

# Politically Extreme Individuals Exhibit Similar Neural Processing Despite Ideological Differences

Daantje de Bruin<sup>1</sup> and Oriel FeldmanHall<sup>1, 2</sup>

<sup>1</sup> Department of Cognitive and Psychological Sciences, Brown University

<sup>2</sup> Carney Institute for Brain Science, Brown University

The current state of political polarization in the United States encompasses a growing divide between partisans and a shift toward more extreme ideologies. Although rising ideological extremism poses societal challenges, the mechanisms supporting extreme views remain uncharacterized. Leveraging a combination of neurophysiological methods, we show that regardless of which side of the political aisle an individual is on, those with more extreme views show heightened neural activity to politically charged content in brain regions implicated in affective processing—including the amygdala, periaqueductal gray, and posterior superior temporal sulcus. Moreover, we observe that those who share an extreme perspective—even when they do not share an ideology—exhibit increased neural synchronization in the broader posterior superior temporal sulcus region while consuming political content. For those on the most extreme ends of the ideological spectrum, this effect is further influenced by listening to extreme language. Finally, we find that shared arousal, measured through galvanic skin conductance responses, modulates the strength of coupling between shared extremity and neural synchrony. Together, our findings suggest a role for affect in shaping ideological extremity, which helps explain why those at the far ends of the political spectrum come to view the world through a shared, extreme lens.

## Statement of Limitations

This study examines the association between ideological extremity and the neurophysiological processing of political content. Although we use a naturalistic approach with real-world political content, this is only a small subset of the political content that exists, warranting caution in generalizing our findings to all types of political content. Second, this study focuses on ideological extremity, computed from *self-reported* political ideology. This measure likely only captures part of the broader, complex construct of extremism. Moreover, this study was run within the United States, and ideological extremity might be differentially defined and/or experienced across different cultures and political systems. Finally, we cannot make any claims about the causality of our findings, as we only study associations between ideological extremity and neurophysiological responses.


**Keywords:** ideological extremity, affective processing, neural synchronization, political polarization


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Although debate and disagreement have always been fundamental properties of the democratic process, bridging the divide between those with opposing views has become more challenging over the past decade (Pew Research Center, 2023). The increase in partisan sorting and intensification of the ideological division between partisans—known as political polarization—has exposed

a surge in ideological extremism. Partisans on both sides of the aisle increasingly exhibit political beliefs that tilt even farther from center (Kleinfeld, 2022; Lange, 2024; Pew Research Center, 2021; Piazza, 2023), although some argue this is driven mainly by political elites (Baldassarri & Page, 2021; DellaPosta, 2020; Holliday et al., 2024). Historically, a rise in political extremism has paved the way to

Chadly Stern served as action editor.

Daantje de Bruin  <https://orcid.org/0000-0003-3936-8067>

Oriel FeldmanHall  <https://orcid.org/0000-0002-0726-3861>

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Correspondence concerning this article should be addressed to Oriel FeldmanHall, Department of Cognitive and Psychological Sciences, Brown University, 190 Thayer Street, Providence, RI 02912, United States. Email: [oriel.feldmanhall@brown.edu](mailto:oriel.feldmanhall@brown.edu)

radicalized, violent behavior (Jensen et al., 2020; Kunst et al., 2019; Neumann, 2013) and, in some cases, a failure of democracy (Axelrod et al., 2021; Torcal & Magalhães, 2022). Despite extremism's imprints on history and its more recent rapid ascent (Public Religion Research Institute, 2023), much remains unknown about the mechanisms that underlie ideological extremism.

Ideologically extreme beliefs—that is, political beliefs that are far from the political center—are thought to be multifaceted, shaped by social, economic, demographic, and psychological factors (Hogg et al., 2013; LaFree & Schwarzenbach, 2021; Lösel et al., 2018). In particular, there is growing evidence that some stable cognitive traits, such as cognitive inflexibility, or psychological features, such as intolerance of uncertainty and cognitive simplicity, are tightly linked with the black-and-white perspectives seen in more extreme ideologies (Decety et al., 2018; Imhoff et al., 2022; van Prooijen & Krouwel, 2017, 2019; Zmigrod et al., 2019, 2021). This suggests that only certain individuals will fall prey to extremism. However, as some theorists pointed out (Druckman et al., 2021; Iyengar et al., 2012, 2019; Iyengar & Westwood, 2015; Lelkes, 2018; Prinz, 2021), there is a more malleable, and far more common, driver that likely also underlies the observed increase in extremist viewpoints: emotion. Extreme attitudes are linked to heightened emotional reactivity, impaired emotion regulation (Barnidge et al., 2018; Zmigrod & Goldenberg, 2021), and negative affect (Canetti-Nisim et al., 2009; Lee & Choi, 2020; Prinz, 2021; Webster & Albertson, 2022). Fear and anger are especially associated with more extreme ideological stances and correlate with support for the use of political violence (Alizadeh et al., 2019; Zeitzoff, 2014) and the derogation of political outgroups (van Prooijen et al., 2015).

The idea that emotion and affect contribute to extremism aligns with the broader theory of *affective polarization*, which posits that an increase in negative feelings, distrust, and hostility toward those with opposing political beliefs drives the increasing ideological divide currently observed in society (Druckman et al., 2021; Iyengar et al., 2019; Lelkes, 2018; Prinz, 2021). Recent work has linked political polarization to brain regions typically associated with processing emotional content, including the amygdala (Gozzi et al., 2010; Westen et al., 2006), as well as to the body's physiological response (Bakker et al., 2020; Gruszczynski et al., 2013; Knoll et al., 2015; Oxley et al., 2008; Petersen et al., 2015; Renshon et al., 2015; Wagner et al., 2015), which can be measured through the galvanic skin conductance response (SCR; Figner & Murphy, 2011; Nikula, 1991) and provides an index of emotional arousal (Boucsein, 2012). Growing evidence from physiological research thus suggests that the process of polarization is entwined in emotional responding. What remains less clear is how emotional and affective processes contribute to the even more distorted perspectives seen in those holding extreme ideologies (Decety et al., 2018; Pretus et al., 2019; Tobeña, 2024; Zhong et al., 2017).

We begin by asking whether heightened emotional responses predict greater ideological extremity regardless of which side of the political aisle. To test whether ideological extremity (operationalized by self-identifying as extremely liberal or conservative) is tracked physiologically, we leverage a multiprong approach, measuring physiological responses in both the body (SCR) and brain while people consume naturalistic political content. Given the theory and empirical evidence that a polarized perception is driven by negative affect (Bakker & Lelkes, 2024; Druckman et al., 2021; Gozzi et al.,

2010; Iyengar et al., 2012, 2019; Iyengar & Westwood, 2015; Lelkes, 2018; Prinz, 2021; Westen et al., 2006), we focus on two brain regions typically linked to affective processing: the amygdala (Adolphs et al., 1995; Fox et al., 2015; LeDoux, 1994) and the periaqueductal gray (PAG; Mobbs et al., 2007; Watson et al., 2016), asking whether ideological extremity is associated with heightened engagement of these regions. Essentially, we interrogate whether ideological extremity is reflected in how the brain processes political content. We also test whether measures of bodily arousal track extremity and whether, when coupled with measures of neural physiology, these affective indices together predict more extreme ideological perspectives. Finally, we collected eye-tracking data, enabling us to test and control for the hypothesis that affective polarization is driven, at least in part, by shared attention (Bacos et al., 2024; Holmqvist et al., 2011; Posner, 1980).

We then turn to a second provocative question posed by political theorists, which asks whether those on the far left and far right actually have more in common than moderates who occupy the middle of the political aisle. This theory is often described as horseshoe politics (Faye, 1996), where those on the opposite ends of the ideological spectrum can be viewed as close together rather than far apart (Clemm von Hohenberg & Bauer, 2021; Moore-Berg et al., 2020). Evidence supporting this theory would require revealing a common neural mechanism for extreme beliefs, regardless of ideology. Put another way, irrespective of whether one's views are more on the left or right, it is possible that, at least on some dimensions, the brain processes extreme perspectives in a similar way.

To test this idea that more extreme individuals share similar neural processing and perspectives despite ideological differences, we measure synchronized blood oxygen level-dependent (BOLD) responses to political content between individuals who share extreme political views, even if the content of those beliefs differs. Interbrain synchrony measures allow us to test for a shared experience between individuals by measuring whether there is a coordinated brain response between individuals (Dumas et al., 2010; Hasson et al., 2012; Nastase et al., 2019; Nguyen et al., 2019; Yeshurun et al., 2017). Prior research on shared experiences, especially in the domain of political polarization (de Bruin et al., 2023; Katabi et al., 2023; Leong et al., 2020; van Baar et al., 2021), points to a neural network largely associated with emotional perception, self-other representations, and theory of mind, which includes adjacent regions—the posterior superior temporal sulcus (pSTS; Arioli et al., 2021; Basil et al., 2017; Isik et al., 2017; Kinreich et al., 2017; Lee Masson & Isik, 2021; Saxe & Powell, 2006) and the temporoparietal junction (TPJ; Saxe & Kanwisher, 2003). The pSTS is often implicated in social cognition, agency, intention, and prediction, broadly speaking, and the TPJ (which is anatomically housed within the broader pSTS region) is well-known for its role in perspective taking and indexing shared interpretations (de Bruin et al., 2023; van Baar et al., 2021; Yeshurun et al., 2017).

