**“The Enemy of My Enemy is My Friend”:
Shared Negative but not Positive Emotional Experience is Associated with Neural
Synchrony in the Medial Prefrontal Cortex**

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Abstract

Prevalent, automatic, and powerful, emotional experience forms an integral part of human life. Despite numerous studies pointing at the impact of emotion in shaping one's interpretation of situation and guiding action, emotional experience has not been studied extensively due to its idiosyncratic nature. However, advances in neuroimaging techniques and statistical analysis methods enabled more rigorous investigation of subjective experience, one of which is neural synchrony. Here we sought to examine if neural synchrony in regions within the default mode network, including medial prefrontal cortex (mPFC), bilateral temporoparietal junctions (TPJ) and inferior parietal lobules (IPL), underlies shared emotional experience. A hundred and four participants watched political videos while being scanned by Functional Near-Infrared Spectroscopy (fNIRS) and rated their emotional experience afterwards. Although initial Inter-Subject Correlation Analysis and Inter-Subject Representational Similarity Analysis did not yield significant findings, we addressed limitations of both approaches – loss of dimensionality and unequal comparisons of dyads – by combining them with k-means clustering. This improved version of analysis revealed that subjects who reported more similarly negative, but not positive, emotional experiences exhibited more synchronized neural fluctuations in mPFC. The results suggest that neural synchrony in mPFC may be driven primarily by negative sentiments and serve as a neural signature for subjective emotional experience.

Keywords: Neural synchrony, emotional experience, mPFC, DMN

Introduction

“It should be possible to present, for every emotion, a corresponding description of how the world looks to the subject.” – Nico Frijda, *The Emotions*, p. 196

When an emotionally intense play such as Shakespeare’s *Hamlet* is shown in front of an audience, some may shed gallons of tears while others might be bored by the sheer length of the play. Idiosyncratic, effortless, and subjective, emotional experience represents one crucial way in which each of us psychologically engage with the world. Indeed, as Nico Frijda pointed out in his quote, emotional experience is one’s perception of the world.

Due to the private nature of emotional experience, research in affective science has largely focused on the measurable channels of emotional expression – behavioral, physiological, and neural – as opposed to studying emotion as a stream-of-consciousness-like experience. With technological advances in neuroimaging and statistics, however, there is greater potential to scientifically investigate subjective experience, by analyzing the real-time progression of neural activity during the experience. Then, by comparing how synchronized two individuals’ neural fluctuations are, one might be able to infer the similarity of their psychological states such as emotional experience.

This approach, termed neural synchrony, has been widely used in cognitive neuroscience studies to examine the neural mechanisms for shared perspective. These studies consistently found an association between common situational interpretations and synchronized neural activity in the default mode network (DMN), which is a group of functionally connected regions primarily responsible for self-referential processing (e.g. reflecting on one’s own beliefs) as well as mentalizing (e.g. thinking about other people’s psychological states) (Yeshurun, Nguyen, &

Hasson, 2021). For example, narratives, which convey perspectives to the audience, have been shown to elicit correlated neural activity in the bilateral temporal parietal junctions (TPJ) and the medial prefrontal cortex (mPFC) (Hasson, Yang, Vallines, Heeger, & Rubin, 2008; Jääskeläinen et al., 2008). Importantly, inter-subject neural synchrony in DMN is driven by shared views to the narratives as opposed to perceptual features of the stimuli, as shown in various studies that such time-locked neural activity is present across different modalities of stimulus presentation. For instance, visual and auditory delivery of stories produced comparable levels of neural synchrony across participants in nodes of the DMN (Regev, Honey, Simony, & Hasson, 2013). Moreover, viewing, verbally recalling, and listening to a summary of the same movie episode all resulted in shared neural representations in DMN regions including the TPJ (Zadbood, Chen, Leong, Norman, & Hasson, 2017). Therefore, neural responses in parts of the DMN are sensitive to meaning, not low-level sensory details, of the external world.

The relationship between inter-subject neural coupling in DMN regions and shared perspectives also holds following experimental manipulation of situational interpretation. When presented with different contexts of the same narrative, people who received the same context and interpreted the characters' intentions and emotions similarly exhibited higher neural synchrony in DMN areas such as rTPJ and mPFC, even though their comprehension of the context-independent parts of the story was largely the same (Yeshurun et al., 2017). Likewise, Ames et al. (2015) showed that subjects who were given valid contextual cues to vignettes and thus successfully comprehended the stories showed elevated neural synchrony in mPFC compared to those who lacked the contextual cues and offered idiosyncratic explanations for the narratives. In unconstrained studies without manipulation, similar results emerged: Saalasti and colleagues (2019) found that semantic similarity of free recalls of narratives predicted ISC in the

inferior parietal lobule (IPL). This suggests that neural responses tend to converge for people who share similar situational interpretation.

