Universiteit van Amsterdam

Ideological Asymmetry: The Subtle Relationship Between Political Ideology and Neural Activation

Student:

Mohammad Hamdan

13572687

Research Master Psychology

Course details:

Brain and Cognition Master Thesis

7205RMTBCY

22 EC

Supervisors:

Dr. Steven Scholte, Dr. Gijs Schumacher, Dr. Frederic Hopp, and Dr. Marte Otten (second assessor)

Submission Date:

July 20, 2023

Ideological Asymmetry: The Subtle Relationship Between Political Ideology and Neural Activation

Mohammad Hamdan[1], Steven Scholte[1], Gijs Schumacher[1], Frederic Hopp[1], & Marte Otten[1]

[1] Universiteit van Amsterdam

Author Note

Our writing follows the submission guidelines of Political Psychology, which can be found here. This document was written in R Markdown using the `papaja` package. This is an important step in making this paper more open-access and reproducible. However, it is important to note that this package currently only supports citations with APA 6 guidelines, rather than APA 7. For that reason, we have taken some steps to manually adjust the paper so that it can meet APA 7 guidelines.

The authors made the following contributions. Mohammad Hamdan: Conceptualization, Writing, Analysis; Steven Scholte: Supervision; Gijs Schumacher: Supervision; Frederic Hopp: Supervision; Marte Otten: Second Assessor.

Correspondence concerning this article should be addressed to Mohammad Hamdan, Amsterdam, The Netherlands. E-mail: mohammad.hamdan@student.uva.nl

Abstract

Can ideology provide insights into neural responses to non-political stimuli when no response is required? In the current project, we investigated ideological asymmetry and asked whether political ideology correlates with a difference in neural activation in non-political contexts. We examined the functional magnetic resonance imaging (fMRI) data from the ID1000 dataset of the Amsterdam Open MRI Collection (AOMIC) database of participants who watched a series of non-political clips and conducted an inter-subject representational similarity analysis (IS-RSA) between the fMRI data and two different conceptualizations of ideology (identity-based and issue-based). Our results indicate that differences in ideology correlate with differences in neural activation, specifically of the cerebellum, insula, and temporal pole. Perhaps, this implies that an increase in conservatism is correlated with reduced tolerance of (social) uncertainty. However, only issue-based ideology, not identity-based ideology, showed this trend and explained only a small fraction of the total variance in the fMRI signal.

Keywords: ideological asymmetry, inter-subject representational similarity analysis, AOMIC, fMRI, issue-based ideology

Word count: 9115

Ideological Asymmetry: The Subtle Relationship Between Political Ideology and Neural Activation

What does your political ideology say about your brain and your daily experiences? Do our brains form different responses to the same things depending on our political ideology?

From Political Ideology to Ideological Asymmetry

Political ideology is a composition of attitudes, values or an identity revolving around a person or group's ideas about the proper goals of society (Becker, 2020; Schumacher et al., n.d.). Previous research suggests that differences between individuals' political ideology can explain differences in both brain and behaviour. This phenomenon is known as ideological asymmetry. For example, when asked to make decisions based on a flow of incoming information, conservatives "jumped to conclusions" earlier than liberals, where "jumping" involves coming to a decision using less information (Petropolous-Petalas & Schumacher, n.d.; Schumacher, 2023). Buechner et al., 2021 presented participants with a set of letters and asked them to generate as many three- or four-letter words as possible in 30 seconds. When instructions changed, for example from asking participants to form three-letter words to forming four-letter words, liberals performed better. However, conservatives performed better when instructions did not change. The results demonstrate that liberals and conservatives have different capabilities for handling changing contexts.

There is evidence for ideological asymmetry in cognition and personality traits. For example, political liberalism is associated with increased cognitive flexibility, a larger working memory load and less caution in perceptual decision-making tasks (Zmigrod et al., 2021). Compared to liberalism, conservatism was associated with an increase in threat perceptions (Jost et al., 2017; Moore et al., 2021), higher levels of conspiratorial thinking (Petropolous-Petalas & Schumacher, n.d.), and a strong distrust of officialdom (van der

Linder et al., 2021). While partisanship predicted differences in threat self-report, it did not predict differences in physiological skin conductance responses to threats (Bakker, Schumacher, Gothreau, et al., 2020; Bakker, Schumacher, & Homan, 2020), indicating that ideological asymmetry might not explain differences in all variables or all measurement types.

Additionally, there is evidence of ideological asymmetry in the structure and function of the brain. For example, liberalism was associated with increased grey matter in the anterior cingulate cortex (ACC), and conservatism was correlated with a larger amygdala (Kanai et al., 2011). Moreover, during a go/no-go task, liberals exhibited larger no-go error-related negativity in the ACC compared to conservatives (Amodio et al., 2007). When presenting politically relevant stimuli, such as the words “immigrant” or “police”, the activation of the striatum, amygdala and temporoparietal junction corresponded to similarities in partisanship (de Bruin et al., 2023). Furthermore, videos of electoral campaigns elicited different activation patterns in the tempropariet al junction, posterior cingulate cortex and dorso-medial prefrontal cortex in left- compared to right-wing people (Broom et al., 2022; Katabi et al., 2021).

Interestingly, the correlations between ideology and attributes of the brain vary significantly. Several studies reported smaller correlations, such as .070 (Schumacher et al., n.d.) or .05 (van Baar et al., 2021), while others reported much larger effects e.g., .53 (Amodio et al., 2007) and .28 (Broom et al., 2022). The specific reason behind this variance is unclear, but it likely results from the use of very different statistical or methodological methods.

Importantly, in the aforementioned non-political contexts, ideological asymmetry was investigated in scenarios where responses are required. For example, in decision-making, in go/no-go tasks or word generating. However, could we find evidence for ideological asymmetry in cases where no responses are required? Do people of different political ideologies experience the world differently? If such an effect exists, how would its size compare to previous findings? Would it bring us one step closer to understanding more specifically why the effect sizes in the correlations between ideology and neural activation vary so greatly?

How Should One Measure Ideology?

When investigating political ideology, previous studies suffer from an important methodological limitation when conceptualizing ideology. Firstly, they approached ideology as one attitude, although it can be divided into multiple attitudes. For example, by focusing on social ideology, we would define social conservatism as an ideology composed of religiosity, higher social dominance and social awareness, with social progressiveness on the opposite end of that scale (Stankov, 2021). This is separate from economic ideology, that concerns redistribution, regulation, and social insurance (Johnston & Ollerenshaw, 2020). Likewise, political ideology can be either identity-based or issue-based, where it is determined based on identification, or on (dis)agreement with various issues. In other words, it can be conceptualized as the response to "How progressive do you identify?" compared to the response to "Should gay people be able to live their lives freely?". Surprisingly, these two measures of ideology are only weakly positively correlated. Crucially, prior studies conceptualized ideology in only one of these ways, mostly identity-based, by asking participants to report their political attitudes on a slider scale (e.g., Amodio et al., 2007) or by asking what party they last voted for (e.g., Bakker, Schumacher, Gothreau, et al., 2020; de Bruin et al., 2023). However, rarely have identity- and issue-based ideology both been addressed in a single study (Schumacher et al., n.d.). This leads us to an important question that currently has an insufficient answer – does the way ideology is conceptualized affect the conclusions of a study?

Statistical Power

Additionally, much of the prior research on ideological asymmetry is underpowered due to a small sample size which is inadequate for effect detection, particularly in functional magnetic resonance imaging (fMRI) studies, where several hundred participants could be necessary (Bossier et al., 2020). Among the aforementioned studies, Amodio et al., 2007 had 43 participants and Moore et al., 2021 had 38. The necessary sample size varies between phenomena, and whether a paradigm is within- or between-participants or whether we want to examine voxel- or cluster-level differences, but it is indisputable that a larger sample improves replicability (Turner et al., 2018). However, collecting a massive amount of data is a long and costly task.