To explore the relationship between shared extremity and neural synchronization in these brain regions, we employed a dyadic regression approach (van Baar et al., 2021), where each individual's continuous BOLD response is compared with every other participant's BOLD response. The degree to which two brains exhibit a coordinated response is then computed for every pair in the sample. We can further test whether neural coupling is sensitive to the degree to which extremist language is used during the political video. To do

this, we leverage a large language model (LLM) to assess extreme language, a method that has been shown to effectively measure text sentiment (Nadi et al., 2024; Obinwanne & Brandtner, 2024; Rathje et al., 2024). Finally, to link our two main questions, we test the role of affect in the formation of shared extreme beliefs, directly interrogating if there is an association between physiological arousal and synchronized neural responses.

We invited participants clustered on both ends of the ideological spectrum to participate in a study on political cognition (Figure 1A). Participants watched naturalistic political content while in the scanner, while we simultaneously measured their SCRs. To obtain a measure of attention, we also collected eye-tracking data while participants watched the political content. We tested the relationship between ideological extremity (agnostic to whether extreme left or right) and neurophysiological responses in two ways. First, at the subject level, we examine the relationship between ideological extremity and the average neurophysiological activity elicited while watching naturalistic political content. Then, at the dyadic level, we test whether similarity in the neurophysiological activity time courses predicts similarity in extremity, even across the political aisle (Figure 1B). Finally, we examine how the use of extremist language may impact this neurophysiological coupling (Figure 1C).

## Method

### Participants

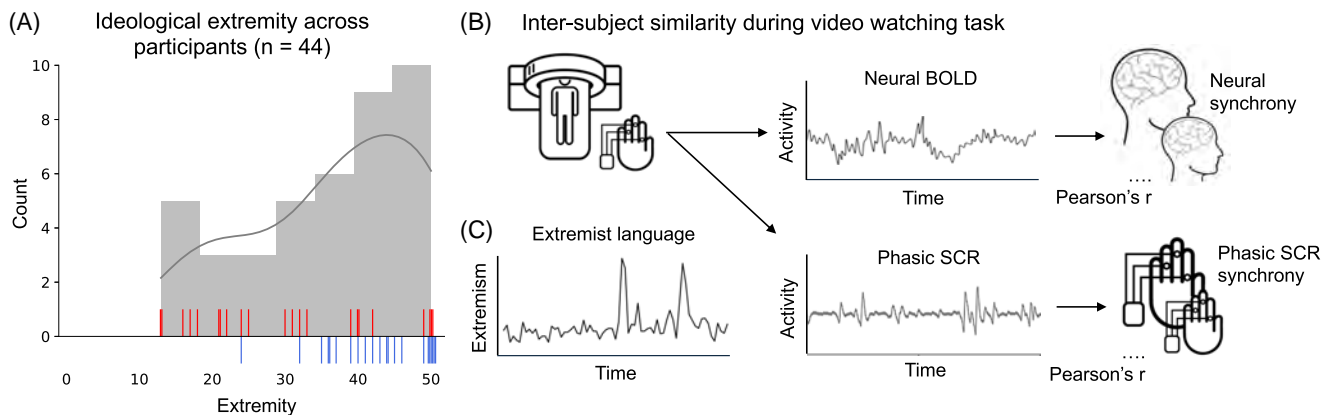
The data analyzed here were collected as part of a larger study exploring the neural mechanisms of political polarization. Participants were recruited through online advertisements on social media, posters, and flyers and via recruitment visits to political meetings. A total of 360 potential participants filled out an online prescreening questionnaire including questions on self-reported political ideology, assessed using a 100-point slider measure ranging from 0 = *extremely*

*liberal* to 100 = *extremely conservative* (Dodd et al., 2012), and basic demographics. Based on sample sizes used in previous neuroimaging studies using similar dyadic measures (e.g., Finn et al., 2018; Leong et al., 2020; Yeshurun et al., 2017), 44 participants, ranging from the extreme liberal side (ideology score  $\leq 50$ ,  $n = 22$ ) to the extreme conservative side (ideology score  $> 50$ ,  $n = 22$ ), were invited to participate in the study. Prior work on sample sizes in dyadic analyses suggests that this sample size is sufficient to obtain large effects (Pajula & Tohka, 2016). All participants were MRI eligible and right handed. Participants provided informed consent and received monetary compensation (\$40) for participating in this study, which was approved by the Brown University's Institutional Review Board. One participant was excluded from the study for indicating a different political ideology on the prescreening questionnaire than on the postscan political surveys. This led to the inclusion of 43 participants, with varying degrees of ideological extremity.

### Procedure

The total duration of the study was approximately 3 hr and consisted of multiple tasks, both in and outside of the MRI scanner. Participants first provided demographics and information about their political beliefs and interest before going into the MRI scanner. The video-watching task described in this research included a 17:47 min subset of the 2016 vice-presidential debate, in which Democrat Tim Kaine and Republican Mike Pence discuss their stance on police reform and immigration (24:30 min to 42:10 min; <https://www.youtube.com/watch?v=ox8PTXwDYdc>). The debate was chosen because of its inflammatory and provocative language, and these topics were selected because of their political relevance at the time of data collection (2018–2019). The topics of policing and immigration were also politically divisive (Council on Criminal Justice, 2020; Daniller, 2019), as illustrated by, for example, the

**Figure 1**  
Experimental Design



**Note.** (A) Forty-four participants who spanned the extreme right (red bars) and extreme left (blue bars) of the political spectrum were invited to participate in a study on political cognition. These participants represented a range of ideologically extreme attitudes, with most participants being on the more extreme end (high extremity = 50). (B) Participants completed a video-watching task inside the magnetic resonance imaging (MRI) scanner, while neuroimaging and skin conductance response (SCR) data were collected. From these time courses obtained while participants watched political content, intersubject similarity or synchronization of the neural and phasic skin conductance response was computed (see the Method section). (C) To test whether neurophysiological synchronization was sensitive to the use of extremist language, we used a large language model to assess extremist discourse in the video. BOLD = blood oxygen level-dependent. See the online article for the color version of this figure.

late 2018 Build the Wall, Enforce the Law Act that was proposed by then-President Donald Trump (Congress, 2018).

The video was obtained from YouTube and was presented on a gray background screen at 80% of the screen size. Participants watched the video twice: once inside the scanner while brain and skin conductance data were obtained and a second time outside of the scanner while eye-tracking data were collected. After completing the video watching task, participants answered a series of questionnaires, including comprehension and engagement questions (see Supplemental Material S1), questions on their agreement with statements made in the video (see Supplemental Material S2), and questions on their attitudes toward the 2016 (vice-) presidential candidates.

## Data Acquisition

### *Skin Conductance Data Acquisition*

Skin conductance signals were recorded using a galvanic skin response sensor for functional magnetic resonance imaging (fMRI) and the BrainVision Recorder system (Brain Products, München, Germany). A sampling frequency of 5,000 Hz was used, with a 2,500 Hz low-pass filter.

### *Eye-Tracking Data Acquisition*

Eye-tracking data were collected using iView X (Version 2.8.26) on the SMI iView X RED eye tracker (SensoMotoric Instruments, Teltow, Germany) with an integrated 22-in. computer screen (1,680 × 1,050). This eye tracker has been designed to be used without a chin rest, as it measures the distance and position of the eyes while tracking the eye movements. Participants were placed approximately 50–70 cm from the screen and instructed to stay as still as possible and to fixate at the middle of the screen. Before watching the video, participants completed a 5-point linear calibration and validation procedure to locate the eyes, which was repeated until the deviation in visual angle between the validation target and the recorded gaze fixations was below 2°. A sampling rate of 120 Hz was used, in combination with bilateral and gaze cursor filtering (saccade length, 80 ms; filter depth, 20 ms). Gaze data were collected for both the left and the right eyes.

### *fMRI Data Acquisition*

MR images were acquired on a Siemens Prisma Fit 3 Tesla research-dedicated scanner (Siemens Healthineers, Erlangen, Germany) at the Carney Institute for Brain Science at Brown University. fMRI data were collected using a 64-channel head coil. Simultaneous multislicing was used to acquire  $T_2^*$ -weighted functional scans, resulting in a three-factor scan time reduction, increasing the number of time points and thus statistical power for the interbrain synchrony analysis. Echo planar images covering the entire brain except part of the cerebellum were acquired using contrast settings optimized for cortical gray matter (repetition time (TR)/echo time 1,500/30 ms, voxel size 3 mm isotropic, 64 × 64 voxels, flip angle 86°, 60 slices, distance factor 0%). The field of view was tilted upward by 25° at the front of the brain to minimize tissue gradient-related signal dropout in the orbitofrontal cortex. To acquire a three-dimensional T1 anatomical scan, the magnetization-prepared rapid acquisition gradient-echo imaging sequence (Mugler & Brookeman, 1990) was used (TR/echo time/inversion time 1,900/3.02/900 ms, voxel size = 1 mm isotropic, 256 ×

256 voxels, parallel imaging [generalized autocalibrating partially parallel acquisition, acceleration factor 2], flip angle = 9°, 160 slices, distance factor = 50%; de Bruin et al., 2023).

## Data Analysis

### *Dyadic Regression Analysis*

To test whether similarity in ideological extremity is associated with similarity in the neurophysiological response to political content, we use a dyadic regression model (Chen et al., 2017; de Bruin et al., 2023; van Baar et al., 2021). This model is a custom implementation of a mixed-effects regression model based on the lme4 and lmerTest packages in R and includes a random participant intercept for both participants in the dyad. The model therefore accounts for the inherent statistical dependencies between dyads. This model uses similarity between participants rather than individual-level measures, which makes it possible to compare and combine results from different modalities (e.g., behavioral and neurophysiological) into one regression model.