Although there is extensive literature on the relationship between shared situational appraisal and neural synchrony, surprisingly little has been done to examine neural correlates of emotional experience. Indeed, research in affective neuroscience has largely been centered around searching for emotion-generating regions and has mostly adopted event-related design to correlate neural activation and behavioral ratings of certain aspects of emotion, such as arousal and valence (Knutson & Greer, 2008; Paulus & Stein, 2006; Singer et al., 2009). Yet, just by uncovering neural correlates of instantaneous emotional responses does not elucidate how emotion is *experienced*. Moreover, whereas affective states can be relatively transient, emotional experience is continuous in nature. The neural synchrony approach, which involves the use of naturalistic paradigms and ISC analysis, is then more suitable for the study of emotional experience. There are a few studies in affective neuroscience that embraced the neural synchrony approach and found mapping between correlations in emotional experience and neural timecourse correlations. For instance, Nummenmaa et al. (2012) showed that movie viewing elicited time-locked activity in sensory regions and corticolimbic emotion circuits. In particular, negative valence synchronized activity in regions supporting inference of other people's mental states and emotion processing, such as the TPJ and mPFC. Chang and colleagues (2020) found that ventral mPFC activity patterns track affective transitions in a movie, such that increased timeseries concordance in ventral mPFC was observed precisely during the most emotionally intense parts of the movie as indicated by subjective ratings and facial expressions. Taschereau-Dumouchel et al. (2020) showed that whereas emotion processing regions such as the insula and the amygdala are mostly associated with subconscious emotions, IPL tracks conscious,

subjective ratings of emotional experience. Taken together, these recent studies suggest that shared emotional experience could manifest as neural synchrony in DMN regions. Given the extensive literature on shared perspectives and DMN neural synchrony, a question raised by these affective neuroscience studies is whether common emotional experience could also play an important role in constructing a shared subjective reality. However, the paucity of affective neuroscience research that incorporates the neural synchrony approach means that this possibility remains unexplored.

A further gap in prior research comes with the fact that all of them used functional Magnetic Resonance Imaging (fMRI), which creates a highly artificial environment that deviates dramatically from real-life experience. This problem can be especially relevant if the construct of interest is emotional experience per se. In fMRI studies, participants have to lay in a confined space and stay perfectly still while enduring noise of the machine. Emotions induced in a setting like this are apparently far from how they are experienced in everyday life. Additionally, body postures affect emotional experience. There is evidence suggesting that the supine position, which can create a feeling of vulnerability, dampens approach-related emotions such as anger (Harmon-Jones & Peterson, 2009). Therefore, using fMRI to study emotions can lead to low ecological validity, which is especially problematic given the context-dependent nature of emotional experience. In contrast, fNIRS is much more lightweight and portable than fMRI. Evidence suggests that fNIRS and fMRI are two neuroimaging modalities of comparable capacity (Huppert et al., 2006; Kleinschmidt et al., 1996; Strangman et al., 2002). Importantly, fNIRS can be utilized when sitting or even moving, thereby avoiding the influence of unnatural body position on emotions and allowing for much more realistic emotional experience. Yet, fNIRS has not been adopted extensively in affective neuroscience, possibly because it does not

cover subcortical structures where the traditional “emotion regions” such as the insula reside. However, as the aforementioned studies on emotional and neural similarities show, certain cortical regions within the DMN that can be reached by fNIRS, including mPFC, TPJ and IPL, are nevertheless sensitive to inter-subject differences in emotional experience. Therefore, fNIRS holds great potential for elucidating the neural mechanisms of shared emotional experience.

In the present study, we sought to exploit the benefits of the neural synchrony approach and fNIRS to examine whether shared emotional experience is underpinned by synchronized neural activity across subjects. Given that previous studies have identified mPFC, TPJ and IPL to be the three regions where inter-subject neural synchrony is associated with similarity in subjective experiences (e.g. narrative understanding, emotional experience), we expected to observe the same pattern of results in the current study. Furthermore, we attempted to extend the prior affective neuroscience studies by examining whether each unit of *individual differences* in emotional experience linearly corresponds to each unit of inter-subject variability in neural synchrony in these three regions.

Method

Participants

We recruited 146 participants from the University of California, Los Angeles and neighboring communities. To be selected, participants must be over 18 years old, right-handed, proficient in English and have lived in the U.S. since childhood, so that they would have sufficient background knowledge about American politics to understand the arguments on gun control in the stimulus videos. Forty-two participants were excluded from data analysis due to incomplete neural or self-report data. Among the remaining 104 participants, the mean age was 20.09 years ($SD = 2.03$) and 51% were female. The majority of them identified as Caucasian, Asian or Hispanic (43% White, 35% Asian, 23% Hispanic, 2% African American, 5% Other; percentages do not add up to 100% because some participants were biracial). 55% of the participants identified as liberals, 35% as conservatives, and 10% as moderates. Participants received either monetary compensation or course credit at the end of the scanning session.

