (n = 21), and non-exposed controls who were age and gender-matched to the directly exposed group (n = 27). The groups were classified based on self-reports on the Life Events Checklist 5 [39], i.e., in the context of the fire, the three groups responded as 'happened to me personally' for the directly exposed group, 'witnessed it happen to someone else' for the indirectly exposed group, and 'learned about it or not applicable' for non-exposed controls, respectively.

All participants provided written informed consent for the study approved by the local university Institutional Review Board (IRB). Specifically, the directly and indirectly exposed participants were located at California State University (CSU) at Chico, within 10–15 miles of the Camp Fire, and were approved by the CSU Chico IRB#22838, while non-exposed controls were located in the San Diego region, 600 miles away from the Camp Fire, and were approved by the University of California, San Diego IRB#180140.

The majority of participants (95%) were right-handed. All participants had normal/corrected-to-normal vision and hearing and no participant reported color blindness. All participants had at least a high-school education.

Sample size and power

Our sample size was adequately powered to detect medium effect size group differences (Cohen's $d>0.5$) at beta of 0.8 and alpha significance level of 0.05 as calculated using the G*Power software [40].

Demographics

All participants provided demographic information by self-report including age, gender, and ethnicity. Socio-economic status was measured on the Family Affluence Scale [41]; this scale measures individual wealth based on ownership of objects of value (e.g., car/computer) and produces a composite score ranging from 0 (low affluence) to 9 (high affluence).

Mental health

All participants self-reported whether they had experienced recent trauma as per the standard PTSD checklist screen ("were you recently bothered by a past experience that caused you to believe you would be injured or killed?" 1: Not bothered at all, 2: Bothered a little, 3: Bothered a lot) [42]. Participants rated anxiety symptoms on the Generalized Anxiety Disorder: GAD7 scale [43] and depression symptoms on the Patient Health Questionnaire: PHQ9 scale [44].

Cognitive assessments

Study participants completed cognitive assessments in a single in-person visit; these data were available for all but one participant in the directly exposed group that had missing data. Cognitive assessments were deployed on the Unity-based *BrainE* platform administered on a Windows-10 laptop at a comfortable viewing distance [24]. The Lab Streaming Layer (LSL) protocol was used to timestamp all stimuli and response events in all cognitive assessments [45]. Each cognitive assessment session lasted ~40 minutes and consisted of cognitive assessments for selective attention, response inhibition, interference processing, working memory and emotion interference processing. **Fig 1** shows the stimulus sequence in each task. All cognitive tasks had a standard trial structure of 500 ms central fixation "+" cue followed by task-specific stimulus presented for task-specific duration and with a task-specific response window. All stimuli were presented in a shuffled order across trials. Response in every task trial was followed by standard response feedback for accuracy as a smiley or sad face emoticon, presented 200 ms post-response for 200 ms duration, followed by a 500 ms inter-trial interval (ITI). At the end of each task block, participants received a percent block accuracy score with a series of happy face emoticons (up to 10) to promote engagement.