### *Behavioral Data Analysis*

In addition to the participant who was excluded based on inconsistency in their self-reported political ideology, two other participants were excluded: one because of missing SCR data and one because of excessive head motion during the MRI acquisition. This led to the inclusion of 41 participants (24 males and 17 females,  $M_{\text{age}} = 32.5 \pm 14.1$  [SD] years) and 820 unique participant pairs or dyads.

From the 100-point ideology scores, which ranged from extremely liberal to extremely conservative, an ideological extremity score was computed. This score reflected the absolute distance from the neutral center of the ideology scale (50) and ranged from 0 to 50. Higher scores thus indicated more extreme political views, whereas lower scores reflected a participant being more moderate and in the political center. On average, participants had an extremity score of  $37.3 \pm 11.5$  (SD), with a range of 13–50. To further validate our extremity measure, and to establish a first association between affect and extremity, we used the measures obtained from the posttask attitude questionnaire, in which participants were asked how much they liked or disliked the 2016 vice-presidential (Tim Kaine and Mike Pence) and presidential (Hillary Clinton and Donald Trump) candidates. These 10-point Likert scale ratings were Spearman's rank correlated with the self-reported extremity scores.

To quantify the intersubject similarity in ideological extremity, two different measures were computed. First, similarity in extremity was computed as  $50 - \text{abs}(\text{extremity}_1 - \text{extremity}_2)$ , where 1 and 2 refer to the two participants in a dyad. The higher this score, the more similar a dyad was in their ideological extremity. Second, we computed the combined extremity of each dyad, to test whether our findings depended on a pair's degree of ideological extremity.

To link the different neurophysiological and extremity measures, dyadic regression models were used, in which similarity in one modality can be regressed onto similarity in another modality. Before running the model, all regressors were  $z$  scored. All reported  $p$  values represent false discovery rate (FDR) corrected estimates (Hochberg & Benjamini, 1995), to control for the inclusion of multiple brain regions.



To test for a possible relationship between ideological extremity and engagement during the video watching task, we used both self-reported political engagement scores and the posttask comprehension scores. A chi-square test was conducted to test for differences between individuals high (extreme) and low (moderate) in ideological extremity (based on a mean split) in how much participants indicated following politics in general. The relationship between ideological extremity and video comprehension was tested using a nonparametric Mann–Whitney *U* test and Spearman’s rank correlation.

To test for individual differences in interpretation or agreement with the video along partisan lines, we used the posttask agreement ratings. Participants were presented with four statements made by either Tim Kaine or Mike Pence (see Supplemental Material S2) and were asked to rate their agreement with the statements on a 7-point Likert scale. Two sample *t* tests were conducted to test for differences in agreement between participants who identified as liberal versus conservative. These *t* tests were also conducted in a subset of the sample, which only included more extreme participants (mean split based on extremity score, cutoff at >37.3). Results for these analyses can be found in the Supplemental Material (see also Supplemental Material S2).

### Video Content Analysis

To test whether the degree of extremist language used in the video modulates the dyadic coupling between individuals (both neurally and physiologically), we created a measure of extremist language using OpenAI’s LLM, GPT 3.5 Turbo (Brown et al., 2020). We divided the video into 15-s fragments and asked the LLM to compute an extremism score for each fragment based on its transcribed text. More specifically, we used the following prompt:

Can you assess the level of political extremism in the following text, focusing on the presence of extreme ideological views, language, or rhetoric? Compute a score between 0 (*not extremist*) and 1 (*extremist*). Please only output a value. Here is the text.

We repeated this process 10 times and averaged the LLM extremist scores per decontextualized 15-s fragments over these iterations, yielding an extremist language time course (Figure 1C). These LLM extremism scores ranged from 0 to 0.84 (see Supplemental Material S3 for sample text chunks and scores), with extremist language being rated as relatively low, on average ( $M = 0.17 \pm 0.16$  [SD]). It is important to note that the LLM does not consider context or previous chunks of text, which could explain the relatively low ratings. Rerunning this analysis with the full video transcript and thus more contextual information yielded a much higher LLM extremism score for the entire video ( $M = 0.78 \pm 0.12$  [SD]).

To test whether there were any differences in extremist language, as measured through the LLM, by either of the vice-presidential candidates, we multiplied the extremist language score for each chunk by the proportion of time each politician spoke during those 15 s. Based on these weighted LLM scores, we found no significant difference between vice-presidential candidates Tim Kaine and Mike Pence in their use of extremist language,  $t(99.2) = 1.056$ ,  $p = .294$ .

To validate the scores provided by the LLM, we asked three independent raters to perform the same task as the LLM. We randomly shuffled the 15-s chunks to imitate the context independence of the LLM and asked the raters to provide a score (ranging from 0 to 1) for each chunk. These scores were *z* scored for each rater and

averaged across raters. Comparing these average human ratings to the LLM ratings yielded a significant correlation between the human and the model ratings ( $p = 0.551$ ,  $p < .001$ ) and no significant difference between the human and model ratings,  $t(133.8) = -0.018$ ,  $p = .986$ .

### Physiological Data Analysis

One participant was excluded from the analyses due to missing SCR data. The SCR data were analyzed using the MNE (Gramfort et al., 2013) and NeuroKit2 (Makowski et al., 2021) packages in Python. Using the NeuroKit2 default settings, a low-pass filter with a 3-Hz cutoff and a fourth-order Butterworth filter were used to preprocess the data. The cleaned SCR signal was decomposed into a slow, tonic component and a faster, phasic component by passing the signal through a high-pass filter with a 0.05-Hz cutoff. The phasic component was used for our analyses.

The phasic SCR signal was resampled to 200 ms, yielding a skin conductance value for every 0.2 s of the video, or a skin conductance time course. To test for an association between ideological extremity and average phasic SCR at the subject level, this time course was averaged and included as an independent variable in a linear regression model. Whereas this approach glosses over the more fine-grained changes in SCR responses over time, this allows us to apply a more standard, univariate approach to our continuous data set, testing whether phasic arousal responses scale with ideological extremity. To compute intersubject similarity in phasic SCR response during the video, the Pearson’s correlation in phasic SCR time courses between every subject pair was computed, providing a measure of shared SCRs. First, we tested a model in which we regressed intersubject similarity in ideological extremity onto phasic SCR synchronization and the combined extremity of the subjects. Second, we included neural synchrony as an additional interaction term in this model, trying to predict intersubject similarity in extremity using SCR synchronization, neural synchronization, and the combined ideological extremity of each dyad.

To test whether dyadic coupling in phasic SCR was modulated by the degree of extremist language used in the video, we used the extremism scores provided by the LLM. To map these scores onto our synchrony measure, we computed SCR synchronization for each 15-s fragment of the video. Building on the previously described models, we then tested a model in which we regressed intersubject similarity in ideological extremity onto the combined extremity of the dyad, phasic SCR synchronization per 15-s fragment, and the LLM’s extremist language score for each fragment.

### Eye-Tracking Data Analysis

Preprocessing of the eye-tracking data was performed using the built-in iView X IDF Event Detector, which detects saccades, fixations, and blinks from a gaze data stream (Salvucci & Goldberg, 2000). To compute a total fixation time for each subject, we first computed the average fixation time across both eyes for every second of the video and then summed across these average fixation durations per second.

To create a measure of shared attention, we leveraged two different approaches. First, we used a heatmap-based approach. Using adjusted code based on the PyGaze Analyser package in Python (Dalmaijer et al., 2014), we created a gaze heatmap for each 1.5 s of the video,

corresponding to the duration of the neural TRs. To compute a gaze heatmap intersubject correlation value, we then Pearson's correlated the flattened heatmaps for each subject pair at every TR. A gaze heatmap intersubject correlation value for the whole video was created by averaging these correlation values (Fisher  $r$ -to- $z$  transformed) across TRs. As a second measure of shared attention, we computed the pairwise similarity between the  $x$ - and  $y$ -coordinate time courses for each dyad. From the fixation data, we created a coordinate time course for the  $x$ -dimension and the  $y$ -dimension of the video screen. Missing data were linearly interpolated. We then computed the correlation for each of these dimensions for every subject pair and averaged these two Fisher  $r$ -to- $z$  transformed correlation values to compute one gaze time course similarity value for each dyad. To test whether our effects were driven by shared attention rather than shared extremity, we ran our models including these subject-level and dyad-level measures of attention.

### fMRI Data Analysis

Preprocessing was performed using fMRIPrep 1.5.1rc2 (RRID: SCR\_016216; Esteban et al., 2019; Gorgolewski et al., 2011). The complete preprocessing pipeline can be found in the Supplemental Material (see also Supplemental Material S4). The anatomical  $T_1$ -weighted images were corrected for intensity nonuniformity, distributed, skull stripped, and segmented before being transformed into standard Montreal Neurological Institute space. Spatial normalization was applied to this  $T_1$ -weighted reference image.

Functional images were collected in one continuous run. Using fMRIPrep, a reference volume was created from the BOLD signal, which was then coregistered to the  $T_1$ -weighted reference image. Spatiotemporal filtering and slice-time correction were applied to the BOLD images before they were resampled into standard space. After preprocessing, the BOLD images were smoothed with a 6-mm full width at half maximum Gaussian kernel with implicit brain masking in Statistical Parametric Mapping, Version 12. General linear models were constructed for each voxel's time series signal, in which motion and physiological noise regressors were included to remove signal components related to movement and other sources of noise. The residual time series of each voxel was used for statistical analysis. One participant's data were excluded from the analysis due to excessive head motion.