Stimuli

We created four Youtube-style videos, each two to three minutes long, in which English speakers discuss their stances on gun control. In two videos, the speakers (one male, one female) express support for stricter gun control, while in the other two videos two separate speakers argue against gun control. Scripts were written by the researchers to control for length and rigor of arguments. In particular, all videos contained approximately equal amounts of both logically sound and logically questionable materials to elicit a wider range of emotional experience. During debriefing, participants generally indicated that they believed the stimuli were genuine Youtube videos and had strong emotional reactions to them.

fNIRS Data Acquisition

We used fNIRS, a non-invasive, lightweight and portable neuroimaging technique, to measure neural activity. fNIRS relies on two principles: 1) neural activation consumes oxygen, which leads to more blood flow in the region, an increase in local concentrations of oxygenated hemoglobin (HbO) and a decrease in local concentrations of deoxygenated hemoglobin (HbR); 2) near-infrared light, whose wavelength is within a certain spectrum (650~950nm), is absorbed strongly by HbO and HbR but poorly by tissues and bones. By projecting near-infrared light through the scalp via optodes, one is able to calculate changes in concentrations of HbO and HbR from the absorption rates of near-infrared light at multiple wavelengths, which is then used as a proxy for levels of neural activation in the area (Liu et al., 2017).

Participants were scanned in a NIRScout fNIRS rig with a layout of 108 channels (32 light sources and 32 detectors), which achieves whole-brain coverage (see Figure 1). This layout was created in accordance with the 10-10 UI external positioning system to ensure consistency across head sizes. Participants had their head sizes measured, and then were fitted with caps that affixed the optodes to the scalp. Raw light intensity data was collected at a sampling rate of 1.95 Hz at wavelengths of 760 and 850 nm.

Figure 1. Full-head layout in the 10-10 system, with 32 sources and 32 detectors comprising 108 data channels.

Self-Report Measurement

Participants rated their emotional experience during the videos in three items with 11-point Likert scales. The first questions asked about how much the participant liked the speaker in the video (-5 = “*Dislike a lot*”, 5 = “*Like a lot*”). The second question concerned the extent to which they were bothered by the arguments (0 = “*Not at all*”, 10 = “*Very much*”). The third question probed for their overall experience while watching a particular video (-5 = “*Extremely negative*”, 5 = “*Extremely positive*”). Participants completed the first two questions immediately after each video, and the third item after the scanning phase concluded.

Procedure

Prior to the scanning session, participants completed a questionnaire that asked about their stances on gun control and demographic information. Participants who fulfilled all inclusion criteria were contacted for the scanning session. In the scanning session, participants watched the four political videos in randomized order while being scanned in four separate functional runs. Both immediately after each video and after all four videos, they rated their emotional experience on 11-point Likert scales.

fNIRS Data Preprocessing

We used a pipeline that incorporated HomER2 functions to preprocess fNIRS data (Huppert, Diamond, Franceschini, & Boas, 2009). Time courses were first trimmed to match stimulus onset and offset. Data was bandpass filtered to 0.01-0.5 Hz to account for signal drift and corrected for motion artifacts using a PCA algorithm which identifies signal spikes. It was then converted into HbO concentrations relative to baseline using the Modified Beer Lambert Law, and z-scored (Delpy et al., 1988).

Analyses and Results

Inter-Subject Correlation (ISC) Analysis

Inter-subject correlation (ISC) is defined as the Pearson correlation of neural timeseries in an anatomical region across subjects, which quantifies the temporal covariance of subjects' neural data in response to naturalistic stimuli (Cohen et al., 2017). A commonly practiced approach to ISC is called the *leave-one-out* framework, which involves correlating each subject's time course with the average neural response of everyone else *minus the subject*. The intuition is that averaging timeseries data across subjects filters out noise, and because the stimulus was held constant, correlation with the group average would capture stimulus-driven activities while leaving out intrinsic processes unrelated to stimulus properties (Nastase, Gazzola, Hasson, & Keysers, 2019).

We applied ISC analysis to relate neural synchrony to similarity in emotional experience. First, for videos of each gun control stance, we divided subjects into two groups based on whether their composite emotion ratings lied above or below the mean. Those who scored higher than the mean were labeled as having positive emotional experience while watching the videos, while the rest were categorized as having negative emotional experience. This procedure resulted in four emotion groups in total: positive experience in anti-gun control videos ($n = 47$), negative experience in anti-gun control videos ($n = 57$), positive experience in pro-gun control videos ($n = 56$), and negative experience in pro-gun control videos ($n = 48$). Participants' neural responses in the regions of interest (ROIs) were computed by averaging timeseries data across channels that fall within each of the ROIs' anatomical locations. Since the sparse distribution of fNIRS channels did not allow us to clearly separate IPL from TPJ, we grouped these two regions together, resulting in three ROIs in total (i.e., mPFC, right TPJ/IPL, left TPJ/IPL). Then, for each subject within an emotion group, we computed the average ROI response of all *other* subjects in the group, which was then correlated to the subject's ROI time course. Repeating this procedure