Large, open-source neuroimaging databases might offer a solution to this problem (Horien et al., 2021; Madan, 2022). One example is the Amsterdam Open MRI Collection (AOMIC; Snoek et al., 2021) which includes pre-processed and normalized functional, structural, and socio-demographic data from hundreds of participants including age, sex, and personality traits. It also includes political variables, such as measurements of ideology and voting behaviour, making it a great candidate for use in political neuroscience research. The largest dataset of the AOMIC databases has almost 1000 participants, which is much more than other studies with larger sample sizes, such as de Bruin et al., 2023 who had 360 participants, or Buechner et al., 2021 who had between 180 and 220. By analyzing this dataset, one can be confident that statistical power should not be an issue.

Inter-Subject Representational Similarity Analysis

The question remains: does political ideology correlate with our perception? And does the way that ideology is conceptualized affect what conclusions we might make about it? One way to approach this question is by using an inter-subject representational similarity analysis (IS-RSA). An IS-RSA comprises an inter-subject correlation (ISC) and a representational similarity analysis (RSA). An ISC is used to assess whether different brain regions elicit a similar or different blood-oxygen-level-dependent (BOLD) response between participants across time (Hasson et al., 2008), while an RSA involves constructing a (dis-)similarity matrix, which captures the distance between participants on a particular scale, such as neural activation or scores on a questionnaire. This method allows us to compare measurements that are on different scales (Kriegeskorte et al., 2008), such as electroencephalography (EEG) and fMRI measurements (Salmela et al., 2018). The IS-RSA approach involves constructing a dissimilarity matrix that maps out Pearson correlations between participants for each region of interest (ROI), and comparing these distances to those in a socio-demographic variable. This analysis allows us to examine whether socio-demographic variables, such as ideology, correlate with BOLD activation patterns.

In the present paper, we examined the relationship between ideology and neural activation, specifically whether ideological differences are related to changes in the BOLD response to naturalistic stimuli. In this exploratory study, we analyzed the data of almost 1000 participants from the ID1000 dataset of the AOMIC databases, specifically the fMRI data collected while they watched an 11-minute video of 22 non-political scenes. We conducted an IS-RSA to compare the BOLD responses with issue- and identity-based social ideology, as well as education level, background social economical status (SES) and sex.

Are differences in identity- or issue-based ideology, related to differences in neural activation patterns? We examined whether there is a correlation between ideology and activation patterns in every region of the brain (H1). This would be evidenced by a correlation between the dissimilarity matrices of each ideology variable and neural activation. We used this reasoning to test whether differences in education level, background SES and sex are related to differences in neural activation patterns.

Could conceptualizing ideology differently lead to different conclusions to the same research question? We examined whether there are correlations in *different* parts of the brain between the two *different* measures of ideology (H2). This would be evidenced by H1 being true for different regions for each variable. For example, if nodes 1 and 2 were significant for issue-based ideology while nodes 3 and 4 were significant for identity-based ideology, this would constitute evidence for H2.

Methods

Participants

Of the three datasets in the AOMIC databases, the ID1000 meets our needs of including political and (f)MRI data of participants The ID1000 dataset includes data from 928 participants ($M_{AGE} = 22.85$, $SD_{AGE} = 1.71$, 483 Females). For more details on how these participants were sampled, please refer to Snoek et al., 2021. Importantly, we are interested in the data of participants who answered the political questionnaires *and* completed the BOLD scan. Therefore, we excluded 46 participants for having no BOLD scan and 28 for not answering the political questionnaires. Thus, the data from 854 participants ($M_{AGE} = 22.86$, $SD_{AGE} = 1.70$, 438 Females) were included in the analyses. The participants' political data is representative of the political demographics of the Dutch population. Therefore, further data collection and a-priori power analyses were not required, and the socio-demographic variables were not normally distributed, as is the case in the Dutch population, and no normality corrections or outlier removal was applied (for more details, please refer to **Appendix D**).

Materials

Questionnaires.

Identity-Based Social Ideology Questionnaire. Participants were asked to identify themselves politically on a slider scale from 1 (progressive) to 7 (conservative).

Issue-Based Social Ideology Questionnaire. Participants were asked to report from 1-7 how much they agreed with the following four prompts:

- *'Homosexuals should be removed from society',*
- *'Homosexuals should be freed as much as possible to live their own way',* (this prompt is reverse coded),
- *'It is unnatural for women to lead men in a company',*
- *'Women are more suitable for raising small children than men'.*

Responses were averaged, mean-centred, and scaled, such that a higher mean score was indicative of a participant being more socially conservative. Cronbach's Alpha was .6. However, participants had lower scores, resulting in a skewed distribution where the mean was 2.88, perhaps due to these prompts being extreme.

Education Level. Participants were asked to report their education level. Those who were not students at the time of scanning were asked to report their highest completed level of education, while participants who were students at the time were asked to report their current level. This was done in order to better represent the education levels of 19 to 26 year-olds in the Netherlands, but it is skewed towards a higher education level compared to the general population.

Background Social Economical Status. Participants were asked to report their parents' education level and income, which was used to calculate their background SES. This was then converted into a scale ranging from 2 (low SES) to 6.5 (high SES) with increments at every 0.5 points. More details about this calculation can be found in Snoek et al., 2021.

Sex. Participants were asked to report whether their assigned sex at birth was male or female. Note that this is different from gender identity, for which data is missing for the first 400 participants, preventing us from using this variable in our analysis. For more details please refer to Snoek et al., 2021.

Age. Participants were asked for their date of birth which was used to compute their age at participation, rounded to the nearest whole number. However, all participants were aged between 19 and 26 resulting in a low variance (2.92).

Stimuli. Participants watched an 11-minute video with no plot. This included several clips originating from the 1982 movie Koyaanisqatsi which varied in colours, textures, themes and speed of movement. The video also included background music. Between scenes, there is a transition period of up to 2 seconds where the previous scene fades into the next. Please see **Figure 1** for examples of scenes.

Figure 1

Examples of Scenes Presented to Participants

Figure 1. Above are four different scenes presented in the video. We recommend watching the full video here to experience all scenes, (under stimuli, download *task-moviewatching_desc-koyaanisqatsi_movie.mp4*).

Data Analysis

IS-RSA. We conducted an inter-subject representational similarity analysis, which included constructing dissimilarity matrices for the neural activation and for the socio-demographic scores of our participants. We then measured the Spearman correlation between these matrices and compared it to a null-distribution generated by permuting the matrices 10,000 times (Mantel, 1967). We then applied a Holm-Bonferroni multiple comparison correction (MCC; Holm, 1979).

This approach is ideal for assessing responses to naturalistic stimuli as it does not require segmentation and categorizing of stimuli. This would be the case for constructing a general linear model (GLM) of BOLD activation which would also require firm knowledge of what aspects of a stimulus drive the effect (Finn et al., 2020; Hasson et al., 2008), and is a computationally more demanding approach (Finn et al., 2020). Since all participants viewed exactly the same sequence of events, the signal produced is time-locked, and it follows that the shared signal is produced by the common stimuli, while differences in the signal are the result of individual differences and error (Finn et al., 2020), which also makes this method more powerful than a GLM (Hasson et al., 2008). It has already been used to investigate neural responses to political and polarizing stimuli, for example measuring the synchrony of polarized individuals to political stimuli (van Baar et al., 2021) or measuring the synchrony relative to political ideology while watching political debates (Broom et al., 2022).