For the statistical analyses, a region of interest (ROI)-based approach was used. Four ROIs were selected based on their prior link to mentalizing and perspective taking (TPJ), social cognition (pSTS), and the processing of affect (bilateral amygdala and PAG). The bilateral TPJ ROI was created by combining two 6-mm spherical ROIs centered at Montreal Neurological Institute voxel coordinates  $[-54, -60, 21]$  and  $[51, -54, 27]$  (Saxe & Kanwisher, 2003). The pSTS and PAG ROIs were defined through Neurosynth, which yielded peak Montreal Neurological Institute voxel coordinates  $[2, -30, -10]$  for the PAG (term "periaqueductal") and  $[-52, -52, 10]$  for the pSTS (term "psts"). The ROIs were created as 6-mm spheres centered on these peak voxel coordinates. The amygdala ROI was defined using the automated anatomical labeling atlas (Tzourio-Mazoyer et al., 2002) in the WFU Pickatlas toolbox for Statistical Parametric Mapping, Version 12 (bilateral amygdala; Maldjian et al., 2003, 2004).

As a first measure of the neural correlates of ideological extremity, we tested the relationship between each participant's ideological

extremity score and the average activity elicited in each ROI throughout the debate video. This averaging of the BOLD time courses allows us to apply this univariate, parametric approach to our continuous data, measuring whether average neural responses are modulated by one's ideological extremity. By selecting and averaging the part of the neural time course that was collected during the video, this approach compares neural activity during the video with baseline activity right before and after the video, enabling us to link average task-related activity to individual differences in ideological extremity. Although our naturalistic task design is not optimized for such univariate analyses, this approach allows us to identify subject-level associations between ideological extremity and neural activity. A linear regression model was used to test for a significant relationship between the  $z$ -scored variables. FDR correction was applied to the output of the neural linear regression models to control for the inclusion of multiple ROIs.

As a second measure, we used an intersubject correlation or neural synchrony approach. For each of our ROIs, the preprocessed BOLD time series was extracted and Pearson's correlated between all possible subject dyads, yielding a measure of neural synchrony for each subject pair. We used different dyadic regression models to investigate the relationship between neural synchronization and shared ideological extremity. First, we regressed intersubject similarity in ideological extremity onto neural synchrony and combined ideological extremity of the pair. Second, we tested whether the relationship between ideological extremity and neural synchronization was modulated by extremist language used in the video. We used a similar approach as described before, where we computed a neural synchronization value for each 15 s (10 TRs) of the video. We reran our model with the extremist language scores provided by the LLM as an additional interaction term.

Finally, we tested the relationship between extremity, neural synchrony, and SCR synchrony by including intersubject similarity in phasic SCR as an additional interaction term in our neural model. FDR correction was again applied to all neural model outputs to correct for the inclusion of multiple ROIs. Model effect sizes (conditional  $R^2$ ) were computed using Nakagawa's  $R^2$  function from the performance package in R. Effect sizes for each of the individual predictors (partial  $R^2$ ) were computed from the regression test statistics (Friedman, 1982) using the effectsize package. However, it is important to note that these effect sizes should be interpreted with caution, as they do not fully account for the nested, interdependent structure of the dyadic data. Because of the shared variance between dyad members, which is partially captured by the random effects in the model, it is difficult to isolate the unique contribution of single predictors in the traditional sense. To visualize the interaction effects, mean splits were applied to the data (see figure legends for details). To compute the statistics corresponding to the simple slopes shown in the figures, we used the emmeans package in R to estimate the marginal means at the average value of the moderator within each data subset. Significance of the slopes was derived from the  $t$  statistics and FDR corrected for the inclusion of multiple ROIs.

To validate the choice of our ROIs and to make sure that no other important regions were omitted from the analyses, we also conducted an exploratory whole-brain analysis for our main dyadic regression model. For each voxel in the brain, intersubject similarity in ideological extremity was regressed onto neural synchrony and combined ideological extremity of the pair. The resulting whole-brain regressor  $\beta$  map was family-wise error (FWE) corrected (Armstrong, 2014) and thresholded at  $p_{\text{FWE}} < .05$ . To extract significant clusters, a

threshold of  $\beta \geq 0.1$  and cluster size  $\geq 15$  voxels ( $405 \text{ mm}^3$ ) was applied. Results for the whole-brain analysis can be found in the Supplemental Material (see also Supplemental Material S5).

As prior work has shown that shared political ideology can be a driver of neural synchrony (de Bruin et al., 2023; Katabi et al., 2023; Leong et al., 2020; van Baar et al., 2021), we wanted to assure that our findings capture more than just shared political ideology. To test the unique contribution of shared ideological extremity, above and beyond shared political ideology, we used the self-reported political ideology scores. We ran a dyadic regression model in which we regressed both shared extremity and shared ideology onto neural synchrony in the TPJ and pSTS. By including both predictors in the same model, we control for the effect of the other variable, in that way measuring their unique contributions to neural synchronization.

## Transparency and Openness

The data analyzed here were collected as part of a larger study exploring the neural mechanisms of political polarization, of which the present study was not preregistered. The hypothesis we tested in the work here was inspired by historical events (COVID-19) and observing current events unfold in the news and around college campuses in 2023, where much of the “us versus them” rhetoric appeared on both ends of the ideological aisle, reflecting the dynamics of horseshoe politics. Sample size rationale, all data exclusions, and all analyses that were conducted are reported. Data and code for all experiments described in this article are publicly available on the Open Science Framework at <https://osf.io/ph8bt/> (de Bruin & FeldmanHall, 2025).

## Results

### Ideological Extremity Is Associated With Heightened Neural Responses to Political Content

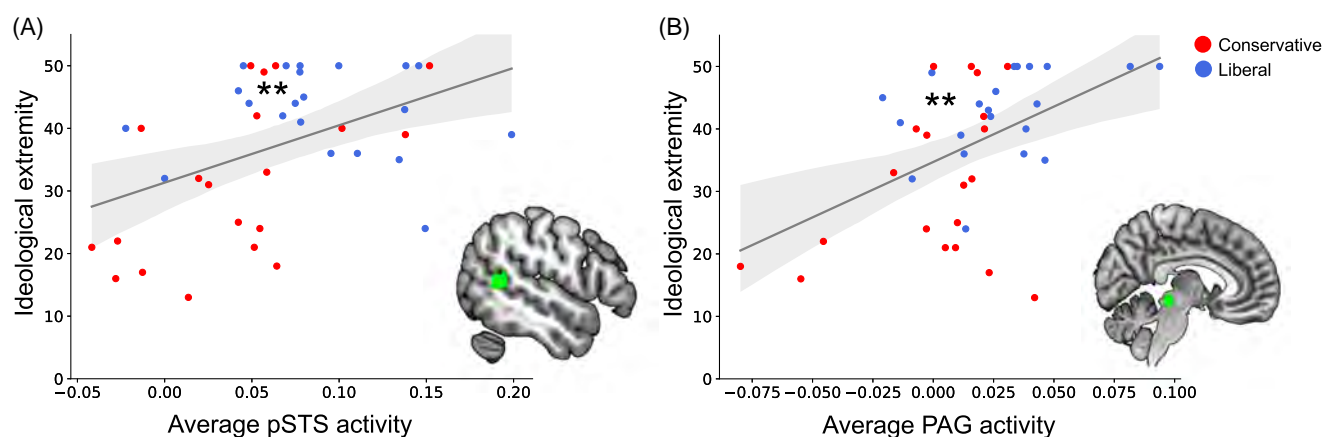
As a first measure of the link between ideological extremity and affect, we probed the relationship between how much individuals

reported liking the 2016 (vice-) presidential candidates and their self-reported extremity score. There was a strong significant correlation between extremity and how much one disliked the outgroup’s politician ( $\rho = -0.649, p < .001$ ), reflecting outgroup hate or derogation. We did not observe a significant relationship for liking one’s ingroup politician ( $\rho = -0.111, p = .489$ ). This aligns with a growing body of work, suggesting that especially outgroup hate or “negative partisanship” drives polarization and radicalization (e.g., Abramowitz & McCoy, 2019; Abramowitz & Webster, 2018; Dimant, 2023; Iyengar et al., 2012; McCauley & Moskalenko, 2008; Rathje et al., 2021; van den Bos, 2020; van Prooijen et al., 2015).

To test this at the neural level, we began by asking whether ideological extremity shapes the neural response to political content. From each individual’s self-reported political ideology, we computed an extremity score, independent of political leaning (see the Method section). To investigate whether ideological extremity is indexed by heightened neural responses to political content in brain regions predominantly associated with processing affect, we collected BOLD time courses obtained while participants watched political content in the scanner. This analysis takes a coarse approach to understanding if regions predominantly involved in affective processing are also involved in processing extreme perspectives. ROIs included the amygdala (bilaterally; Adolphs et al., 1995; Fox et al., 2015; LeDoux, 1994) and the PAG (Mobbs et al., 2007; Watson et al., 2016), which have been extensively linked to the processing of fear and threat, and the pSTS, which has been shown to engage during negative social interactions (Arioli et al., 2021)—which were abundant in the debate between two political opponents. For each region, we computed the average neural activity during the video. Regressing the average neural response onto the ideological extremity scores yielded a significant relationship between ideological extremity and the neural response to the political video in all three ROIs—similar to a parametric modulation but adapted for time course data. The bilateral amygdala,  $\beta = 0.346 \pm 0.150$  (SE),  $R^2 = 0.120, t(39) = 2.303, p_{\text{FDR}} = .036$ ; pSTS,  $\beta = 0.450 \pm 0.143$  (SE),  $R^2 = 0.202, t(39) = 3.145, p_{\text{FDR}} = .006$  (Figure 2A); and PAG,

**Figure 2**

*Average Neural Activity While Watching the Debate Video Is Associated With Ideological Extremity*



**Note.** More extreme individuals showed heightened average activation in the (A) pSTS and (B) PAG while watching the debate video. A similar pattern was found for the bilateral amygdala. The scatter plots show the raw data for participants identifying as liberal (blue) or conservative (red). Shading represents the 95% confidence interval. pSTS = posterior superior temporal sulcus; PAG = periaqueductal gray. See the online article for the color version of this figure.