for every ROI and emotion group, we yielded twelve sets of Pearson correlation coefficients measuring within-group neural synchrony. Furthermore, we calculated between-group neural synchrony by correlating each subject's ROI response with the average neural activity of those who had the opposite emotional experience while watching the same videos, again producing twelve sets of correlation coefficients. All correlation coefficients were then Fisher z-transformed (Fisher, 1915). To test whether differences between within- and between-group synchronies were statistically significant, we first performed a one-tailed paired samples t-test on within- and between-group correlation coefficients to get a sample t-statistic for each gun-control stance. We then applied a Mantel permutation test by randomly shuffling within- and between-group correlation coefficients subject-wise, computing a t-statistic between artificial within- and between-group correlations, and repeating this procedure 10,000 times to generate a null distribution of t-statistics. P-value of the sample t-statistic was calculated as the percentage of t-statistics in the null distribution that were greater or equal to the observed t-statistic (G. Chen et al., 2016; Mantel, 1967). Finally, p-values were corrected across three ROIs using a false-discovery rate (FDR) of $q < 0.05$ (Benjamini & Hochberg, 1995).

Results showed that in none of the ROIs and for neither video stance did subjects exhibit more neural synchrony with those who shared similar emotional experience than out-group members ($p > 0.05$ for all combinations of ROI and video stance). As an exploratory analysis, we also compared how synchronized neurally subjects were to their in-group members when they had negative emotional experience versus positive. Interestingly, participants showed significantly more time-locked neural fluctuations with in-group members when they had negative emotional experience while watching the anti-gun control videos than when they had

positive emotional experience ($t = 2.76, p = 0.0076$). However, the same was not true for pro-gun control videos.

Inter-Subject Representational Similarity Analysis (IS-RSA)

Despite being a well-established analysis method, ISC suffers from two limitations. First, averaging neural responses across subjects left little room for us to investigate the relationship between inter-subject differences in emotion and neural measures. And second, using composite ratings to measure emotional experience may have masked key differences between the different dimensions of emotion we measured (i.e. like, bothered, overall experience), which might better explain idiosyncrasies in neural activity. Therefore, we adopted a recent extension of ISC, termed *Inter-Subject Representational Similarity Analysis (IS-RSA)*, to test the hypothesis that individual differences in emotional experience would be reflected by variations in neural synchrony (Finn et al., 2020).

Instead of using mean emotion scores to categorize participants and collapsing neural responses across in-group members to derive prototypical neural profiles, in IS-RSA we examined whether *each unit* of inter-subject variability in emotion ratings linearly corresponded to that in brain dynamics. Although this would typically be achieved by comparing the similarity structure in behavioral data to that in neural data, because it would not make sense to correlate only six emotion questions, we instead compared patterns of *dissimilarity* in behavioral and neural measures. For the fNIRS data, we concatenated timeseries data across videos of each stance, and averaged them across channels corresponding to each ROI. We operationalized inter-subject neural dissimilarity via the Euclidean distance between each pair of subjects' time courses, using the formula:

$$D = \sqrt{\sum_t (c_1(t) - c_2(t))^2}$$

where $c_1(t)$ and $c_2(t)$ are two subjects' time courses averaged within ROI. This resulted in a Representational Dissimilarity Matrix (RDM) of inter-subject Euclidean distances for each ROI * video stance combination, and six (three ROIs * two stances) neural RDM's in total. For emotion ratings, we projected participants into a multidimensional feature space comprised of six dimensions (three dimensions for each video * two videos per stance). Then, we calculated the Euclidean distance between each pair of subjects' emotion ratings using the same formula we applied on fNIRS data, producing two emotion RDMs (one for each video stance). Afterwards, we computed Spearman's rank correlation between each neural RDM and behavioral RDM, and FDR-corrected all Spearman's ρ 's across the three ROIs using $q < 0.05$ (Benjamini & Hochberg, 1995; P.-H. A. Chen, Jolly, Cheong, & Chang, 2020).

Results revealed that in none of the ROIs were inter-subject variations in multivariate emotional experience correlated with that in neural synchrony. However, we did observe a marginally significant correlation in mPFC for anti-gun control videos ($\rho = 0.031, p = 0.076$). Considering the fact that most of our subjects were liberals who should dislike anti-gun control videos, the result, if truly significant, would mean that subjects who shared emotional experience exhibited higher levels of neural synchrony in mPFC when watching videos that most of them found aversive.