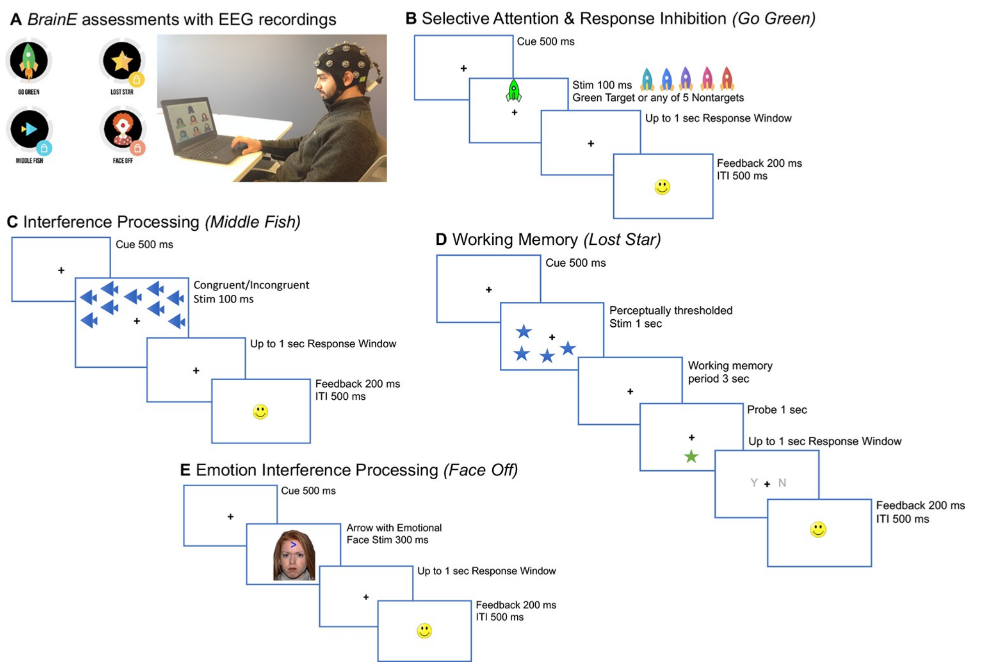

Fig 1. Cognitive assessments delivered on the *BrainE* platform. (A) *BrainE* assessment dashboard with the wireless EEG recording setup. (B) The selective attention and response inhibition tasks differ only in the frequency of targets; sparse 33% targets needing a response appear in the Selective Attention task block, while frequent 67% targets appear in the Response Inhibition task block. (C) In the Flanker interference processing task flanking fish may either face the same direction as the middle fish on congruent trials, or the opposite direction on incongruent trials. (D) The working memory task is presented with perceptually thresholded stimuli. (E) The emotion interference processing task presents neutral, happy, sad, or angry faces superimposed on the arrow, whose direction is discriminated by participants.

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1. Selective attention & response inhibition. Participants accessed the game-like task, "Go Green" modeled after the standard test of variables of attention [46]. In this simple two-block task, colored rockets were presented either in the upper/lower central visual field. Participants were instructed to respond to green colored rocket targets and ignore, i.e., withhold their response to distracting rockets of five other iso-luminant colors (shades of cyan, blue, purple, pink, orange). Post-fixation cue, a target/non-target stimulus appeared for 100 ms duration, followed by up to a 1 sec response window followed by emoticon feedback. To further reinforce fast and accurate responding within 100–400 ms, two happy face emoticons were simultaneously presented during the feedback period [47]. Both task blocks had 90 trials lasting 5 min each, and a brief practice period of 4 trials preceded the main task blocks. In the first task block, green rocket targets were sparse (33% of trials), hence, selective attention was engaged as in a typical continuous performance attention task. In the second block, green rocket targets were frequent (67% of trials), hence, participants developed a prepotent impulse to respond. As individuals must intermittently suppress a motor response to sparse non-targets (33% of trials), this block provided a metric of response inhibition [48,49].

2. Interference processing. Participants accessed the game-like task, "Middle Fish", which was an adaptation of the Flanker assessment [50,51]. Post-fixation on each trial, participants viewed an array of fish presented either in the upper or lower central visual field for 100 ms. On each trial, participants had a 1 sec response window to detect the direction of the middle fish in the set (left or right) while ignoring the flanking distractor fish that were either congruent or incongruent to the middle fish, i.e., faced the same or opposite direction to the middle fish. 50% of task trials had congruent distractors and 50% were incongruent. A brief practice of 4-trials preceded the main task of 96 trials presented over two blocks for a total task time of 8 min.

3. Working memory. Participants accessed a game-like task, "Lost Star", which was based on the visuo-spatial Sternberg task [52]. Post-fixation cue on each trial, participants viewed a spatially distributed test array of objects (i.e., a set of blue stars) for 1 sec. Participants were required to maintain the locations of these stars for a 3 sec delay period, utilizing their working memory. A probe object (a single green star of 1 sec duration) was then presented in either the same spot as one of the original test stars, or in a different spot than any of the original test stars. The participant was instructed to respond whether the probe star had the same or different location as one of the test stars. We implemented this task at the threshold perceptual span for each participant, which was defined by the number of test star objects that the individual could correctly encode without any working memory delay. For this, a brief perceptual thresholding period preceded the main working memory task, allowing for equivalent perceptual load to be investigated across participants [51]. During thresholding, the set size of test stars increased progressively from 1–8 stars based on accurate performance where 100% accuracy led to an increment in set size; <100% performance led to one 4-trial repeat of the same set size and any further inaccurate performance aborted the thresholding phase. The final set size at which 100% accuracy was obtained was designated as the individual's perceptual threshold. Post-thresholding, the working memory task consisted of 48 trials presented over 2 blocks [53] with total task duration of 6 min.

4. Emotion interference processing. Participants accessed the game-like assessment, "Face Off", adapted from studies of attentional bias in emotional contexts [54,55]. The task integrated a standardized set of culturally diverse faces from the NimStim database [56]. We used an equivalent number of male and female faces, each face with four sets of emotions, either neutral, positive (happy), negative (sad) or threatening (angry), presented on an equivalent number of trials in each task block. Post-fixation cue on each trial, participants viewed an emotional face with a superimposed arrow of 300 ms duration. The arrow occurred in either the upper or lower central visual field on equal number of trials, and participants responded to the direction of the arrow (left/right) within an ensuing 1 sec response window. Participants completed 144 trials presented over three equipartitioned blocks; a practice set of 4-trials preceded the main task. The total task duration was 10 min.