\*\*  $p_{\text{FDR}} < .01$ .

$\beta = 0.489 \pm 0.140$  ( $SE$ ),  $R^2 = 0.239$ ,  $t(39) = 3.500$ ,  $p_{FDR} = .005$  (Figure 2B), all exhibited greater activation as a function of increasing ideological extremity. We did not find this effect for the TPJ ROI ( $p_{FDR} = .149$ ). The significant effects in the amygdala, PAG, and pSTS seemed to not just reflect individual differences in interest or attention, based on self-reported video comprehension and general political engagement (see Supplemental Material S1), as well as eye-tracking-based measures of attention (see Supplemental Material S6).

While this provides some evidence that regions involved in affect, and fear in particular, are associated with ideologically extreme views, we can more directly probe the relationship between affective arousal and extremity while consuming naturalistic political content. We measured the body's physiological arousal response by obtaining a physiological measure that has been extensively shown to index emotional arousal: the galvanic SCR (Boucsein, 2012; Howell et al., 2016; Nikula, 1991). This measure was collected while participants watched political content, providing us with a continuous time series measure that mirrors BOLD time courses. We extracted the phasic component, which reflects fast, sudden changes in emotional arousal (see the Method section). For each participant, we computed an average value of this physiological measure, which we then regressed onto ideological extremity. We observed no significant relationship between ideological extremity and average phasic SCR response to the political video ( $p = .668$ ).

### Shared Extreme Views Are Accompanied by Synchronized Neurophysiological Responses

Univariate methods (used above) can help us understand how individual variability in ideological extremity is reflected at the neural level. However, this method glosses over the much more complex, multimodal experience and fine-grained temporal dynamics that unfold while a participant watches the political debate. The use of a naturalistic video-viewing task creates an ideal experimental testbed to study these more complex and dynamic emotional experiences in a realistic, ecologically valid fashion, which is particularly important in the domain of politics, where emotions are highly salient (Druckman et al., 2021; Iyengar et al., 2012, 2019). To test whether individual differences in the neural dynamics during the video watching task are associated with interindividual variability in ideological extremity, we used a data-driven neural synchrony approach (Dumas et al., 2010; Nguyen et al., 2019; Nummenmaa et al., 2018). This method allows us to test whether those who are similar in their degree (but not content) of extremity exhibit similar temporal patterns of activity when consuming political content. As before, we limit our analysis to the same regions of interest but posit that two ROIs in particular—the pSTS and the TPJ—which are most often implicated in perspective taking (Isik et al., 2017; Lee Masson & Isik, 2021; Saxe & Kanwisher, 2003), may reflect greater synchronized responses given their involvement in shared interpretations (de Bruin et al., 2023; van Baar et al., 2021; Yeshurun et al., 2017).

We began by creating a measure of neural synchrony for each of our ROIs by computing the Pearson's correlation between the neural BOLD time series data for all possible subject pairs and then created a measure of intersubject similarity in extremity by computing the absolute distance between the extremity scores of each possible subject dyad (see the Method section). Although this measure tells us how similar or dissimilar two people are in their ideological extremity, it does not convey any information about whether the pair

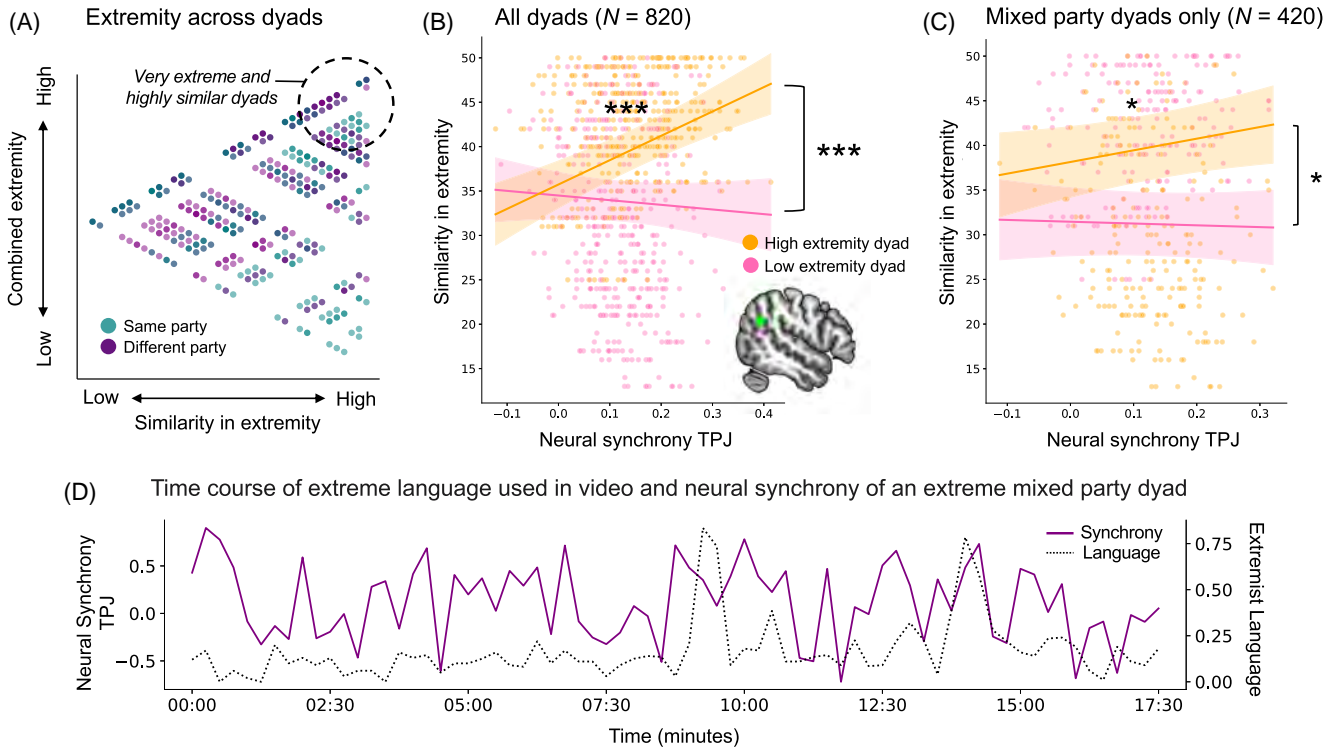
is high in extremity or not (extreme vs. moderate). Therefore, we created a second measure of shared extremity, which reflects the combined extremity of the subject pair, enabling us to test whether the degree of shared extreme beliefs shapes the neural response for participant pairs that are high, versus low, in extremity (Figure 3A).

To combine these different measures, we used a dyadic regression model, which is a custom implementation of a linear mixed-effects regression model that includes random participant intercepts for each participant pair (see the Method section; Chen et al., 2017; de Bruin et al., 2023; van Baar et al., 2021). This model yielded a significant interaction between neural synchronization and combined extremity: Similarity in extremity is predicted by more similar neural responses during the political video but only in dyads that are high in extremity (Table 1). This effect was found in both the TPJ (two-way interaction:  $\beta = 0.168 \pm 0.032$  [ $SE$ ],  $p_{FDR} < .001$ ; Table 1; Figure 3B) and the pSTS (two-way interaction:  $\beta = 0.289 \pm 0.035$  [ $SE$ ],  $p_{FDR} < .001$ ; Table 1) and remains significant when controlling for shared attention (using eye-gaze measurements; see Supplemental Material S6). Moreover, this effect continues to hold when you only include dyads with *opposing* political views (half of the sample, which may explain the attenuated effect; pSTS:  $p_{uncorrected} = .016$ ,  $p_{FDR} = .060$ ; TPJ:  $p_{uncorrected} = .041$ ,  $p_{FDR} = .060$ , Figure 3C; see Supplemental Material S7). An additional exploratory whole-brain analysis confirmed these effects, revealing a significant interaction effect in the TPJ and the pSTS, which extended to the broader superior and temporal middle gyrus (see Supplemental Material S5). These results suggest that ideological extremity appears to shape the way in which we perceive political content.

To measure the unique contribution of extremity beyond political ideology (de Bruin et al., 2023; Katabi et al., 2023; Leong et al., 2020; van Baar et al., 2021), we tested whether neural synchrony in the TPJ and pSTS is predicted by shared extremity when ideology is also included in the model (see the Method section). Synchrony in the TPJ is significantly predicted by both shared ideology and shared extremity, indicating that this region encodes both the contents of ideology and how extreme one's views are. By contrast, once we include ideology in the model, extremity becomes nonsignificant in the pSTS (see Supplemental Material S8), revealing that the pSTS is more involved in processing ideology than extremity. These findings illustrate that people can exhibit shared synchrony along numerous dimensions and that holding extreme ideologies may bias perceiving the world in a way that is similar to others who hold extreme views, even if the content of those views differs.