K-Means Cluster-Based ISC & IS-RSA

While allowing us to examine the nuanced relationship between emotion and neural similarities, IS-RSA also raised an important issue: Is behavioral (dis)similarity invariant to subject's position in the behavioral spectrum, as assumed by IS-RSA? Or, is it more akin to the situation described in the opening line of Leo Tolstoy's *Anna Karenina*: "All happy families are alike; each unhappy family is unhappy in its own way" (Finn et al., 2020)? Consider a

simplified univariate example: On a scale of 1 to 10 measuring overall emotional experience, four subjects rated 2, 3, 7 and 8 respectively. In IS-RSA, the 2&3 pair and the 7&8 pair would both have a distance of 1 from each other. However, people who had really bad experiences (the 2&3) may not differ from each other *equally* as those who really enjoyed the videos (the 7&8). If this was true, then brain responses of the 2&3 would be differentially (dis)similar to each other than that of the 7&8, which would not be captured by traditional IS-RSA. Even though we used Euclidean distance between multivariate emotion ratings in the current study, since Euclidean distance is the sum of squared differences taken square root, we would still suffer from the problem of unequal comparisons. Therefore, it might be beneficial to first group subjects based on emotion ratings, just like the initial step of ISC, then apply IS-RSA on each emotion subgroup separately. In this way, a 7&8 would be compared to a 6&7 instead of a 2&3. Nevertheless, grouping was based on composite emotion scores in our previous ISC analysis, which led to the loss of individual variability along dimensions of emotional experience. Thus, grouping needs to be done on multivariate emotion data. We chose to accomplish this task via *k-means clustering*, an unsupervised learning algorithm that partitions observations into k clusters in a way that minimizes within-cluster variances (i.e. Euclidean distances) (Hartigan & Wong, 1979). We first applied k -means clustering on multivariate emotion data to identify two clusters of subjects (see Figures 2 and 3). Judging from the center means (see Table 1), it seems that Cluster 1 was comprised of subjects who consistently had negative emotional responses to the pro-gun control videos and positive emotional experience when watching the anti-gun control videos, while Cluster 2 was the exact opposite. Clustering results were also moderately correlated with self-reported political affiliation ($r = 0.60$), with more conservatives in Cluster 1 and more liberals in

Cluster 2 (Cluster 1: 37 conservatives vs. 23 liberals; Cluster 2: 6 conservatives vs. 54 liberals).

Then, we repeated the procedures for ISC and IS-RSA on each cluster.

Figure 2. Based on average silhouette width (i.e. on average, how close subjects are to their own cluster as opposed to the other cluster), the optimal number of clusters was determined to be two.

Figure 3. Visualization of clustering results using principal components. Cluster 1 appears to have larger within-group variation than Cluster 2.

Table 1

Cluster center means for each emotion question and video.

Emotion Question & Video	Cluster 1	Cluster 2
Like_Pro1	0.75	3.03
Like_Pro2	-1.07	2.70
Bother_Pro1	6.65	8.92
Bother_Pro2	5.32	9.07
Experience_Pro1	0.82	3.25
Experience_Pro2	-1.30	2.72
Like_Anti1	-0.02	-2.35
Like_Anti2	1.15	-0.68
Bother_Anti1	6.77	2.90
Bother_Anti2	7.45	4.22
Experience_Anti1	1.43	-1.35
Experience_Anti2	0.38	-2.72

Note. “Bother” questions were recoded so that higher numbers reflect more positive emotional experience. “Pro” and “anti” refer to the stances of the videos (pro- vs. anti-gun control).

For both pro- and anti-gun control videos, cluster-based ISC revealed no significant differences between within- and between-cluster neural synchronies in mPFC, rTPJ/IPL and lTPJ/IPL. However, before FDR correction we observed effects in mPFC for Cluster 2 when

watching anti-gun control videos ($t = 1.76$, $p_{uncorrected} = 0.041$) and in rTPJ/IPL for Cluster 1 when watching pro-gun control videos ($t = 1.73$, $p_{uncorrected} = 0.045$). Importantly, Clusters 1 and 2 reported negative emotional experience in response to pro- and anti-gun control videos respectively. In other words, although not statistically significant, subjects with similar emotional experience were somewhat more neurally synchronized with each other than with others only when they watched videos they did not enjoy.

Similar but statistically significant patterns of results appeared in cluster-based IS-RSA. Within Cluster 2, the more similar a dyad's emotional experiences were when watching anti-gun control videos (to which they overall had negative emotional responses), the more neural synchrony they showed in mPFC ($\rho = 0.57$, $p < 0.001$). No effects were observed in bilateral TPJ/IPL. When it comes to the pro-gun control videos, similarity in emotional experience was negatively correlated with neural synchrony in all three ROIs ($\rho = -0.09 \sim -0.15$, $p = 0.0014 \sim < 0.001$). Regarding Cluster 1, there was no relationship between emotional and neural similarities in response to pro- and anti- gun control videos in all three ROIs.