Electroencephalography (EEG). EEG data were collected in conjunction with all cognitive tasks using a 24-channel system with saline-soaked electrodes and electrode locations as per the 10–20 system attached to a wireless SMARTING^{TM} amplifier. Signals were acquired at 500 Hz sampling frequency at 24-bit resolution. The LSL protocol was used to time-stamp EEG markers and integrate cognitive markers [45], and files were stored in xdf format. Neural data were obtained from 18 of 27 participants in the directly exposed group, 14 of 21 participants in the indirectly exposed group, and all 27 participants in the control group.

Behavioral analysis. Behavioral data for all cognitive tasks were analyzed for signal detection sensitivity, d', computed as z(Hits)-z(False Alarms) [57]; all d' values were divided by max theoretical d' of 4.65 to obtain scaled d' in the 0–1 range. Cognitive task speeds were calculated as log(1/RT), where RT is response time in seconds; longer RTs have less speed while shorter RTs have higher speed. For the working memory task, perceptual span was also calculated. All metrics were checked for >5sd outliers (null found), and verified for normal distributions prior to statistical analyses.

Neural analysis. A uniform processing pipeline was applied to EEG data based on the cognitive event markers. The pipeline included data pre-processing and computation of event related potentials (ERPs) at scalp channels.

Data pre-processing utilized the EEG processing software EEGLAB toolbox in MATLAB [58]. EEG data were first resampled at 250 Hz and filtered in the 1-45Hz range to exclude ultraslow DC drifts at <1Hz and high-frequency noise produced by muscle movements and external electrical sources at >45Hz. EEG data were average electrode referenced and epoch to cognitive task-relevant stimuli based on the LSL timestamps, within the -1.0 to +1.0 sec event time window. The epoch data were then cleaned using the *autorej* function of EEGLAB, which automatically removes noisy trials (>5sd outliers rejected over max 8 iterations). EEG data were further cleaned by excluding signals estimated to be originating from non-brain sources, such as electro-oculographic, electromyographic or unknown sources, using the Sparse Bayesian learning (SBL) algorithm (https://github.com/aojeda/PEB) explained below [59,60]. We verified that for cleaned data, channel peak activity in individual participant data did not exceed 5 standard deviations from average channel activity across all subjects. ERPs were then computed as trial averaged activity at each scalp channel using the -750 ms to -550 ms time window prior to stimulus presentation as the baseline. Scalp topographies were plotted in the peak post-stimulus time window.

Statistical analyses. Demographic characteristics and mental health data were compared between groups using χ^2 (Chi-Square) statistics derived from non-parametric group comparisons.

Cognitive performance metrics of d' and speed were compared across tasks using repeated measures analyses of variance (rm-ANOVA) with within-subject factor of task-type and between-subjects factor of group. An omnibus rm-ANOVA including task-type as within-subject factor was used instead of separate comparisons for each task because all tasks together can be regarded as part of global cognitive functioning. The Greenhouse-Geisser correction was applied to adjust for lack of sphericity. Effect sizes were calculated and reported for all group ANOVA comparisons as partial eta squared in SPSS: $\eta^2 < 0.06$ small, 0.06–0.14 medium, and $\geq$0.14 large [61]. Post-hoc ttests were conducted to compare individual group differences with FDR (False Discovery Rate) corrections applied for multiple comparisons across tasks and groups. Effect sizes for all ttest results were reported using the Cohen's d measure, 0.2: small; 0.5: medium; 0.8: large [61]. The working memory span measure was compared across groups using the non-parametric Kruskal-Wallis test.

ERP neural responses were selectively analyzed on tasks that showed cognitive performance differences between groups, specifically the interference processing task (see Results). Activity in the peak post-stimulus time window was compared between groups using unpaired ttests with permutation testing applied to correct for multiple comparisons across time. For this, 100 iterations of random permutations were performed across the time vector; only continuous time segments that survived significance at $p < .05$ using permutation testing (>97.5%le of the right tail of the random vector permutation distribution) were reported [62]. Neural activity ttest effect sizes were reported using Cohen's d.

Peak ERP activity was related to behavior using partial correlations accounting for fire-exposure group or other variable of interest such as recent trauma. The partial correlation coefficient (rho) follows standard effect sizes, 0.1: small; 0.3: medium; 0.5 large.