However, as the approach is still new, there are uncertainties about which distance metric better captures the true variance of different socio-demographic variables (not neural variables, as the distance across time is measured using the ISC). For example, the Nearest Neighbours (NN) model uses the Euclidean distance, which is a relative distance measure (Finn et al., 2020). This means that the distance between participants who score 99 and 100 is the same as that of participants who score 0 and 1. Another relative distance measure is the Mahalanobis distance, which carries the advantage of de-correlating different variables from each other (De Maesschalck et al., 2000). However, we might also consider an absolute measure of distance, such as that of the Anna Karenina (AK) model which considers that high scorers are placed similarly for the same reasons, while low scorers do not. This is inspired by the Tolstoy quote *"All happy families are alike; each unhappy family is unhappy in its own way"*. This is calculated as a standardized distance of each participant from their mean with another participant (Finn et al., 2020).

Thus, the aims of this paper were two-fold. Firstly, we assessed whether there is a relationship between perception and ideology using an IS-RSA, while considering two different measurements for ideology and three other factors which might drive this effect. Secondly, we contributed to the growing body of literature on IS-RSA as a research method by assessing three distance metrics: the Euclidean distance (NN model), a Mahalanobis distance model, and an Anna Karenina (AK) distance model, and determining which better captures the distribution of the different variables.

Does each distance metric capture the variance of the same variables differently? For each variable, we compared whether across different distance metrics, different nodes exhibited significant correlations (H3). This would be evidenced by different nodes being significant for the same variable in different models. For example, if nodes 1 and 2 were significant for issue-based ideology in the NN model, but not in the AK model, this would constitute support for H3.

Split-Half. Our analysis consisted of two steps: exploratory and confirmatory. Our main research question aims to identify which brain regions exhibit different activation patterns depending on the ideology of the observer. As such, this has not been identified in previous research, and we do not yet have ROIs. We therefore utilized our large data set and split our data into two halves at random (Anderson & Magruder, 2017), which allowed us to conduct correct research practices and to fulfill the conceptual goals of pre-registration without actually pre-registering as there is nothing worth pre-registering in an exploratory, whole-brain analysis (Lakens, 2019). Firstly, we conducted an exploratory IS-RSA, looping over the entire brain to find potential regions of interest. Secondly, we conducted a confirmatory IS-RSA where we tested for significant differences in the ROIs of the first analysis.

We split our 854 participants into two samples at random, and ensured that both sub-samples represented the whole sample in terms of all our socio-demographic variables: identity-based ideology, issue-based ideology, background SES, education, sex and age (while this is not a variable included in the analysis, it is an important demographic variable worth considering). For a visualisation of this splitting, please refer to **Appendix A**.

Results

Inter-Subject Correlation

For each sample, we performed an inter-subject correlation. We also observed whether early areas of the brain, such as early visual areas, have the highest degree of synchrony compared to other areas, as should be the case. This can be see in **Figure 2** (with more details in **Appendix C**). Importantly, this is in line with Hasson et al. (2008), who claimed that unstructured movies tend to yield lower ISC values (lower than .60) even in earlier cortical areas, because viewers might look at different parts of the screen.

Representational Dissimilarity Matrices

For each participant, we extracted activity time-series from every node in a 268-node functional parcellation by applying the Shen atlas (Shen et al., 2013) and averaging signal across all volumes for each region. We then constructed the representational dissimilarity matrices for each socio-demographic variable, for each distance metric, as specified above. An example of this can be seen in **Appendix C**.

Figure 2

ISC Values for Exploratory Sample

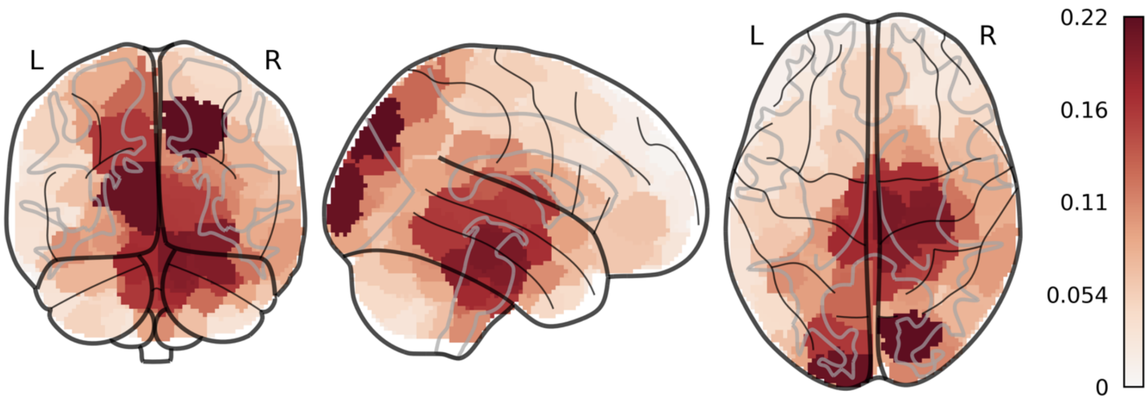


Figure 2. In this figure is a plot of the mean ISC values for all 268 nodes in the exploratory sample (N = 427). A darker colour indicates that for a given region, the mean correlation between every pair of participants was higher, indicating a higher synchrony. The ISC for the confirmatory sample yielded similar results and is therefore not pictured.

IS-RSA: Exploratory Analysis

The results of this IS-RSA suggest that there are no differences in the fMRI activation of any brain regions relative to any of our variables (after MCC, all $p > .05$). This implies that there is no difference in neural activation relative to any of the five socio-demographic variables, regardless of the distance metrics used. This sets up a barrier, making it more difficult to discuss H2 and H3. However, upon further inspection, it appeared that before correcting for multiple comparisons, for each variable in NN and AK models there were between 104-188 regions that were significant ($p < 0.03$) and showed some correlation with the given variable. While these correlations were extremely small (all smaller than .1), some were highly significant ($p < .001$) but they did not survive corrections for 4020 (268 nodes x 5 socio-demographic variables x 3 distance metrics) comparisons. Interestingly, for the Mahalanobis model, all nodes were non-significant even before MCC. However, as this is an exploratory analysis, the potential significance of some nodes in the NN and AK models can still provide a test worthy of examining in the confirmatory analysis.

IS-RSA: Confirmatory Analysis

Since the goal of the exploratory analysis was to draw hypotheses for a more robust, reliable and focused confirmatory hypothesis, we tested the ten most significant nodes (pre-MCC) of each variable in the NN and AK models. This means that for each variable in each of the NN and AK models, we specifically examined the top 10 nodes with the smallest p-values. Several of these nodes remained significant in this analysis after applying a Holm-Bonferroni style MCC. Consequently, all p-values in this section refer to Holm-Bonferroni adjusted values. The full list of these nodes can be found in **Appendix E**. The Mahalanobis model was excluded from this analysis as there were no significant nodes even prior to MCC.

Table 1

Correlations Between Issue-Based Social Ideology and Neural Activation Patterns

Region name	Pearson Correlation	Significance
BA 18 (temporal pole)	-0.02	$< .001$
BA 13 (insula)	-0.005	$< .001$
Cerebellum	-0.01	$< .001$

Note. The following table illustrates the brain regions for which Pearson correlations between neural activation and issue-based ideology were significant. p-values refer to Holm-Bonferroni adjusted values. Note that these only display the Brodmann areas, not Shen atlas nodes, because when two nodes corresponded to sub-regions of the same Brodmann Area, they always had exactly the same correlation and p-value. These effects are visualised in **Figure 3**.

Nearest Neighbours Model.