Figure 4. Schematic illustration of ISC. Subjects were first divided into groups based on composite emotion scores. Each subject's neural timecourse was correlated with the average timecourse of all other in-group members except themselves (In-Group Average TC) and with the average timecourse of all out-group members (Out-Group Average TC).

Figure 5. Schematic illustration of IS-RSA. Neural and behavioral RDM's were constructed by calculating the Euclidean distance between dyads' neural timecourses and multivariate emotion scores, respectively. The lower triangular parts of both RDM's were then correlated.

Figure 6. Schematic illustration of Cluster-Based ISC & IS-RSA. Subjects were first divided into two clusters by applying the k-means clustering algorithm on multidimensional emotion data. ISC and IS-RSA were then repeated on each cluster separately.

Discussion

In the present study, we utilized two analytic techniques – ISC and IS-RSA – to investigate whether similarity in emotional experience is instantiated in the brain as time-locked neural dynamics. In addition, we noted limitations of these two analyses, namely the loss of dimensional variability in data and comparisons of dyads on distinct positions of a scale. We thus explored the possibility of combining the multidimensionality of IS-RSA and the grouping procedure of ISC, repeating both analyses on k-means clusters based on multivariate behavioral data. We had two main findings. First, we found that to varying degrees, the four approaches uncovered consistent patterns in data: When individuals had negative emotional experience, their neural fluctuations in mPFC were more synchronized with those who had similar emotional experience than with others. When subjects had positive emotional experience, however, there was no relationship between shared emotional experience and neural coupling. Second, marginally significant statistical trends became truly significant when analyses were performed on k-means clusters.

mPFC and Emotion

Although not an “emotion area” in the traditional sense, mPFC is often co-activated with the limbic system and related regions such as the amygdala, the ventral striatum and the periaqueductal gray, all of which play important roles in generating core affective responses (Kober et al., 2008). For example, ventral mPFC has been implicated in emotion regulation: it is negatively correlated with the amygdala following successful emotion regulation, and this inverse pattern of activation is disrupted among patients with mood disorders (Johnstone, van Reekum, Urry, Kalin, & Davidson, 2007; Urry, 2006). Moreover, the dorsal portions of mPFC are involved in metacognitive processing of affective inputs, which is crucial for context-

dependent generation of emotions. Such processes include reflecting on and attributing meanings to core affective states (Ochsner & Gross, 2005; Ochsner et al., 2004). In the context of this study, subjects may have been prompted to make sense of and control their aversive affective feelings to a greater extent by negative emotional experiences than by the positive ones. This explains why we only observed effects in mPFC following negative emotional experiences.

Why Neural Synchrony in mPFC?

Despite the well-established function of mPFC in exerting cognitive control on affective experience, conceptualizing mPFC solely as a higher-order emotion processing region does not address why *neural alignment*, not activation intensity per se, in this area is associated with shared emotional experience. As a node of the DMN, mPFC has often been discussed in the context of internally oriented processes. These include: 1) Self-referential thinking such as reflecting on one's own psychological states, judging one's own personality traits and abilities, and processing self-specific stimuli (Johnson et al., 2002; Qin & Northoff, 2011); 2) Thinking about other individuals' mental states in social interactions (Nguyen, Vanderwal, & Hasson, 2019; Zadbood et al., 2017). Thus, shared emotional experience may have resulted from similar reflection on the gun-control attitudes of subjects themselves and of the speakers, which was manifested as temporally aligned mPFC responses. This is supported by previous research showing heightened ISC in mPFC for subjects with similar narrative interpretations and recalls (Nguyen et al., 2019; Yeshurun et al., 2017). Furthermore, the function of mPFC is not limited to intrinsic processing. A recently proposed theory suggests that the DMN bridges extrinsic and intrinsic information at different timescales, integrating sensory input in the moment and in the immediate past (e.g. since the event onset) together with ongoing internal experience (e.g. emotional experience) and preexisting mental states (e.g. beliefs, attitudes and memories)

(Yeshurun et al., 2021). This sophisticated process of information channeling thus enables us to construct a subjective reality out of the present situation. The theory situates our study in the literature: While prior research showed that similarity in current and long-standing mental representations (e.g. narrative interpretations, political beliefs) are associated with neural synchrony, our study showed that shared affective experience, another piece of information channeled into mPFC, also corresponds to unified brain dynamics. Moreover, this view is supported by the empirical evidence linking ISC in mPFC to heightened emotional intensity in videos, which suggests that mPFC attributes meaning to the current situation by tracking affective experience (Chang et al., 2020; Jääskeläinen et al., 2008). Our study further strengthened this claim by showing that emotional experience directly measured in self report also modulates neural synchrony in mPFC.

Why Neural Synchrony Only for Negative Emotional Experience?