Results

Demographics and mental health

Comparisons between the three subject groups are shown in Table 1. Age, gender and SES scores did not differ between the three groups. Only self-reported ethnicity differences emerged as significant, given the larger percentage of Asian participants in the unexposed control group, consistent with the local demographic distribution of the groups.

Table 1. Demographic characteristics & self-reported mental health for participants by group.

Demographics & Mental Health	Directly exposed (n = 27)	Indirectly exposed (n = 21)	Not exposed (n = 27)	p-value
	Mean ± Std	Mean ± Std	Mean ± Std	
Age	24.4 ± 5.9	25.7 ± 7.0	23.9 ± 5.9	0.59
Gender n (%)				0.90
Male	4 (14.8)	4 (19.0)	4 (14.8)	
Female	23 (85.2)	17 (81.0)	23 (85.2)	
Ethnicity n (%)				
Caucasian	21 (77.8)	12 (57.1)	8 (29.6)	0.004
Black/African American	1 (3.7)	0 (0)	0 (0)	
Asian	0 (0)	2 (9.5)	11 (40.7)	
More than one ethnicity	4 (14.8)	5 (23.8)	6 (22.2)	
Other	1 (3.7)	2 (9.5)	2 (7.4)	
SES	4.0 ± 1.7	4.0 ± 1.7	4.9 ± 2.0	0.59
Recent Trauma	18 (66.7)	3 (14.3)	0 (0)	< .001
Anxiety (GAD7)	10.1 ± 6.6	9.7 ± 5.2	3.2 ± 2.1	0.004
Depression (PHQ9)	8.9 ± 6.5	11.8 ± 6.1	2.6 ± 2.1	0.012

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For mental health reports, there were significantly more individuals who reported experience of recent trauma in the directly exposed group (directly exposed: 66.7%, indirectly exposed: 14.3%, not exposed: 0%, $p < .001$). Anxiety and depression symptom scores were significantly greater in the directly and indirectly exposed groups, in the range of mild to moderate symptom levels, relative to no symptoms in the control group; in post-hoc tests the directly and indirectly exposed groups did not differ in anxiety ($p>0.8$) or depression symptoms ($p>0.1$). These results were overall consistent with our larger 725 person study of mental health reports in this population [7].

Cognitive performance

Performance metrics are reported in Table 2. Signal detection sensitivity (scaled d') and speed measures are reported for each of the five cognitive assessments: selective attention, response inhibition, interference processing, working memory and emotion interference processing.

Repeated measures ANOVAs were conducted on the d' and speed measures. In the d' rm-ANOVA, we observed a significant effect of group ($F_{2,71} = 4.29$, $p = 0.017$, $\eta^2 = 0.11$), a significant effect of task ($F_{4,284} = 64.91$, $p < 0.001$, $\eta^2 = 0.48$), but the group by task interaction was not significant ($F_{8,284} = 1.62$, $p = 0.152$, $\eta^2 = 0.04$). For speed, we only observed a significant effect of task ($F_{4,284} = 22.16$, $p < 0.001$, $\eta^2 = 0.24$); the group effect for speed as well as the group by task interactions were non-significant ($p>0.6$). For the working memory task, we additionally compared item span across groups but there were no significant differences in span ($p>0.5$).

We conducted post-hoc ttests on the scaled-d' measure, which showed a significant group effect in the rm-ANOVA, and fdr-corrected these for multiple comparisons across five tasks and three group comparisons. We wanted to explore these outcomes despite no group x task interaction in the rm-ANOVA, given the observations were made in this first of its kind climate trauma study. Results showed that only interference processing d' measures significantly differed across the fire-exposed versus control groups (directly exposed vs. controls: $t(51) = -3.27$, $p = 0.002$, Cohen's $d = 0.91$; indirectly exposed vs. controls: $t(46) = -2.76$, $p = 0.01$, Cohen's $d = 0.87$) but that there was no significant difference between the two fire-exposed groups on this measure (directly vs. indirectly exposed: $p = 0.48$). All other task d' measures

Table 2. Cognitive performance across tasks for the three groups. Scaled d' on the interference processing task significantly differed across groups with lower performance in the directly and indirectly exposed groups relative to the control group.