Ideology. Firstly, for issue-based social ideology, a total of six nodes displayed differences in patterns of activation which corresponded to differences in ideology. This supports H1 for these six nodes, which included sub-regions of different Brodmann Areas (BA) - the cerebellum, insula and temporal pole, as can be seen in **Table 1** and **Figure 3**. For identity-based social ideology, no nodes displayed any significant correlation, providing no support for H1 for any nodes. The discrepancy in the pattern of results between issue- and identity-based ideology provides strong support for H2.

Control: Education Level, Background SES and Sex. For education level and background SES, no correlations were significant in this model. For sex, only one

Figure 3

Correlation Between Issue-Based Social Ideology and Neural Activation Patterns

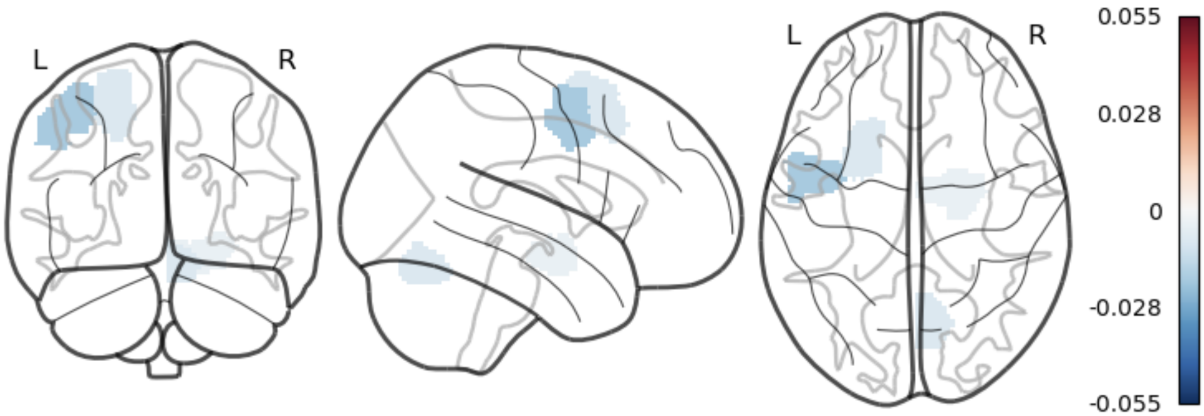


Figure 3. The figure illustrates the significant, negative correlations between issue-based ideology and neural activation patterns in the cerebellum, insula and temporal pole in the confirmatory sample (N = 427), which correspond to **Table 1**.

sub-region of the insula remained significant (r = -.004, p < .001), providing support for H1 for this node.

Anna Karenina Model.

Ideology. No nodes in either of the ideology measurements showed a significant correlation between neural activation and ideology when using the AK distance metric, providing no support for H1 for any nodes. The difference in patterns between the AK and NN models supports H3.

Control: Education Level, Background SES and Sex. For education level, background SES and sex there were multiple significant nodes, which corresponded to regions in the cerebellum, insula and temporal pole, as can be seen in **Table 2**, **Figure 4**, **Figure 6**, and **Figure 5**. The differences in the active regions between the two models provide support for H3.

Figure 4

Correlation Between Education Level and Neural Activation Patterns

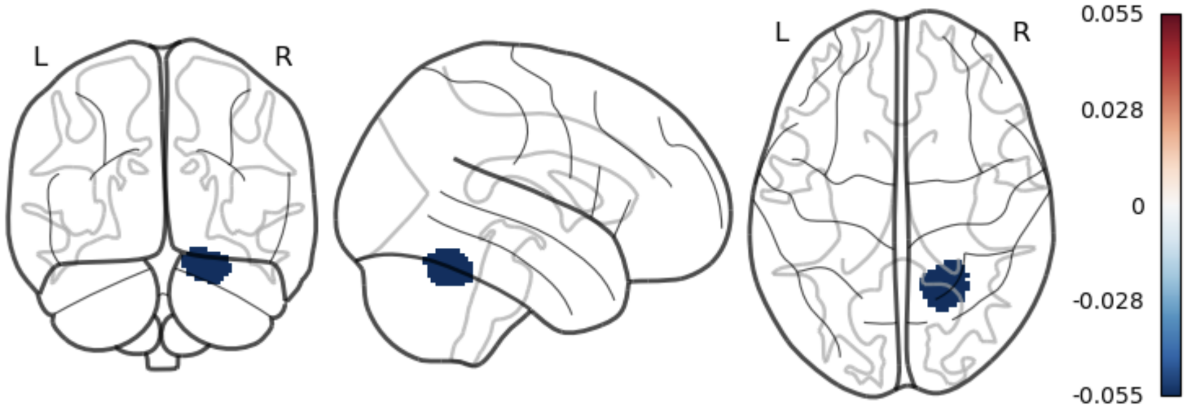


Figure 4. This figure illustrates the correlation between education level and neural activation patterns in the cerebellum.

Figure 5

Correlation Between Background SES and Neural Activation Patterns

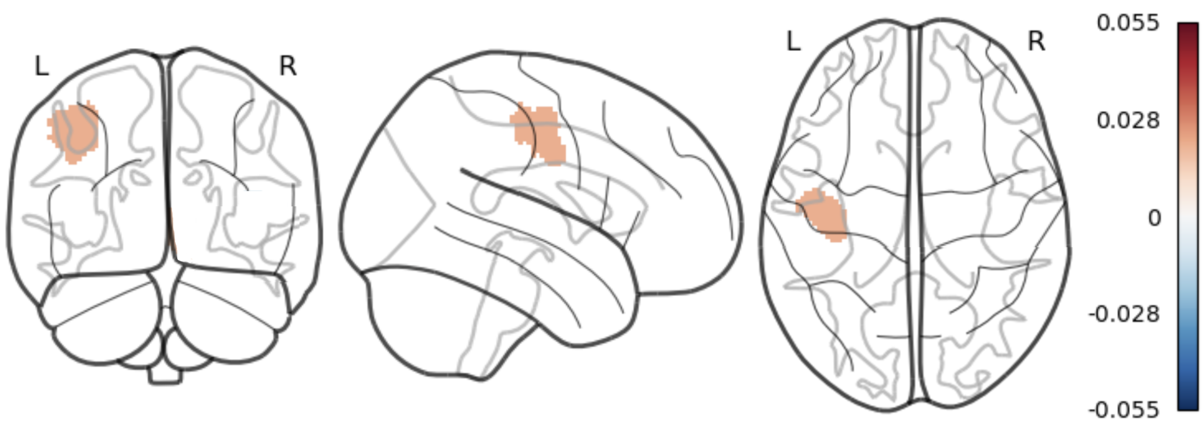


Figure 5. This figure illustrates the correlation between background SES and neural activation patterns in the temporal pole.

Table 2

Significant Correlations in the Anna Karenina Model

Variable	Region name	Pearson Correlation	Significance
Education level	Cerebellum	-0.0549	$< .001$
Education level	BA 13 (insula)	-0.022	$< .001$
Background SES	BA 18 (temporal pole)	0.022	$< .001$
Background SES	Cerebellum	0.014	$< .001$
Sex	Insula	-0.041	$< .001$

Note. This table illustrates the brain regions for which significant Pearson correlations between neural activation and a given socio-demographic variable were significant. p-values refer to Holm-Bonferroni adjusted values. Note that these only display the Brodmann areas, not Shen atlas nodes, because when two nodes corresponded to sub-regions of the same BA, they always had exactly the same correlation and p-value.