If mPFC neural coupling indicates shared perspectives, then similarity in positive and negative emotional experiences should be both related to enhanced ISC in this region. Why, then, did we only observe the effect for subjects who had negative emotional experience? Here we propose three interpretations that explain our unique findings while cohering with the general conclusion about shared perspectives. First, when experiencing bad emotions, participants may be more motivated to ponder on the beliefs and attitudes of their own and the speakers than when feeling positive emotions. This ties back to mPFC's role in self-referential thinking and mentalizing, which may be enhanced by aversive emotional experience. Second, one of the measures of emotional experience – the extent of being bothered – might have also captured degrees of attention, such that being more bothered means being more engaged in video watching. Previous studies have uncovered the modulating effect of attention on neural

alignment in mPFC: neural synchrony in mPFC is positively correlated with how captivating the naturalistic stimulus is as well as how attentive individuals are to the stimulus (Ki, Kelly, & Parra, 2016; Schmäzle, Häcker, Honey, & Hasson, 2015). Therefore, participants who had particularly negative emotional responses towards the videos could have been more absorbed with the gun control arguments and processed them more homogeneously than those who were not quite as engaged. The third, and perhaps the most interesting yet speculative explanation, is that shared negative emotions may unify people's perspectives to a greater extent than shared positive emotions. Or, as the ancient proverb goes, "the enemy of my enemy is my friend." Although no studies have explicitly linked together similarities in emotional experience and subjective reality, prior research has associated negative affective properties of naturalistic stimuli with increased time-locked mPFC activity. For instance, Nummenmaa et al. (2012) showed that negative valence and high arousal, which tended to co-occur, drive more synchrony in mPFC than positive valence and low arousal. Leong et al. (2020) also suggested that moral-emotional language in political arguments produced greater ISC in dorsal mPFC with people of the same partisan group and greater neural polarization between conservatives and liberals, implying that emotionally evocative content more robustly creates divergent interpretations of political messages. Similarly, participants' understandings of the videos in our study may have been better unified by shared negative emotional experiences. Our study also extends on prior research by using IS-RSA to show that neural synchrony in mPFC relates to shared negative emotional experiences in a unit-by-unit, linear fashion, such that each unit increase in the inter-subject similarity of negative emotional experiences corresponded to that in the temporal alignment of mPFC activity.

Of note, these three explanations are not mutually exclusive; in fact, combining the three together may paint a more holistic picture. For example, upon feeling negative emotions, participants might pay more attention to the videos they found unpleasant. Those who had strongly negative emotions may then more heavily analyze the speakers' arguments and intentions and compare them to their own gun control beliefs. This increased cognitive processing of stimuli shared by experiencers of particularly unpleasant emotions could then result in a common subjective reality for these people. Taken together, our findings raised the possibility that the lens through which we experience and interpret ongoing events could be shaped more by what we find emotionally problematic than by what we already find enjoyable. We are not only defined by what we agree with, but also what we disagree with.

K-means Clustering in ISC and IS-RSA

A methodological advance made in this study was adding k-means clustering to conventional ISC and IS-RSA. As explained in the Analyses and Results section, this was motivated by 1) the concern that variability in emotional experience may be better captured by multivariate patterns as opposed to univariate summary scores; 2) the desire to avoid comparing dyads at the opposite ends of the behavioral spectrum who could have equal emotional distance but vastly different neural similarities. Because marginally significant effects emerged significant when IS-RSA was repeated on k-means clusters, this may confirm our hypotheses that subjects are better differentiated by emotion "fingerprints" than aggregate ratings, and that the original IS-RSA performed on the entire population suffered from the problem of unequal comparisons. Indeed, Finn et al. (2020) attempted to address the same issues by modeling differences in working memory capacity as the mean summary score of two subjects, and that in personality as Euclidean distances between multivariate ratings. They found that the correlations

between behavioral and neural RDMs increased significantly after these changes. Finn and colleagues' approach bears resemblance to ours, in the sense that we both tried to distinguish dyads on different ends of the behavioral spectrum and preserve dimensionality information. The only difference is that unequal dyads were mathematically modeled but kept within the same sample by Finn and colleagues, while we partitioned them out for separate analyses. Therefore, the increase in effect size following the transition to cluster-based IS-RSA in our study is consistent with findings in prior research attempting to address the same problems. Due to the exploratory nature of cluster-based IS-RSA, we would like to think of the results as opening doors for future investigation more so than providing statistical guidance. For example, since we did not directly compare neural synchrony of dyads with different emotional experiences, future research could specifically examine how dyadic neural synchrony varies as a function of subjects' absolute positions on the behavioral scale. Moreover, it would be interesting to compare k-means clusters with groups produced by existing clustering variables of relevant dimensions. In our study, examples of such variables include gun control beliefs and political affiliation. In addition, it is possible that the relationship between neural and behavioral similarities depends on what the behavioral scale measures. For instance, Finn et al. (2020) found that the mean summary score model yielded less significant effects for personality than for working memory, suggesting that individual differences in personality may not follow the same pattern as working memory and decrease as subjects move up the scale. Just like personality, emotional experience is qualitative in nature, whereas working memory capacity is measured quantitatively. The fact that univariate scores failed to capture the qualitative constructs in both studies but not the quantitative one suggests that individual variations in behavioral and neural

responses may need to be modeled differently depending on the behavioral construct of interest, a claim that needs to be tested more rigorously in future studies.