One way to further interrogate the neural mechanisms of extremity is to probe whether those on the far ends of the ideological spectrum are more sensitive to extreme language. In particular, we can probe whether increasingly extreme language shapes the neural coupling effect we observed in extreme dyads. If more extreme individuals are attuned to such extreme language, then we should see that in the portions of the video where extreme language increases, the neural synchrony effect becomes even stronger. We therefore used an LLM (OpenAI's GPT; Brown et al., 2020) to compute an unbiased extremism score for every 15 s of the video (see the Method section). For each dyad, we then compute the neural synchrony for each of these 15-s fragments, allowing us to map the LLM's extremism score to the degree of each dyad's neural coupling. Including the LLM's computed extremism scores as an additional interaction term in a model with neural synchrony for each 15-s fragment yielded a three-way interaction of neural synchrony, combined extremity, and



**Figure 3***Shared Ideological Extremity Is Associated With More Synchronized Neural Responses but Only for Those High in Extremity*

**Note.** (A) To investigate whether shared ideologically extreme beliefs are associated with more similar processing of political content, we created two measures of extremity for each dyad: the similarity in their ideological extremity (whether two individuals are both extreme, regardless of political views, or more moderate; x-axis), and their combined extremity (y-axis). Dyads consisting of political partisans and dyads consisting of individuals on opposing sides of the political aisle were distributed across this 2D space: The darkest purple dots reflect those that are both extreme (high combined extremity) and similar in their extremity but who do not share a political party (a conservative and a liberal). (B) A significant interaction effect was found, with similarity in extremity being predicted by increased synchronized neural responses in dyads high in extremity. A similar pattern was found for the posterior superior temporal sulcus (see Table 1). (C) When only looking at dyads that consist of political opponents (shared extremity but from opposite sides of the political aisle), a similar pattern was found in the TPJ (simple slope for high-extremity dyads:  $\beta = 0.100 \pm 0.049$  [standard error],  $p_{\text{FDR}} = .088$ ). For visualization purposes, a mean split was applied to the measure of combined extremity, but the analyses were run on continuous data. The scatter plots show the raw, unstandardized data points. The regression lines reflect the model predictions and simple slopes for low- and high-extremity dyads, and shading represents the 95% confidence interval. (D) Visualization of neural synchronization in the TPJ during the video for one dyad that is matched on extremity, but from opposite sides of the ideological spectrum (e.g., liberal/conservative: upper right corner in Panel A; purple line). For visualization purposes, the dyad's neural synchrony is overlaid on the large language model's assessment of extremist language used throughout the video (black line). TPJ = temporoparietal junction; FDR = false discovery rate. See the online article for the color version of this figure.

\*  $p_{\text{FDR}} < .1$ . \*\*\*  $p_{\text{FDR}} < .001$ .

extremist language predicting similarity in extreme views in the TPJ (three-way interaction:  $\beta = 0.009 \pm 0.004$  [SE],  $p_{\text{uncorrected}} = .016$ ,  $p_{\text{FDR}} = .064$ ; Table 2). In other words, the synchronization of neural responses to the political video for dyads that are high in extremity is strongest during parts of the video wherein more extremist language is used (Figure 3D). This suggests that extremist language modulates the neural synchrony between extreme individuals.

To better understand whether the body's arousal response plays a role in the neural coupling effect we observed between individuals high in extremity, we turned to the phasic SCR collected during the video. Similar to the approach used to measure neural synchronization, we computed intersubject similarity in subject-level phasic SCR signals by correlating each pair's time series data. Evidence of greater intersubject similarity in SCR responses would indicate that individuals felt emotionally aroused at similar time points in the video.

When we include intersubject similarity of phasic SCR responses as an additional interaction term in our neural dyadic regression model reported above (see the Method section), we find a significant three-way interaction between coordinated neural responses, synchronized SCRs, and combined ideological extremity, when predicting similarity in extremity—an effect observed in both the TPJ (three-way interaction:  $\beta = 0.137 \pm 0.033$  [SE],  $p_{\text{FDR}} < .001$ ; Table 3) and the pSTS (three-way interaction:  $\beta = 0.125 \pm 0.030$  [SE],  $p_{\text{FDR}} < .001$ ; Table 3), but not in any of the other regions ( $ps > .05$ ). This interaction effect still holds after controlling for shared attention (see Supplemental Material S6). To better understand this three-way interaction effect, we subsetted the data based on shared arousal responses and reran the analysis (Figure 4 for TPJ; see Supplemental Material S9 for pSTS, which shows a similar effect). In dyads that exhibit a strong shared arousal response, there is a positive relationship

**Table 1**

*Main and Interaction Effects for the Dyadic Regression Model in Which Shared Extremity Is Predicted Using Combined Extremity and Neural Synchrony*

Model and effect	Statistic			
	$\beta \pm SE$	$R^2$	$t$	$p_{FDR}$
Similarity in Extremity ~ Neural Synchrony $\times$ Combined Extremity				
TPJ				
Overall model		0.289		
Neural synchrony	0.098 $\pm$ 0.039	0.009	2.529	.047*
Combined extremity	0.345 $\pm$ 0.071	0.386	4.858	<.001***
Neural Synchrony $\times$ Combined Extremity	0.168 $\pm$ 0.032	0.033	5.262	<.001***
Simple slope high-extremity dyads	0.234 $\pm$ 0.043			<.001***
Simple slope low-extremity dyads	−0.045 $\pm$ 0.051			.508
pSTS				
Overall model		0.328		
Neural synchrony	−0.019 $\pm$ 0.042	0.0004	−0.448	.680
Combined extremity	0.408 $\pm$ 0.075	0.434	5.451	<.001***
Neural Synchrony $\times$ Combined Extremity	0.289 $\pm$ 0.035	0.079	8.385	<.001***
Simple slope high-extremity dyads	0.215 $\pm$ 0.048			<.001***
Simple slope low-extremity dyads	−0.265 $\pm$ 0.054			<.001***

*Note.* All variables were standardized ( $z$  scored;  $M = 0$ ,  $SD = 1$ ). Model conditional  $R^2$  and partial  $R^2$  values are reported.  $SE$  = standard error;  $FDR$  = false discovery rate; TPJ = temporoparietal junction; pSTS = posterior superior temporal sulcus.

\*  $p_{FDR} < .05$ . \*\*\*  $p_{FDR} < .001$ .

between neural synchronization in the TPJ and shared ideological extremity but only for pairs that are the most extreme (Figure 4, left panel, orange line). By contrast, there is a negative relationship between neural synchronization and shared ideological extremity in pairs that are low in ideological extremity (Figure 4, left panel, pink line). We found no significant relationship between sharing an extreme perspective and neural synchrony in dyads who did not show this synchronized arousal response (Figure 4, right panel) and no effect of the degree of extremity of the pair (see Supplemental Material S9). This suggests that sharing an extreme perspective (regardless of the ideology) is associated with increased coupling at the neural level and that this synchronized neural response is amplified in individuals who also show more similar bodily arousal responses.

Directly testing the effects of combined extremity and shared arousal responses on shared extremity did not yield a significant interaction effect ( $p = .162$ ). However, rerunning this model with the LLM computed extremity scores yielded a significant two-way interaction of SCR synchronization and combined extremity predicting shared extremity (two-way interaction:  $\beta = 0.033 \pm 0.004$  [ $SE$ ],  $p < .001$ ; Table 4). When controlling for the degree of extremist language, similarity in extremity is predicted by more similar arousal responses during the video, and this association was stronger for higher levels of shared extremity. This two-way interaction remains significant when only looking at opposing party dyads ( $p_{FDR} < .001$ ), illustrating that the effect is not driven by sharing a political ideology.

**Table 2**

*Main and Interaction Effects for the Dyadic Regression Model in Which Shared Extremity Is Predicted Using Combined Extremity, TPJ Synchrony, and Extremist Language as Computed by the Large Language Model*

Model and effect	Statistic			
	$\beta \pm SE$	$R^2$	$t$	$p_{FDR}$
Similarity in Extremity ~ Neural Synchrony $\times$ Combined Extremity $\times$ Extremist Language				
TPJ				
Overall model		0.252		
Neural synchrony	0.011 $\pm$ 0.003	0.0002	3.234	.005**
Combined extremity	0.387 $\pm$ 0.063	0.493	6.157	<.001***
Extremist language	−0.002 $\pm$ 0.003	<0.0001	−0.442	.994
Neural Synchrony $\times$ Combined Extremity	0.020 $\pm$ 0.003	0.0006	5.843	<.001***
Neural Synchrony $\times$ Extremist Language	0.009 $\pm$ 0.004	0.0001	2.399	.066*
Combined Extremity $\times$ Extremist Language	−0.002 $\pm$ 0.003	<0.0001	−0.662	.986
Neural Synchrony $\times$ Combined Extremity $\times$ Extremist Language	0.009 $\pm$ 0.004	0.0001	2.410	.064*

*Note.* All variables were standardized ( $z$  scored;  $M = 0$ ,  $SD = 1$ ). Model conditional  $R^2$  and partial  $R^2$  values are reported. TPJ = temporoparietal junction;  $SE$  = standard error;  $FDR$  = false discovery rate.

\*  $p_{FDR} < .1$ . \*\*  $p_{FDR} < .01$ . \*\*\*  $p_{FDR} < .001$ .