Cognitive Task	Directly exposed (n = 26) Mean ± Std	Indirectly exposed (n = 21) Mean ± Std	Not exposed (n = 27) Mean ± Std
Selective Attention			
scaled-d'	0.86 ± 0.27	0.93 ± 0.18	0.97 ± 0.06
speed	0.36 ± 0.10	0.36 ± 0.11	0.35 ± 0.05
Response Inhibition			
scaled-d'	0.84 ± 0.24	0.92 ± 0.13	0.93 ± 0.10
speed	0.40 ± 0.10	0.40 ± 0.11	0.40 ± 0.07
Interference Processing			
scaled-d'	0.64 ± 0.25	0.65 ± 0.27	0.83 ± 0.13
speed	0.29 ± 0.09	0.33 ± 0.11	0.31 ± 0.05
Working Memory			
scaled-d'	0.47 ± 0.24	0.51 ± 0.24	0.50 ± 0.21
speed	0.34 ± 0.14	0.36 ± 0.14	0.33 ± 0.10
span	4.35 ± 2.71	3.81 ± 2.73	4.59 ± 2.83
Emotion Interference Processing			
scaled-d'	0.73 ± 0.13	0.69 ± 0.15	0.74 ± 0.16
speed	0.30 ± 0.08	0.31 ± 0.07	0.32 ± 0.05

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did not reach significance across group comparisons. All task scaled-d' and speed measures are illustrated in Fig 2.

Given the processing efficiency theory for anxiety-related disorders, i.e. performance impacts in the context of such disorders should be considered in terms of quality of performance divided by effort put in [63], we also looked at performance efficiency, specifically for the interference processing task that showed d' differences. Performance efficiency can be calculated as the product of d' sensitivity (that represents quality of performance) and processing speed (that is the log inverse of response time and a measure of the effort put in) [24,64,65]. For the interference processing task, differences in performance efficiency mimicked d' sensitivity, i.e. directly/indirectly exposed individuals showed significantly lower efficiency than controls (directly exposed efficiency 0.19 ± 0.09 mean ± std units vs. controls 0.25 ± 0.05 units: t(51) = -3.20, p = 0.003, Cohen's d = 0.89; indirectly exposed efficiency 0.19 ± 0.09 units vs. controls 0.25 ± 0.05 units: t(46) = -2.69, p = 0.012, Cohen's d = 0.84) but there was no significant difference between the two fire-exposed groups on this measure (directly vs. indirectly exposed: p = 0.74).

Finally, as the three study groups differed in the demographic ethnicity variable and the mental health self-reports of recent trauma, anxiety and depression, we also checked whether the interference processing d' and efficiency measures were influenced by these covariates. In an ANOVA for d' sensitivity that included between-subjects effect of group and covariates of ethnicity, recent trauma, anxiety and depression, we found that the group effect was still significant ($F_{2,67} = 5.19$, p = 0.008, $\eta^2 = 0.13$) but no covariate showed a significant effect on d' ($p>0.2$). Similar results were obtained for interference processing efficiency, the effect of fire-exposure group was significant ($F_{2,67} = 3.17$, p = 0.048, $\eta^2 = 0.09$) but neither ethnicity nor mental health covariates showed a significant effect on efficiency ($p>0.1$).

Neural activity

We next examined electrophysiological activity, specifically event-related responses on the Flanker interference processing task that showed cognitive differences between groups. Fig 3A