Limitations

Finally, the current study nevertheless suffered from several limitations that could have led to some of the uninterpretable or null findings, which again paves the way for future research. First, we observed negative correlations between emotional and neural variabilities when Cluster 2 watched pro-gun control videos, which are not consistent with the literature. Moreover, bilateral TPJ/IPL, two prominent nodes of the DMN, did not produce significant effects in any of the conditions. Upon delving further into the raw fNIRS data, we noticed that fNIRS signal quality was inadequate for several channels within the bilateral TPJ/IPL region and for many subjects' time courses in response to the pro-gun control videos. This means that 1) many subjects' bilateral TPJ/IPL timeseries data were in fact just the average of a couple of channels; 2) the sample size for the pro-gun control videos was smaller than that for the anti-gun control videos. The bad signal quality could have resulted from the limited capacity of infrared light to penetrate through dark thick layers of hair that cover TPJ/IPL but not mPFC. In addition, we did not use functional localizers to determine the precise ROI locations for each subject, and fNIRS caps may have slipped on participants' heads due to movement. All of these factors may have lowered the quality of fNIRS data and explain our null findings. Future research could thus enhance the spatial accuracy of neuroimaging data by incorporating well-validated functional localizers and ensuring consistent cap placement.

Second, if negative emotional experience drives neural synchrony in mPFC, the same significant effect observed on Cluster 2 when watching anti-gun control videos should also hold for Cluster 1 watching pro-gun control videos. Yet, we did not find any relationship between

neural and emotional similarities for the latter. A closer look at the video ratings revealed that the two pro-gun control videos might not have worked equally well to elicit partisan sentiments. For example, Figure 7 shows the mean liking ratings by cluster and by political affiliation. All except the first pro-gun control video resulted in polarizing liking ratings for Clusters 1 and 2 and for conservatives and liberals. Similar patterns were also observed for the other two emotion questions. Therefore, our null findings may be explained by the failure to evoke negative emotional responses from Cluster 1 via the pro-gun control videos. Future research could ensure that naturalistic stimuli robustly elicit unpleasant emotions by having independent raters rate the emotional intensity and valence of the stimuli, preferably using a sliding time window.

Figure 7. Liking ratings of the four videos by cluster and political ideology. One of the pro-gun control videos (circled in red), which were supposed to be disliked by Cluster 1 which was primarily comprised of conservatives, did not seem to achieve the intended effects.

Finally, being part of a larger project that was not designed to examine emotional experience, the study was limited in terms of data availability. Although emotional experience is a dynamic, stream-of-consciousness like construct, we were restricted to measuring it via post-hoc self-report ratings. Moreover, we only had three emotion questions per video, and were not able to explore other dimensions of emotional experience, such as arousal and valence. However, the fact that such impoverished data still revealed interesting relationships between individual variations in neural and emotional responses underscores the importance of extending this line of research in the future. To better operationalize emotional experience, one could either do so indirectly by measuring the affective properties (e.g. valence) of the stimulus in sliding windows, or directly by recording online physiological markers of affective responses (e.g. galvanic skin

response) and/or having subjects report ongoing emotional experience multiple times while viewing the naturalistic stimulus.

Conclusion

Central to our human existence yet notoriously difficult to study, emotional experience has been eluding the attention of scholars until recently, when new technology enabled researchers to design experiments that maximally suits the study of internal experiences. The neural synchrony approach quantifies inter-subject similarities in neural responses to naturalistic stimuli, which can then be related to individual differences in behavioral constructs to examine the neural correlates of a shared endogenous process such as emotional experience. In the current study, we applied ISC and IS-RSA, two analytic techniques that both relate neural synchrony to behavioral similarities, on self-reported emotional experience and neural timeseries data when subjects watched provocative videos on gun control. Moreover, to tackle the limitations of the analyses, we explored the possibility of adding k-means clustering as the initial step of both analyses. We found that only negative, not positive, emotional experience drove neural synchrony in mPFC, and that previously marginally significant effects became truly significant in cluster-based ISC and IS-RSA. Given the crucial role of mPFC in the sense-making process, the present study suggests that unpleasant emotions may powerfully unify people by contributing to a shared subjective reality, which is manifested as mPFC neural synchrony.

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