**Table 3**

*Main and Interaction Effects for the Dyadic Regression Model in Which Shared Extremity Is Predicted Using Combined Extremity, Neural Synchrony, and SCR Synchrony*

Model and effect	Statistic			
	$\beta \pm SE$	$R^2$	$t$	$p_{FDR}$
Similarity in Extremity ~ Neural Synchrony $\times$ Combined Extremity $\times$ SCR Synchrony				
TPJ				
Overall model		0.306		
Neural synchrony	0.080 $\pm$ 0.039	0.006	2.060	.159
Combined extremity	0.343 $\pm$ 0.072	0.376	4.773	<.001***
SCR synchrony	−0.017 $\pm$ 0.034	0.0003	−0.487	.700
Neural Synchrony $\times$ Combined Extremity	0.147 $\pm$ 0.032	0.025	4.544	.001***
Neural Synchrony $\times$ SCR Synchrony	0.007 $\pm$ 0.032	<0.0001	0.206	.883
Combined Extremity $\times$ SCR Synchrony	0.048 $\pm$ 0.034	0.003	1.414	.211
Neural Synchrony $\times$ Combined Extremity $\times$ SCR Synchrony	0.137 $\pm$ 0.033	0.022	4.181	<.001***
pSTS				
Overall model		0.346		
Neural synchrony	−0.033 $\pm$ 0.042	0.001	−0.787	.576
Combined extremity	0.412 $\pm$ 0.075	0.436	5.465	<.001***
SCR synchrony	−0.025 $\pm$ 0.031	0.0008	−0.792	.700
Neural Synchrony $\times$ Combined Extremity	0.284 $\pm$ 0.035	0.077	8.225	.001***
Neural Synchrony $\times$ SCR Synchrony	0.012 $\pm$ 0.025	0.0003	0.484	.883
Combined Extremity $\times$ SCR Synchrony	0.048 $\pm$ 0.033	0.003	1.454	.211
Neural Synchrony $\times$ Combined Extremity $\times$ SCR Synchrony	0.125 $\pm$ 0.030	0.022	4.220	<.001***

*Note.* All variables were standardized ( $z$  scored;  $M = 0$ ,  $SD = 1$ ). Model conditional  $R^2$  and partial  $R^2$  values are reported. SCR = skin conductance response;  $SE$  = standard error;  $FDR$  = false discovery rate; TPJ = temporoparietal junction; pSTS = posterior superior temporal sulcus.

\*\*\* $p_{FDR} < .001$ .

## Discussion

Although rising ideological extremism is a pressing issue that poses great societal challenges, the neurobiological mechanisms underlying extreme ideology remain understudied. In line with recent work highlighting the role of emotions in political polarization, we show that ideological extremism is reflected in heightened neural responses to political content in brain regions predominantly involved in affective processing, namely, the PAG and amygdala. Sharing a more extreme perspective when consuming political content is reflected in synchronized brain responses in the TPJ and pSTS, regions involved in perspective taking and social cognition writ large. Although shared political ideology is an important contributor to synchronized neural responses, this synchrony effect was observed even in dyads that do not share an ideology but are only similar in how extreme their views are. In other words, what is particularly surprising is that both extreme liberals and extreme conservatives consumed the same political content and, despite not sharing the same political views, showed synchronized neural responses that predicted the extremity of their beliefs. This neural coupling between more extreme individuals was especially pronounced when the content being consumed contained extreme language. Unlike these extreme ideologues who exhibit the most synchronized neural responses, moderates show heterogeneous responses to political content. As increased neural synchronization is believed to reflect more similar processing, these findings suggest that moderates might be a more diverse group than those who hold more extreme beliefs—a finding that aligns with prior work in a different domain (Finn et al., 2020). We also show that those high in extremity exhibit increased coupling of physiological affective responses when presented with politically inflammatory content, a relationship not found in individuals with more moderate political views. These

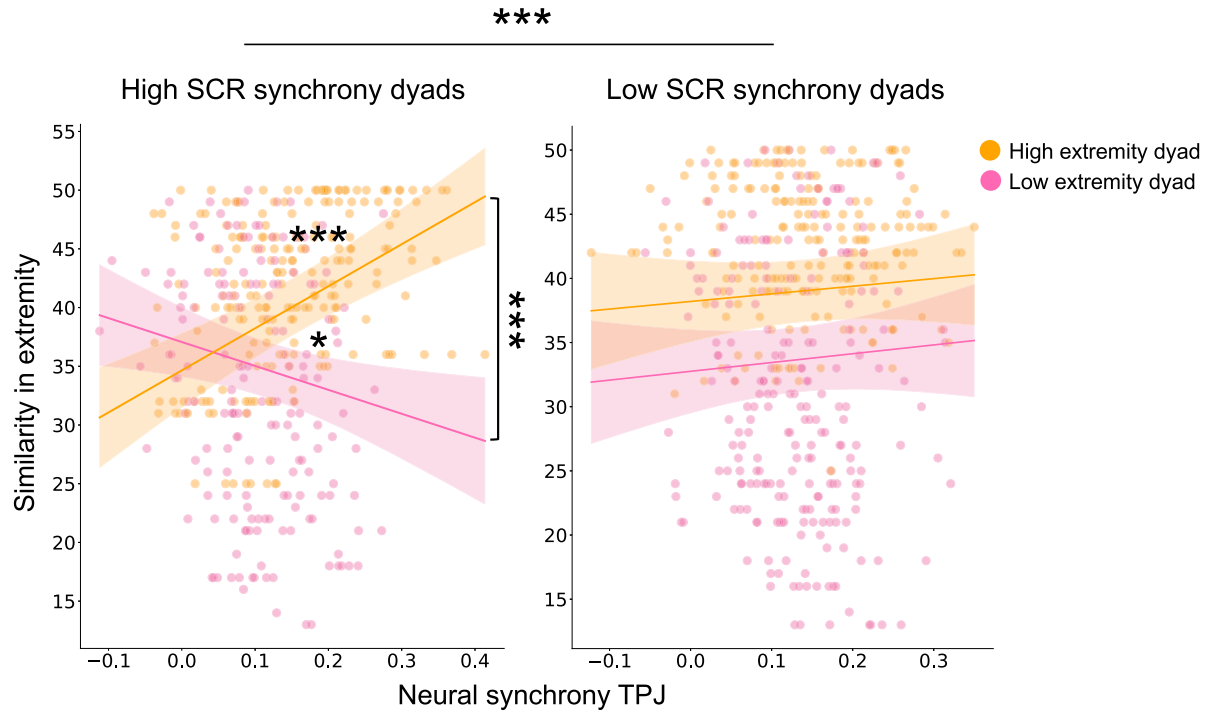
synchronized affective responses across body and brain may aid in exacerbating the fervent views held by those on the far ends of the ideological spectrum.

Univariate analyses showed that for individuals high in ideological extremism, watching two politicians debate one another elicited stronger neural responses in brain regions often implicated in the processing of affect and, in particular, in contexts that evoke threat and fear (Adolphs et al., 1995; Fox et al., 2015; LeDoux, 1994; Mobbs et al., 2007; Watson et al., 2016). The more extreme the individual, the more we observed that these two regions were engaged while watching politically provocative content about immigration and police reform. That we find this effect in brain regions often linked to affective processing aligns well with theoretical work suggesting that emotion is a prominent driver of ideological extremism (Druckman et al., 2021; Iyengar et al., 2012, 2019; Iyengar & Westwood, 2015; Lelkes, 2018; Prinz, 2021). We also find this ideological extremism effect in the pSTS, a multi-sensory integration region that tracks negative social interactions (Arioli et al., 2021; Isik et al., 2017). These effects did not depend on which side of the political aisle the participant was on, suggesting that *both* extreme liberals and extreme conservatives show heightened neural activity to the *same* political content.

Using a second, more fine-grained, data-driven intersubject similarity approach, we find that those with shared extreme views also appear to process political content in a similar way—despite not sharing the same political ideology. As with our univariate analysis, a neural synchronization effect was observed in the pSTS, as well as the TPJ—a region well-known for its role in perspective taking (Saxe & Kanwisher, 2003) and which is anatomically close to the pSTS. This coordinated neural response was modulated by the dyad's degree of extremity, suggesting that while there might be more variability

**Figure 4**

*Extreme Perspectives Are Associated With Increased Coupling Between the Body's Physiological Response and the Brain's Neural Response to Political Content*



*Note.* A significant three-way interaction effect of TPJ synchronization, phasic SCR synchronization, and combined extremity on shared extremity was found. For dyads that showed increased phasic SCR synchronization (left panel), more similar neural responses to the video predicted similarity in ideological extremity, but only for more extreme individuals (orange line;  $\beta = 0.340 \pm 0.061$  [standard error],  $p_{\text{FDR}} < .001$ ). By contrast, this relationship was negative in dyads low in extremity (pink line;  $\beta = -0.197 \pm 0.075$  [SE],  $p_{\text{FDR}} = .018$ ). We did not find this effect in those who did not show a synchronized arousal response (right panel,  $p_s > .05$ ). For visualization purposes, mean splits were applied to the measure of combined extremity and phasic SCR synchronization. The scatter plots show the raw, unstandardized data points. The regression lines reflect the model predictions and simple slopes for low- and high-extremity dyads, and shading represents the 95% confidence interval. TPJ = temporoparietal junction; SCR = skin conductance response; FDR = false discovery rate. See the online article for the color version of this figure.