Discussion

Political ideology comprises a person's values or an identity regarding what they believe should be the goals and structure of society (Becker, 2020; Schumacher et al., n.d.). Differences in political ideology have been shown to correspond to differences in brain activation patterns and behaviour when giving responses in non-political contexts. For example, in word generation (Buechner et al., 2021), in go/no-go tasks (Amodio et al., 2007), or in memory recall (Zmigrod et al., 2021). In the present study, we sought to discover whether, even in situations where responses are not required (i.e., in mere observation), differences in neural activation correlate with differences in political ideology. We also examined whether other, non-political, socio-demographic variables can explain this effect. Furthermore, we wanted to examine whether different conceptualizations of

Figure 6

Correlation Between Sex and Neural Activation Patterns

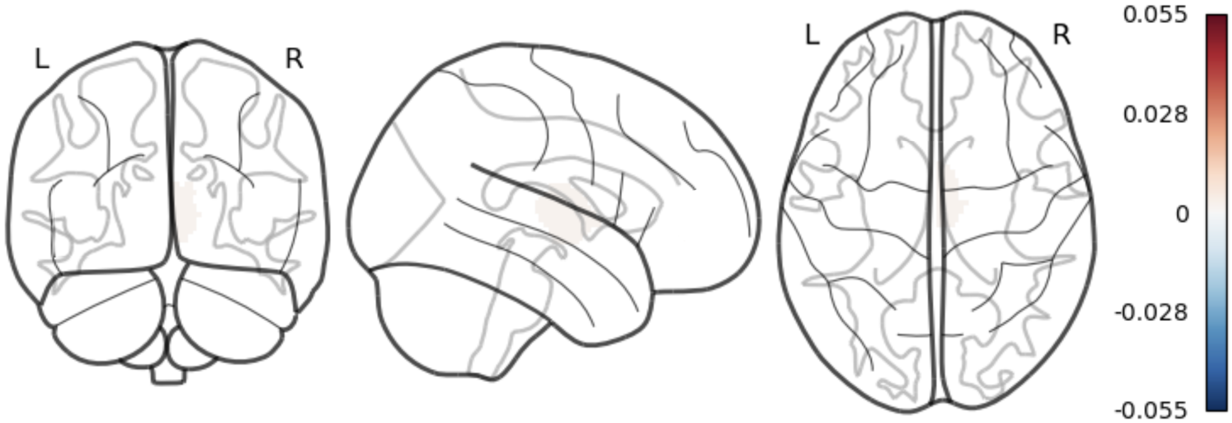


Figure 6. This figure illustrates the correlation between sex and neural activation patterns in the insula.

political ideology (identity- vs. issue-based) could lead to different conclusions for the same research question.

We analyzed data from the ID1000 dataset of the AOMIC databases (Snoek et al., 2021), where nearly 1000 participants viewed a series of non-political clips while their BOLD signal was measured using fMRI. We conducted an inter-subject representational similarity analysis on their data, meaning that we calculated the correlation between the time-series of every pair of participants, and compared these correlations to the distances between participants on the socio-demographic variables: identity-based social ideology, issue-based social ideology, education level, background SES and sex.

We split the large sample into two sub-samples, and ran an exploratory analysis on the first half. We examined the entire brain looking for differences, which would then allow us to concentrate on specific regions to test in the second half. We considered three possible distance metrics (Euclidean/NN, AK, Mahalanobis) in an effort to contribute to the growing IS-RSA literature about how different variables are better, or differently, represented using different distance metrics.

The results of the exploratory analysis indicated that differences in political ideology, education level, background SES and sex do not correlate with differences in neural activation patterns. However, we suspected that these null results were partly due to correction for a large number of comparisons. Therefore, in the confirmatory analysis, we tested the ten nodes (for each variable in the NN and AK models) which were most significant before applying multiple comparison corrections. Several of these nodes remained highly significant *after* applying a Holm-Bonferroni correction.

Our central finding thus indicates that political ideology correlates with differences in neural activation patterns recorded during video observation when no responses were required. However, we found this correlation only when conceptualizing ideology as issue-based rather than identity-based. Additionally, differences in education level, background SES and sex also correlated with differences in neural activation patterns. Importantly, even though these patterns were significant, they corresponded to small correlations, where the largest was less than .06. Therefore, this necessitates discussing the potential meaning of such small but highly significant correlations.

Political Beliefs, But Not Political Identification, Correlate with Neural Activation

In line with our main hypothesis, our results indicate that ideology does play a role, albeit small, in forming our neural activation patterns to stimuli which require no behavioural responses. We found significant correlations between issue-based social ideology and patterns of activation in the cerebellum, insula and the temporal pole.

Strikingly, the two conceptualizations of ideology yielded entirely different results, whereby only issue-based ideology was correlated with neural activation in some regions of the brain, but there was no correlation for any region when conceptualizing ideology as identity-based. This difference indicates that the way people identify politically is not necessarily representative of the way in which they truly feel about various issues. This raises the question of whether this is a flaw in self report, that participants do not want to identify themselves as extreme, and therefore will place themselves on a more moderate point on a political identity scale. Alternatively, this might indicate a lack of insight into how political beliefs translate into a political identity. Perhaps people are less aware of what makes particular beliefs more left- or right-wing, creating a mismatch between the two types of report.

The discrepancy in the pattern of results between the two conceptualizations could present a considerable flaw in research that only approaches ideology in an identity-based manner, such as partisanship. This could explain why previous research found correlations between BOLD responses to political stimuli (such as election campaign ads or presidential debates) but not politically neutral stimuli (such as advertisements) because these studies conceptualized ideology as being equivalent to partisanship (e.g., Broom et al., 2022, de Bruin et al., 2023, Katabi et al., 2021).

Importantly, while all three regions which exhibited a correlation between their activation patterns with issue-based ideology each have a set of unique neural functions, they all share one important function. For example, the cerebellum is involved in many different computations in the brain, from motor control and sensory motor integration (Ohyama et al., 2003), to attention (Strick et al., 2009). The insula plays a role in monitoring the physical state of the body, such as perceiving one's own breathing and heart rate (Uddin et al., 2017). The temporal pole is involved in object recognition and labeling (Herlin et al., 2021). Yet, all are involved in social cognition, and seem to be particularly active in emotionally ambiguous situations (Herlin et al., 2021; van Overwalle et al., 2014; Uddin et al., 2017).

Notably, political ideology correlated negatively with neural activation. This indicates that being more socially conservative is correlated with stronger activation in the three brain regions. One interpretation of these findings can be made through the lens of the ambiguity hypothesis (Karakale, Moore, & Kirk, 2019; Karakale, Moore, McNair, & Kirk, 2019), which states that stronger activation in a particular brain region might be indicative of difficulty in comprehending a (social) situation. Drawing on this reasoning, this pattern of results points to a lower tolerance for (social) ambiguity as conservatism increases, which is in line with previous research (e.g., Farmer et al., 2021; van Hiel et al., 2016). However, considering the stimuli in the present study, the different regions could have taken on scene-specific roles. For example, some scenes included people with an ambiguous facial expression. Their faces could warrant activation from all three regions. Alternatively, other scenes included fast movement, such as flying over a canyon. This movement might elicit (only) cerebellar activation.

Differences in Activation Patterns Relative to Education Level, Background SES and Sex

Importantly, education level, background SES and sex were correlated with neural activation patterns in the cerebellum, insula and temporal pole. For education level, as education level increases, activation patterns decrease. Following the ambiguity hypothesis, this pattern of correlations could indicate that people at higher education levels have less difficulty in ambiguous situations. The opposite trend can be seen in background SES, where it seems people of a lower background SES are better at dealing with ambiguous situations. For sex, it seems females are better at deciphering socially ambiguous situations than males.