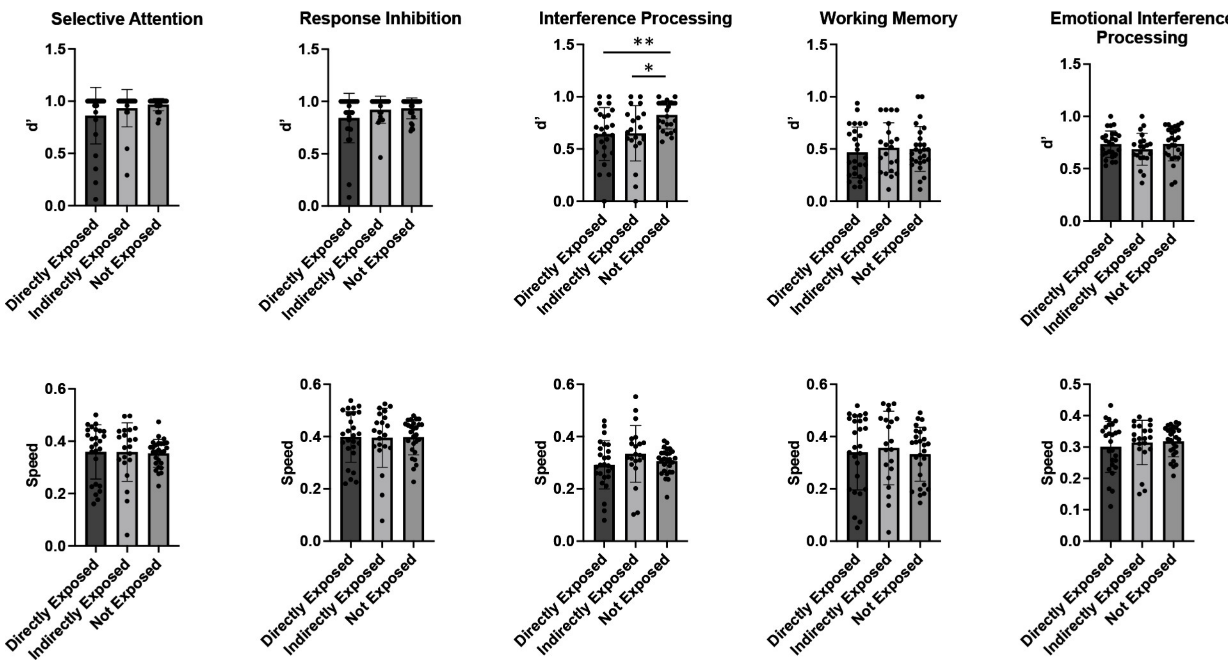

Fig 2. Comparisons of cognitive task performance across the three groups. d' signal detection sensitivity is shown on top and processing speed measures are on bottom for the five tasks (1) selective attention, (2) response inhibition, (3) interference processing, (4) working memory and (5) emotion interference processing. Individual data points are shown as scatterplot with bar length showing mean and error bars showing standard deviation. d' performance measures are scaled to 1, and speed is measured as the log of the inverse of response time. The asterisks indicate significant group difference in interference processing across groups, with the two fire-exposed groups showing lower d' than the fire-unexposed controls. *: p< .05, **: p< .005.

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shows ERPs plotted at frontal (F3, F4) and parietal (P3, P4) channels for the three groups. Peak post-stimulus ERPs were observed in the 100–200 ms time window with corresponding topography plots in Fig 3B. Peak ERP latencies did not show any group differences (p>0.6). Yet peak amplitudes, especially at left frontal and right parietal sites, showed significant group differences between the directly exposed and not exposed control group, as well as between the directly and indirectly exposed groups, with largest ERP amplitudes in the directly exposed group (Fig 3C, between-group peak amplitude ttest comparisons were conducted at all electrodes, and scalp topography maps are shown with p < .05 threshold applied at each electrode). ERP amplitude differences between the indirectly exposed vs. control group were not significant. Group ERP comparisons were corrected for multiple comparisons across time using permutation testing.

Left frontal activity is typically related to cognitive control, hence we investigated correlations between this activity (mean of peak activity F3, FC3 channels) and behavioral performance on the interference processing task. As participants belonged to three separate fire-exposure groups, we conducted a partial correlation analysis between neural activity and behavior while accounting for fire-exposure group. In this analysis, the relationship between d' sensitivity and left frontal activity did not reach significance (p = 0.06). Given the processing efficiency theory for anxiety-related disorders [63], we also looked at the neurobehavioral relationship for left frontal activity and performance efficiency. We found that the partial correlation between performance efficiency and left frontal activity, accounting for exposure group was significant (Fig 3D, rho(56) = 0.28, p = 0.036). Thus, participants showing greater left frontal activity, indicative of greater cognitive control, were also more efficient at the interference processing task.