\*  $p_{\text{FDR}} < .05$ . \*\*\*  $p_{\text{FDR}} < .001$ .

in responses between moderates, more extreme individuals exhibit increasingly similar BOLD time courses while consuming ongoing political content. These findings begin to shed light on the mechanisms that likely govern an ideologically extreme mind. Given that synchronized TPJ responses to naturalistic data have been linked to similar interpretations of content (de Bruin et al., 2023; van Baar et al., 2021; Yeshurun et al., 2017), it is possible that those with strong ideological beliefs, regardless of the content of those beliefs, come to view the world through a lens that alters the way in which events are processed. This is further supported by the finding that the neural coupling between individuals high in extremity was strongest when more extreme language was consumed, suggesting that sensitivity to extreme language is one driver of seeing the world through the same lens.

Based on a growing body of work on neural synchronization, it is increasingly becoming clear that brains can synchronize along many different dimensions. Prior work has shown that people can exhibit synchronized neural responses based on shared prior knowledge (Yeshurun et al., 2017), stable traits (Finn et al., 2018; Klammer et al., 2024), personality profiles (Matz et al., 2022), or, more closely related to the present study, shared political ideology (de Bruin et al., 2023;

Leong et al., 2020; van Baar et al., 2021). In line with the notion that people can exhibit neural synchrony on numerous dimensions, our findings reveal neural selectivity, depending on the dimension. In the TPJ, both political ideology and extremity appear to contribute to neural synchronization, while the pSTS appears more sensitive to ideological similarity. This illustrates that the brain will synchronize along numerous discrete dimensions. Despite their anatomical proximity, the TPJ and pSTS appear to play different roles in encoding ideology versus extremity. While synchronization can occur for a number of reasons, including (but not limited to) shared cognitive, attentional, perceptual, or emotional processing, the fact that we find that the coupling between extremity and neural synchrony is especially strong in pairs who also show similar arousal (as measured through galvanic SCRs; see Figure 4) suggests that this neural coupling may be attributable, in part, to emotional processing of the political content.

We observed a moderating effect of shared physiological arousal on the relationship between extremity and neural synchrony: Synchronized arousal exacerbates synchronized neural activity to predict similarity in extreme views—regardless of ideology—but only for those who are most extreme. While there is no prior work we are aware of linking the body's physiological responses and



**Table 4**

*Main and Interaction Effects for the Dyadic Regression Model in Which Shared Extremity Is Predicted Using Combined Extremity, SCR Synchrony, and Extremist Language as Computed by the LLM*

Model and effect	Statistic			
	$\beta \pm SE$	$R^2$	$t$	$p_{FDR}$
Similarity in Extremity $\sim$ SCR Synchrony $\times$ Combined Extremity $\times$ Extremist Language				
Overall model		0.253		
SCR synchrony	0.016 $\pm$ 0.004	0.0004	4.657	<.001***
Combined extremity	0.387 $\pm$ 0.063	0.493	6.164	<.001***
Extremist language	0.0003 $\pm$ 0.003	<0.0001	0.100	.921
SCR Synchrony $\times$ Combined Extremity	0.033 $\pm$ 0.004	0.001	9.262	<.001***
SCR Synchrony $\times$ Extremist Language	0.004 $\pm$ 0.004	<0.0001	1.013	.311
Combined Extremity $\times$ Extremist Language	−0.0001 $\pm$ 0.003	<0.0001	−0.029	.977
SCR Synchrony $\times$ Combined Extremity $\times$ Extremist Language	−0.002 $\pm$ 0.004	<0.0001	−0.609	.543

*Note.* All variables were standardized ( $z$  scored;  $M = 0$ ,  $SD = 1$ ). Model conditional  $R^2$  and partial  $R^2$  values are reported. SCR = skin conductance response;  $SE$  = standard error;  $FDR$  = false discovery rate; LLM = large language model.

\*\*\*  $p_{FDR} < .001$ .

brain responses to political content, our findings suggest the body's arousal system likely plays a critical role in shaping the most extreme perspectives.

Interpreting our neural synchrony effects solely as a function of shared emotional engagement must be taken with caution, however, because we did not find that arousal alone predicts extremity—using either a standard univariate approach or dyadic regression approach. A potential explanation of these null findings is the analytical framework of our study. Phasic SCR arousal responses are unsigned: Both negative and positive affect can lead to a peak in an SCR signal (Boucsein, 2012), possibly smoothing out potential differences in valenced responses while watching political content. The only time we found that synchronized arousal predicts shared extremity in those on the further ends of the ideological spectrum is if we control for the level of extremist language being consumed. This hints that there might be an association between more extreme beliefs and physiological arousal to extreme content. Regardless, the relationship between extremity and arousal is likely complicated, consistent with the mixed findings on physiological responses and political ideology in the literature (Bakker et al., 2020; Dodd et al., 2012; Gruszczynski et al., 2013; Knoll et al., 2015; Renshon et al., 2015; Smith et al., 2011; Wagner et al., 2015).

Whereas there is a large body of work linking the TPJ and broader pSTS region to social cognition and theory of mind (Arioli et al., 2021; Basil et al., 2017; Isik et al., 2017; Kinreich et al., 2017; Lee Masson & Isik, 2021; Saxe & Kanwisher, 2003; Saxe & Powell, 2006), there are also scholars who argue that these brain regions are more fundamentally related to attention. Both the TPJ and pSTS are involved in the orienting of attention and the detection of unexpected stimuli (Corbetta et al., 2008; Mitchell, 2008; Patel et al., 2019). Our findings may therefore reflect a relationship between ideological extremity and attention rather than affect more specifically. However, such an interpretation seems unlikely given that when we control for potential attentional effects measured using eye tracking—which has extensively been shown to be a reliable measure of attention (Bacos et al., 2024; Holmqvist et al., 2011; Posner, 1980)—we still observe these main effects. This is further strengthened by the fact that we did not find a relationship between extremity and comprehension of the debate or extremity and the degree to which an individual indicated following politics. Together, this thus suggests that our effects are not driven by attention, per se.

Focusing on ideological extremity as a social and affective process allows us to move toward an account of polarization that acknowledges how deeply intertwined extreme political beliefs are with social groups and (collective) emotions. It has been repeatedly suggested that cultivating extreme beliefs is a largely social process (e.g., Decety et al., 2018; McCauley & Moskaleiko, 2008; van den Bos, 2019), where feelings of exclusion can push people toward the social fringe and into extremist groups. These groups can help fulfill a need for belonging, but they can also lead to increased ingroup love and outgroup derogation (Charkawi et al., 2021; Iyengar et al., 2012; Tajfel & Turner, 1979). In addition, emotions like anger and fear can make people more susceptible to seeing the world in black and white terms and thus more amenable to holding extreme ideas (Amadio & Sakhi, 2025; Tausch et al., 2024). These findings therefore stress the need for focusing on polarization as not just a cognitive or rational process but also one that considers socioemotional dimensions.

Although this study provides insights into the inner workings of extreme perspectives, several limitations of the study should be noted (Table 5). Whereas a strength of the study is the use of naturalistic, real-world political content, these materials only cover a small subset of political topics and political content that exists, warranting caution in generalizing our findings to all types of political content. Second, this study was designed and conducted in the United States, and it is unclear whether these findings would generalize to other cultures or countries with a different political system or with different levels of political polarization. Third, this study focuses on ideological extremity, computed from *self-reported* political ideology. This measure likely does not capture the broader, complex construct of extremism, which is why we focus on ideological extremity specifically. Extreme liberals or conservatives are not necessarily *extremists*, who are often defined by their willingness to use extreme actions to pursue their goals (Böttcher, 2017; Knight et al., 2017). Finally, we cannot make any claims about the causality of our findings, as we only study associations between ideological extremity and neurophysiological responses. These limitations motivate the need for further research, using more diverse content and samples, and support the need for longitudinal research on the development of extreme views.

With the current rise in ideological extremism, gaining a better understanding of how people come to more extreme viewpoints is

**Table 5***Table of Limitations*

Limitation	Implication for future work
Internal validity	
Ideological extremity was measured using self-reported political ideology, which does not capture the broader construct of extremism.	Future work should focus on the relationship between ideological extremity and other types of extremism, including extremism or radicalization broadly construed.
Large language models were used for the video content analysis rather than participant ratings.	Future work should collect more continuous behavioral ratings from participants, which would allow for a more individualized comparison between behavioral and neurophysiological responses.
Generalizability	
This study focuses on participants in the United States and uses U.S. political content. It is therefore unclear whether these findings would generalize to other cultures or countries with a different political system or with different levels of political polarization.	Future work should be conducted with participants and stimuli from countries with different political systems (i.e., multiparty systems) and different levels of political polarization.
While this study uses naturalistic, real-world video content to measure responses, it only covers a subset of political topics.	Research using different types of stimuli, covering different political topics, should be conducted.
Theoretical limitations	
This study is unable to make any causal claims about the relationship between ideological extremity and the neurophysiological response to political content.	Longitudinal research would help make causal claims about how ideological extremity and neurophysiological processing influence each other.

now a pressing issue. By identifying what factors contribute to ideological extremism, more effective prevention and intervention strategies can be developed to mitigate the risk of individuals engaging in radicalized behaviors. Extending prior work suggesting a multifaceted approach to tackling ideological extremity (LaFree & Schwarzenbach, 2021; Lösel et al., 2018; Rottweiler et al., 2022), these findings stress the importance of considering the emotional drivers of extremism in future counterextremism efforts while also helping to explain the surge in ideological extremism we observe today. Belief uniformity can lead to echo chambers in which these extreme views are reinforced, leading to the normalization of an extreme stance (Bright, 2018; Van Swol et al., 2022; Warner & Neville-Shepard, 2014). A better understanding of the mechanisms underlying more extreme views provides a starting point for how to encourage a more balanced perspective and promote common ground, fostering successful collaboration and debate within the political sphere.

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