Differences Between Distance Metrics

Do the three distance metrics (NN, AK, and Mahalanobis) represent our variables differently? When examining the NN model, we found significant correlations only for issue-based ideology, with one significant node for sex. However, when examining the AK model, both measures of ideology yielded no significant correlations, but education, background SES and sex each had several nodes with a significant correlation. It seems that ideology might be better captured with an NN model, while the other socio-demographic variables are better represented with the AK model. We speculate that perhaps the AK model is better at capturing the variance of categorical variables (sex and education level) compared to the NN model. Interestingly, the Mahalanobis model yielded zero significant correlations between neural activation and any of our variables of interest. This finding raises the question of whether the Mahalanobis distance metric is not a sensitive enough measure of distance and provides false negatives, or whether it is actually the most accurate distance measure and successfully avoids false positives. Further research is required to answer this question.

What Constitutes a Meaningful Correlation?

The largest correlation in our set of results is between education level and cerebellar activation, placing our noise ceiling at r = -.055. In other words, this is the maximal amount of stimulus-related variance in the fMRI signal, while the rest is considered noise (Lage-Castellanos et al., 2019). In that sense, we would interpret a correlation of .02 (between issue-based ideology and activation patterns in the temporal pole) as quite large. We can then claim that our largest identity-related correlation can explain roughly 40% of the total stimuli-related variance in our dataset.

It follows that, while small, our correlations seem to align with previous studies, such as van Baar et al., 2021 and Schumacher et al., n.d., who found correlations of up to .07 between ideology and neural activation or brain structure. Importantly, Schumacher et al., n.d. used the same dataset as in the present study. However, in order to be more certain of the importance of an effect with a significant p-value but a small correlation, we should aim to amplify an effect through various techniques, or in other words, attempt to minimize the noise and maximize the stimulus-related signal. Anvari et al. (2023) suggest several methods. Firstly, we should consider interaction effects and scaling up. For example, that we should consider that our effect might be much stronger in a subset of the population, as we explain in more detail below. Secondly, that we should consider cascades, or in other words, how different variables might interact with each other over time. For example, this could manifest in people who were against (for) taking the COVID vaccines would interact with posts on social media in a way that could potentially polarize their views on this topic, as well as on other related topics, resulting in them being much more polarized to the right (left) than they would have been before vaccine roll out.

Alternatively, Primbs et al. (2023) suggest qualitative considerations. Instead of relying (only) on a p-value, correlation size, and effect size, researchers should consider the contribution of a particular effect to society. They demonstrate this using the example of having a correlation of $r = .03$ between taking aspirin and reducing a heart attack. The correlation between these variables is very small namely because people take aspirin for many reasons, and reducing a heart attack is only one of the many benefits. In the present study, while we also have small effects, they could lead us one step closer to understanding how the socio-political brain works, which is especially relevant considering how polarized the world is becoming. Within this framework, we would not dismiss the small correlations, but rather see their value in explaining even a small portion of neural activation, and what that could imply about politics and the brain.

Specifically, our (political) world is becoming more polarized. This means that people are becoming more extreme yet more certain in their political beliefs, which can cause them to reject undisputed scientific facts that are backed up by publicly available data, such as climate change, or COVID-19 vaccine efficacy, due to their political ideology (Rekker, 2021). The past ten years have seen unprecedented extremism which is due in part to social media use, such as Twitter (Kubin & Von Sikorski, 2021). For example, Donald Trump notoriously used Twitter during his presidential campaign and time in office to communicate with his voters and opponents (Wells et al., 2020). The Trump presidency polarized both Republicans and Democrats in the United States, where Republican voters became more extreme in their beliefs, and Democrat voters actively changed their product consumption and brand loyalty to avoid brands that supported Donald Trump or his right-wing values (Schoenmueller et al, 2023). Such political polarization can lead to terrorism, where people fueled by hateful words from their political leaders become extreme and violent (Piazza, 2020). Therefore, understanding all variables, such as political ideology, that can construct a particular world view and lead to violence is crucial.

Limitations and Future Directions

Limitations of ID1000 Data Set. To assess whether ideology is correlated with neural activation, we used the questionnaires included in the ID1000 dataset. Importantly, while we can rely on the statistical power of this dataset, there is no influencing the questionnaires or stimuli used, and therefore any interpretation is still restricted. For example, we cannot change the prompts used to measure social ideology which were quite extreme and led to distributions of ideology which were skewed to the right.

Also, while it does include a lot of data, it cannot include everything. Notably, data on political interest is missing (it was included but only for some participants, meaning that we cannot use it for our analysis). This variable is important because we need it to examine whether there is a moderator effect: that our intended effects only exist in people who find these identities central to their life. In other words, it might be the case that participants do not find social and political issues particularly relevant or important in their daily lives and only think about them when they are obliged to (e.g., before an election, or in the context of a study).

Moreover, while the clip presents many benefits, allowing us to investigate ideological asymmetry in a strictly non-political context (such as not including any explicitly political themes, and having no plot), its main drawback is that participants did not fixate on the same point on the screen. This led to substantially lower ISCs, which may have also led to the small correlations and low noise ceiling. This also raises the question of whether, in the absence of fixation instructions, does political ideology correlate with eye gaze? We suggest that future research explore this avenue, and determine if a substantial amount of neural ISC can be explained using eye movement ISC.

Limitations of the Analysis. In the representational similarity analysis that we deployed, we compare each socio-demographic variable to the fMRI data separately. This means we could not detect an interaction effect, which Anvari et al. (2023) claim is important. In the future, it might be beneficial to consider a multiple regression model of an IS-RSA, which could help us map out the relations of all socio-demographic variables to each other.

Interestingly, Finn et al. (2020) reported that they found no significant nodes when creating RDMs based on the final score of a Big-5 scale. However, they then constructed item-wise RDMs and found as many as 16 significant nodes for some items. We have chosen not to take this approach for our issue-based ideology variable, where scores were composed of the average of responses to four prompts. This is because such an approach demands an answer to an interpretability question. Since the activity would be related to each specific prompt, would this region then be involved in forming attitudes toward the LGBTQ+ community? Would it be a region involved in the perception of sexuality (whether of self or other)? Maybe it is indicative of a difference in perception of the way that the prompt was phrased. For example, perhaps different people respond differently to the use of the word “homosexual”, compared to “gay”. Keeping this lack of coherent interpretability in mind, we have chosen not to conduct this analysis.

Finally, with the growing body of literature on inter-subject synchrony, there are also multiple emerging methods of conducting this analysis. For example, one could also examine multivariate neural synchrony (MVNS), a classifier-based analysis that is effectively a multivariate version of an ISC (Hanke et al., 2009). Importantly, multivariate neural synchrony and ISC offer different insights into how psychological phenomena are represented in the brain. This means that they can uncover some of the same but also very different patterns of activation (Broom et al., 2022; Chang et al., 2021; Jolly & Chang, 2021). MVNS does so by considering the inter-subject correlation on a voxel-wise level first. This method has been shown to yield meaningful, significant correlations on the same data where a univariate ISC has returned null results (Broom et al., 2022).

Concluding Remarks

In the present study we investigated whether differences in activation patterns can be explained by differences in political ideology. Our results suggest that differences in the activation in the cerebellum, insula and temporal pole can be explained by differences in issue-based social ideology. These regions are involved in various functions, but one common function might be deciphering (social) ambiguity, which could indicate that social conservatism is correlated with increased intolerance for social ambiguity. Alternatively, these activation patterns might indicate differences in perception of movement.
Importantly, we found no correlation when examining identity-based social ideology, which indicates that the two conceptualizations might be measuring different phenomena, which can provide an alternative explanation for results from previous studies. In future research, we recommend a careful consideration of how ideology is conceptualized. It should be done in a way that ensures relevance and coherence to one's research question.