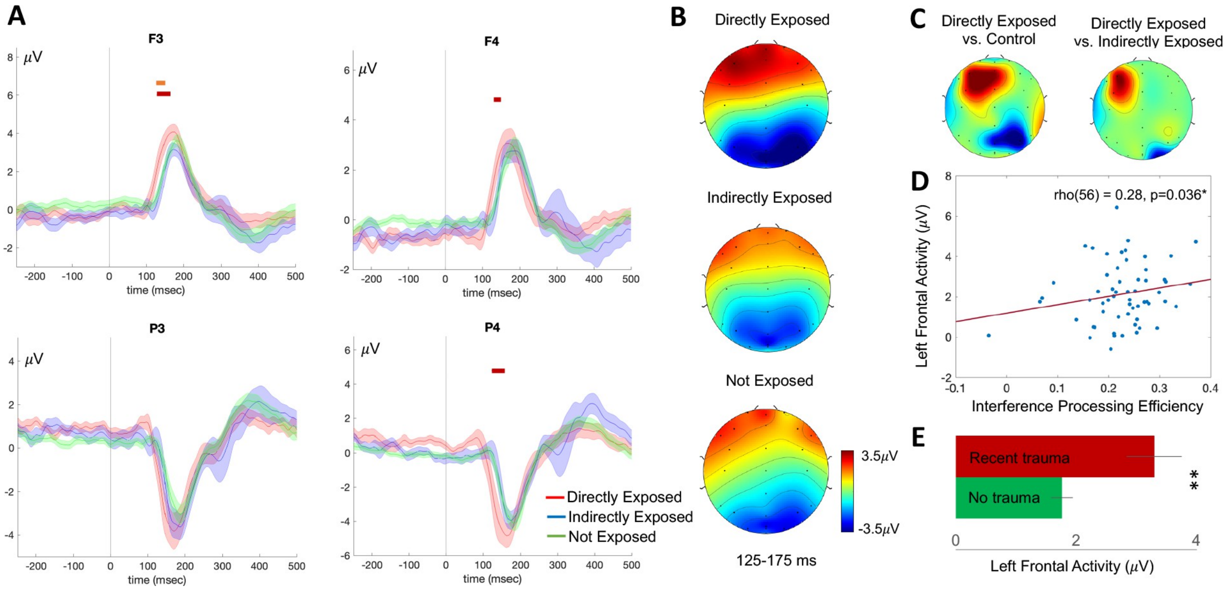

Fig 3. Event-related potential responses (ERPs) elicited on the interference processing task and their relationship to behavior. (A) Group averaged ERPs ± standard error are shown at frontal (F3, F4) and parietal (P3, P4) channels corresponding to the directly exposed (red), indirectly exposed (blue) and unexposed control (green) groups. Red and orange bars depict significant peak amplitude differences between the directly exposed vs. control group, and the directly exposed vs. indirectly exposed group ($p<0.05$, permutation tested across time). (B) Group averaged ERP scalp topographies are plotted in the peak 125–175 ms latency window. (C) Peak ERP scalp topographies of the directly exposed group masked by group ttest comparisons show significant left frontal and right parietal activity differences; group comparisons at all electrodes are thresholded at $p<0.05$. (D) Significant partial correlations are observed between peak left frontal activity (average of F3, FC3 channels) and interference processing efficiency, accounting for exposure group. (E) Peak left frontal activity is significantly greater in individuals reporting recent trauma ($p = 0.006$).

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Finally, we investigated the influence of ethnicity and mental health variables of recent trauma, anxiety and depression on the left frontal activity, while accounting for between-subjects effect of exposure group. This ANOVA showed a significant effect of recent trauma ($F_{1,52} = 5.60$, $p = 0.02$, $\eta^2 = 0.10$), while other variables were not significant ($p>0.2$). Individuals reporting recent trauma had significantly greater left frontal activity than those not reporting recent trauma ($t(57) = 3.11$, $p = 0.006$, Cohen's d effect size = 1.14, Fig 3E). The neurobehavioral relationship between left frontal activity and interference processing efficiency, accounting for recent trauma (instead of fire-exposure group) in partial correlations remained significant ($rho(56) = 0.25$, $p = 0.05$).

Discussion

This study aimed to understand the chronic impacts on cognitive and brain function in the aftermath of California's deadliest wildfire, the Camp Fire of 2018. Studying cognitive abilities is important because they are core to all daily life functioning and can be key to understanding individual needs as they rebuild and rehabilitate in disaster affected communities. From a basic science perspective, neuro-cognitive effects can reveal the mechanisms of overt mental health symptoms [66]. Yet, there are significant gaps in the understanding of neuro-cognition within climate change impacted communities, with no known studies to-date to the best of our knowledge conducted in this context, i.e. addressing both cognitive and underlying neural sequelae.

Hence, in this study, we used a comprehensive and validated cognitive assessment platform, the *BrainE* platform to assess several aspects of cognition along with synchronized EEG recordings to measure brain function [24]. We evaluated cognition on a set of standard measures that included tests of selective attention, response inhibition, working memory and both non-emotional and emotional interference processing. These specific measures were selected for testing as they are core to human cognitive abilities and have been shown to be meaningful in the context of trauma, anxiety and depression related mental health problems [26,27,28–38], which are relevant in climate change-impacted communities. We measured response accuracy in terms of d' signal detection sensitivity, which accounts for both correct responses and false alarms, and also measured response processing speed. We found significant group differences specifically in interference processing d' sensitivity. Concomitant to this finding, we also found significant group differences in interference processing efficiency, calculated as the product of d' and speed, but no group differences were found for processing speed alone. Relative to controls, the interference processing d' accuracy and efficiency measures were significantly impacted in individuals exposed to the wildfire, in both directly exposed individuals who personally experienced the fire in terms of impacts on personal family/property and indirectly exposed individuals who witnessed the fire but were not personally affected by it. Notably, all data were recorded 6 months– 1 year after the Camp Fire, such that interference processing group differences suggest specific chronic effects. While the groups also differed in ethnicity (more Caucasians and less Asians in the fire-exposed relative to non-exposed group) and in mental health variables (greater recent trauma, anxiety and depression in the fire-exposed relative to non-exposed group), these variables were not found to further impact interference processing performance differences. In other words, being a member of the fire-exposed groups, which suffered greater mental health impacts, was the main significant factor determining interference processing functioning. Indeed, cognitive impacts on interference processing are important from a trauma and anxiety perspective. Prior studies have shown that interference processing such as Stroop interference is impacted in PTSD [29,34] and others have found emotional interference processing to also be impacted [67]. These studies have suggested that the intrusive internal re-experiencing of traumatic recollections may weaken cognitive performance and amplify hypervigilance and anxiety, along with the inability to inhibit irrelevant stimuli, especially on cognitively demanding tasks that require speeded responses [29,68]. In this regard, the processing efficiency theory for anxiety-impacted performance may also apply, that anxious individuals may use compensatory strategies such as enhanced effort and increased processing resources to accomplish cognitively demanding tasks [63]. Indeed we find interference processing efficiency is impacted in the fire-exposed individuals, who report greater trauma, anxiety and depression relative to controls. Overall, these cognitive impacts may contribute to the daily-life functional and social impairments and reduced wellbeing in the context of PTSD symptoms [69,70].

That we did not observe other domains of cognition, other than interference processing, to be affected could be due to those being susceptible to acute but not chronic impacts. Indeed in one natural disaster study of a major earthquake in New Zealand, significant errors on a response inhibition task were detected only in impacted individuals but during the acute phase, within one month of the disaster [71].

With regards to neural data, task-evoked EEG recordings analyzed for the interference processing task showed differential evoked activity in the fire-exposed groups relative to controls. Specifically, these data showed significant peak neural activity differences, most prominently for the directly exposed group at left frontal and right parietal brain sites relative to the age and gender-matched non-exposed control group. Left frontal peak brain activity in the 100–200 ms post-stimulus period was most heightened in the directly exposed group, and this group also showed a significantly greater neural response relative to the indirectly exposed group. Frontal neural activity is a signature of cognitive effort [72], and left frontal dysfunction and dysconnectivity in particular has been observed in relevant neuropsychiatric conditions such as depression [73,74] and PTSD [75,76]. Indeed in partial correlations that accounted for fire-exposure group, we found that left frontal activity correlated with interference processing efficiency, i.e. greater cognitive effort represented by this neural signature was associated with better performance. Yet, left prefrontal activity was also significantly associated with subjective trauma reports, i.e. individuals who reported experiencing recent trauma had greater task-evoked left frontal activity than those who did not report having a traumatic experience. This finding may align with evidence in PTSD showing frontal hyperarousal and cortical hyperexcitability [77,78]. Notably, this observation may also reflect a compensatory mechanism of an increased need for cognitive effort during the interference processing task in individuals with recent climate trauma exposure in line with the processing efficiency theory for anxious performance [63]. Overall these results suggest neuro-cognitive mechanisms in play during climate trauma that resemble PTSD-like frontal hyperarousal and processing efficiency deficits.

Limitations of this study include the possibility that the group differences observed are trait effects, i.e. were present even before the traumatic wildfire event. Notably, this limitation is shared with all disaster studies; all have investigated outcomes post-disaster. In one disaster survey study, subjective recall was used to find out how subjects may have responded pre vs. post disaster, yet the survey itself was disseminated one year post-disaster [79]. To the best of our knowledge there is no study with objective neuro-cognitive measurement made pre vs. post-disaster. Another limitation is that we used a moderate channel density EEG system for neural recordings, and the results could be confirmed in future by using a high density EEG system or other neuroimaging methods such as functional magnetic resonance imaging. Yet, we note that we used the moderate channel density EEG system because it is low-cost and highly scalable to community settings, and community studies need to balance scalable feasibility, cost and data resolution [80].

Overall, our findings provide first evidence of the chronic effects of climate trauma driven by wildfire exposure. Cognitively, we observed diminished interference processing alongside heightened frontal ERP responses, which parallel findings in individuals with PTSD [29,33,34]. Interestingly, interference control training has been shown to alleviate PTSD symptoms [81]. Also, we have shown that scalable intervention approaches such as digital meditation can ameliorate interference processing deficits in the context of trauma [82]. Such promising approaches may also be adapted as potential intervention strategies for climate trauma. As the planet warms, more and more individuals face extreme climate exposures and hence, novel resiliency tools need to be investigated from multiple perspectives. Here, we provide an important neuro-cognitive mechanistic target for future intervention, which may serve as a complement to other socio-behavioral intervention targets [7].

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