Data Availability

The full AOMIC databases are available here, along with detailed instructions on how to download the different types of data. The scripts used to conduct the analyses in this report are available in `Jupyter notebook` format here, along with the `.csv` files produced after data wrangling and sample splitting. The `.Rmd` file used to write this report is also included, and is the where code for the descriptive statistics used in this report can be found (e.g., the mean and standard deviation of age), while the `Jupyter notebooks` include all other data and code. Importantly, in order to extract node names for the Shen atlas, we referred to the BioImage Suite Web.

Conflict of Interest

None.

References

Amodio, D. M., Jost, J. T., Master, S. L., & Yee, C. M. (2007). Neurocognitive correlates of liberalism and conservatism. *Nature Neuroscience*, *10*(10, 10), 1246–1247. https://doi.org/10.1038/nn1979

Anderson, M., & Magruder, J. (2017). *Split-Sample Strategies for Avoiding False Discoveries* (No. w23544; p. w23544). Cambridge, MA: National Bureau of Economic Research. https://doi.org/10.3386/w23544

Anvari, F., Kievit, R., Lakens, D., Pennington, C. R., Przybylski, A. K., Tiokhin, L., … Orben, A. (2023). Not All Effects Are Indispensable: Psychological Science Requires Verifiable Lines of Reasoning for Whether an Effect Matters. *Perspectives on Psychological Science*, *18*(2), 503–507. https://doi.org/10.1177/17456916221091565

Bakker, B. N., Schumacher, G., Gothreau, C., & Arceneaux, K. (2020). Conservatives and liberals have similar physiological responses to threats. *Nature Human Behaviour*, *4*(6, 6), 613–621. https://doi.org/10.1038/s41562-020-0823-z

Bakker, B. N., Schumacher, G., & Homan, M. D. (2020). Yikes! Are we disgusted by politicians? *Politics and the Life Sciences*, *39*(2), 135–153. https://doi.org/10.1017/pls.2020.16

Becker, J. C. (2020). Ideology and the promotion of social change. *Current Opinion in Behavioral Sciences*, *34*, 6–11. https://doi.org/10.1016/j.cobeha.2019.10.005

Bossier, H., Roels, S. P., Seurinck, R., Banaschewski, T., Barker, G. J., Bokde, A. L. W., … Moerkerke, B. (2020). The empirical replicability of task-based fMRI as a function of sample size. *NeuroImage*, *212*, 116601. https://doi.org/10.1016/j.neuroimage.2020.116601

Broom, T. W., Stahl, J. L., Ping, E. E. C., & Wagner, D. D. (2022). They Saw a Debate: Political Polarization Is Associated with Greater Multivariate Neural Synchrony When Viewing the Opposing Candidate Speak. *Journal of Cognitive Neuroscience*, *35*(1), 60–73. https://doi.org/10.1162/jocn_a_01888

Buechner, B. M., Clarkson, J. J., Otto, A. S., Hirt, E. R., & Ho, M. C. (2021). Political Ideology and Executive Functioning: The Effect of Conservatism and Liberalism on Cognitive Flexibility and Working Memory Performance. *Social Psychological and Personality Science*, *12*(2), 237–247. https://doi.org/10.1177/1948550620913187

Chang, L. J., Jolly, E., Cheong, J. H., Rapuano, K. M., Greenstein, N., Chen, P.-H. A., & Manning, J. R. (2021). Endogenous variation in ventromedial prefrontal cortex state dynamics during naturalistic viewing reflects affective experience. *Science Advances*, *7*(17), eabf7129. https://doi.org/10.1126/sciadv.abf7129

de Bruin, D., van Baar, J. M., Rodríguez, P. L., & FeldmanHall, O. (2023). Shared neural representations and temporal segmentation of political content predict ideological similarity. *Science Advances*, *9*(5). https://doi.org/10.1126/sciadv.abq5920

De Maesschalck, R., Jouan-Rimbaud, D., & Massart, D. L. (2000). The Mahalanobis distance. *Chemometrics and Intelligent Laboratory Systems*, *50*(1), 1–18. https://doi.org/10.1016/S0169-7439(99)00047-7

Farmer, A., Kidwell, B., & Hardesty, D. M. (2021). The Politics of Choice: Political Ideology and Intolerance of Ambiguity. *Journal of Consumer Psychology*, *31*(1), 6–21. https://doi.org/10.1002/jcpy.1176

Finn, E. S., Glerean, E., Khojandi, A. Y., Nielson, D., Molfese, P. J., Handwerker, D. A., & Bandettini, P. A. (2020). Idiosynchrony: From shared responses to individual differences during naturalistic neuroimaging. *NeuroImage*, *215*, 116828. https://doi.org/10.1016/j.neuroimage.2020.116828

Hanke, M., Halchenko, Y. O., Sederberg, P. B., Hanson, S. J., Haxby, J. V., & Pollmann, S. (2009). PyMVPA: A Python toolbox for multivariate pattern analysis of fMRI data. *Neuroinformatics*, *7*(1), 37–53. https://doi.org/10.1007/s12021-008-9041-y

Hasson, U., Landesman, O., Knappmeyer, B., Vallines, I., Rubin, N., & Heeger, D. J. (2008). Neurocinematics: The Neuroscience of Film. *Projections*, *2*(1), 1–26. https://doi.org/10.3167/proj.2008.020102

Herlin, B., Navarro, V., & Dupont, S. (2021). The temporal pole: From anatomy to function—A literature appraisal. *Journal of Chemical Neuroanatomy*, *113*, 101925. https://doi.org/10.1016/j.jchemneu.2021.101925

Holm, S. (1979). A Simple Sequentially Rejective Multiple Test Procedure. *Scandinavian Journal of Statistics*, *6*(2), 65–70. Retrieved from https://www.jstor.org/stable/4615733

Horien, C., Noble, S., Greene, A. S., Lee, K., Barron, D. S., Gao, S., … Scheinost, D. (2021). A hitchhiker's guide to working with large, open-source neuroimaging datasets. *Nature Human Behaviour*, *5*(2), 185–193. https://doi.org/10.1038/s41562-020-01005-4

Johnston, C. D., & Ollerenshaw, T. (2020). How different are cultural and economic ideology? *Current Opinion in Behavioral Sciences*, *34*, 94–101. https://doi.org/10.1016/j.cobeha.2020.01.008

Jolly, E., & Chang, L. J. (2021). Multivariate spatial feature selection in fMRI. *Social Cognitive and Affective Neuroscience*, *16*(8), 795–806. https://doi.org/10.1093/scan/nsab010

Jost, J. T., Stern, C., Rule, N. O., & Sterling, J. (2017). The Politics of Fear: Is There an Ideological Asymmetry in Existential Motivation? *Social Cognition*, *35*(4), 324–353. https://doi.org/10.1521/soco.2017.35.4.324

Kanai, R., Feilden, T., Firth, C., & Rees, G. (2011). Political Orientations Are Correlated with Brain Structure in Young Adults. *Current Biology*, *21*(8), 677–680. https://doi.org/10.1016/j.cub.2011.03.017

Karakale, O., Moore, M. R., & Kirk, I. J. (2019). Mental Simulation of Facial Expressions: Mu Suppression to the Viewing of Dynamic Neutral Face Videos. *Frontiers in Human Neuroscience*, *13*. Retrieved from https://www.frontiersin.org/article/10.3389/fnhum.2019.00034

Karakale, O., Moore, M. R., McNair, N., & Kirk, I. J. (2019). *Increased sensorimotor activity during categorisation of ambiguous emotional expressions* [Preprint].

Neuroscience. https://doi.org/10.1101/717553

Katabi, N., Simon, H., Yakim, S., Ravreby, I., & Yeshurun, Y. (2021, November 27). Deeper than you think: Partisan-dependent brain response. https://doi.org/10.1101/2021.11.23.469735

Kriegeskorte, N., Mur, M., & Bandettini, P. (2008). Representational similarity analysis - connecting the branches of systems neuroscience. *Frontiers in Systems Neuroscience*, *2*. Retrieved from https://www.frontiersin.org/articles/10.3389/neuro.06.004.2008

Kubin, E., & Von Sikorski, C. (2021). The role of (social) media in political polarization: A systematic review. *Annals of the International Communication Association*, *45*(3), 188–206. https://doi.org/10.1080/23808985.2021.1976070

Lage-Castellanos, A., Valente, G., Formisano, E., & Martino, F. D. (2019). Methods for computing the maximum performance of computational models of fMRI responses. *PLOS Computational Biology*, *15*(3), e1006397. https://doi.org/10.1371/journal.pcbi.1006397

Lakens, D. (2019). *The Value of Preregistration for Psychological Science: A Conceptual Analysis* [Preprint]. PsyArXiv. https://doi.org/10.31234/osf.io/jbh4w

Madan, C. R. (2022). Scan Once, Analyse Many: Using Large Open-Access Neuroimaging Datasets to Understand the Brain. *Neuroinformatics*, *20*(1), 109–137. https://doi.org/10.1007/s12021-021-09519-6

Mantel, N. (1967). The detection of disease clustering and a generalized regression approach. *Cancer Research*, *27*(2), 209–220.

Moore, A., Hong, S., & Cram, L. (2021). Trust in information, political identity and the brain: An interdisciplinary fMRI study. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *376*(1822), 20200140. https://doi.org/10.1098/rstb.2020.0140

Ohyama, T., Nores, W. L., Murphy, M., & Mauk, M. D. (2003). What the cerebellum computes. *Trends in Neurosciences*, *26*(4), 222–227. https://doi.org/10.1016/S0166-2236(03)00054-7

Petropolous-Petalas, D., & Schumacher, G. (n.d.). *Jumping to Conclusions.*

Piazza, J. A. (2020). Politician hate speech and domestic terrorism. *International Interactions*, *46*(3), 431–453. https://doi.org/10.1080/03050629.2020.1739033

Primbs, M. A., Pennington, C. R., Lakens, D., Silan, M. A. A., Lieck, D. S. N., Forscher, P. S., … Westwood, S. J. (2023). Are Small Effects the Indispensable Foundation for a Cumulative Psychological Science? A Reply to Götz et al. (2022). *Perspectives on Psychological Science*, *18*(2), 508–512. https://doi.org/10.1177/17456916221100420

Rekker, R. (2021). The nature and origins of political polarization over science. *Public Understanding of Science*, *30*(4), 352–368. https://doi.org/10.1177/0963662521989193

Salmela, V., Salo, E., Salmi, J., & Alho, K. (2018). Spatiotemporal Dynamics of Attention Networks Revealed by Representational Similarity Analysis of EEG and fMRI. *Cerebral Cortex*, *28*(2), 549–560. https://doi.org/10.1093/cercor/bhw389

Schoenmueller, V., Netzer, O., & Stahl, F. (2023). Frontiers: Polarized America: From Political Polarization to Preference Polarization. *Marketing Science*, *42*(1), 48–60. https://doi.org/10.1287/mksc.2022.1408

Schumacher, G. (2023, February). *Gijs Schumacher @ Hot Politics Lab: Affective Representation.* Presented at the Amsterdam, The Netherlands. Retrieved from https://www.hotpolitics.eu/lab-meetings-archive/#lab_2023_schumacher

Schumacher, G., Petropolous-Petalas, D., & Scholte, S. H. (n.d.). *Are Political Orientations Correlated with Brain Structure? A Preregistered Replication of the Kanai et al. (2011) study.*

Shen, X., Tokoglu, F., Papademetris, X., & Constable, R. T. (2013). Groupwise whole-brain parcellation from resting-state fMRI data for network node identification. *NeuroImage*, *82*, 403–415. https://doi.org/10.1016/j.neuroimage.2013.05.081

Snoek, L., van der Miesen, M. M., Beemsterboer, T., van der Leij, A., Eigenhuis, A., & Steven Scholte, H. (2021). The Amsterdam Open MRI Collection, a set of multimodal MRI datasets for individual difference analyses. *Scientific Data*, *8*(1, 1), 85.

https://doi.org/10.1038/s41597-021-00870-6

Stankov, L. (2021). From social conservatism and authoritarian populism to militant right-wing extremism. *Personality and Individual Differences*, *175*, 110733. https://doi.org/10.1016/j.paid.2021.110733

Strick, P. L., Dum, R. P., & Fiez, J. A. (2009). Cerebellum and Nonmotor Function. *Annual Review of Neuroscience*, *32*(1), 413–434. https://doi.org/10.1146/annurev.neuro.31.060407.125606

Turner, B. O., Paul, E. J., Miller, M. B., & Barbey, A. K. (2018). Small sample sizes reduce the replicability of task-based fMRI studies. *Communications Biology*, *1*(1, 1), 1–10. https://doi.org/10.1038/s42003-018-0073-z

Uddin, L. Q., Nomi, J. S., Hebert-Seropian, B., Ghaziri, J., & Boucher, O. (2017). Structure and function of the human insula. *Journal of Clinical Neurophysiology : Official Publication of the American Electroencephalographic Society*, *34*(4), 300–306. https://doi.org/10.1097/WNP.0000000000000377

Van Baar, J. M., Halpern, D. J., & FeldmanHall, O. (2021). Intolerance of uncertainty modulates brain-to-brain synchrony during politically polarized perception. *Proceedings of the National Academy of Sciences*, *118*(20), e2022491118. https://doi.org/10.1073/pnas.2022491118

van der Linden, S., Panagopoulos, C., Azevedo, F., & Jost, J. T. (2021). The Paranoid Style in American Politics Revisited: An Ideological Asymmetry in Conspiratorial Thinking. *Political Psychology*, *42*(1), 23–51. https://doi.org/10.1111/pops.12681

Van Hiel, A., Onraet, E., Crowson, H. M., & Roets, A. (2016). The Relationship between Right–wing Attitudes and Cognitive Style: A Comparison of Self–report and Behavioural Measures of Rigidity and Intolerance of Ambiguity. *European Journal of Personality*, *30*(6), 523–531. https://doi.org/10.1002/per.2082

Van Overwalle, F., Baetens, K., Mariën, P., & Vandekerckhove, M. (2014). Social cognition and the cerebellum: A meta-analysis of over 350 fMRI studies. *NeuroImage*, *86*, 554–572. https://doi.org/10.1016/j.neuroimage.2013.09.033

Wells, C., Shah, D., Lukito, J., Pelled, A., Pevehouse, J. C., & Yang, J. (2020). Trump, Twitter, and news media responsiveness: A media systems approach. *New Media & Society*, *22*(4), 659–682. https://doi.org/10.1177/1461444819893987

Yang, S. E., Wilson, J. D., Lu, Z.-L., & Cranmer, S. (2022). Functional connectivity signatures of political ideology. *PNAS Nexus*, *1*(3), pgac066. https://doi.org/10.1093/pnasnexus/pgac066

Zmigrod, L., Eisenberg, I. W., Bissett, P. G., Robbins, T. W., & Poldrack, R. A. (2021). The cognitive and perceptual correlates of ideological attitudes: A data-driven approach. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *376*(1822), 20200424. https://doi.org/10.1098/rstb.2020.0424

Appendix A

Split Half

Figure A1

Results of Splitting Full Sample (N = 854) Into Two Half-Samples (N = 427)

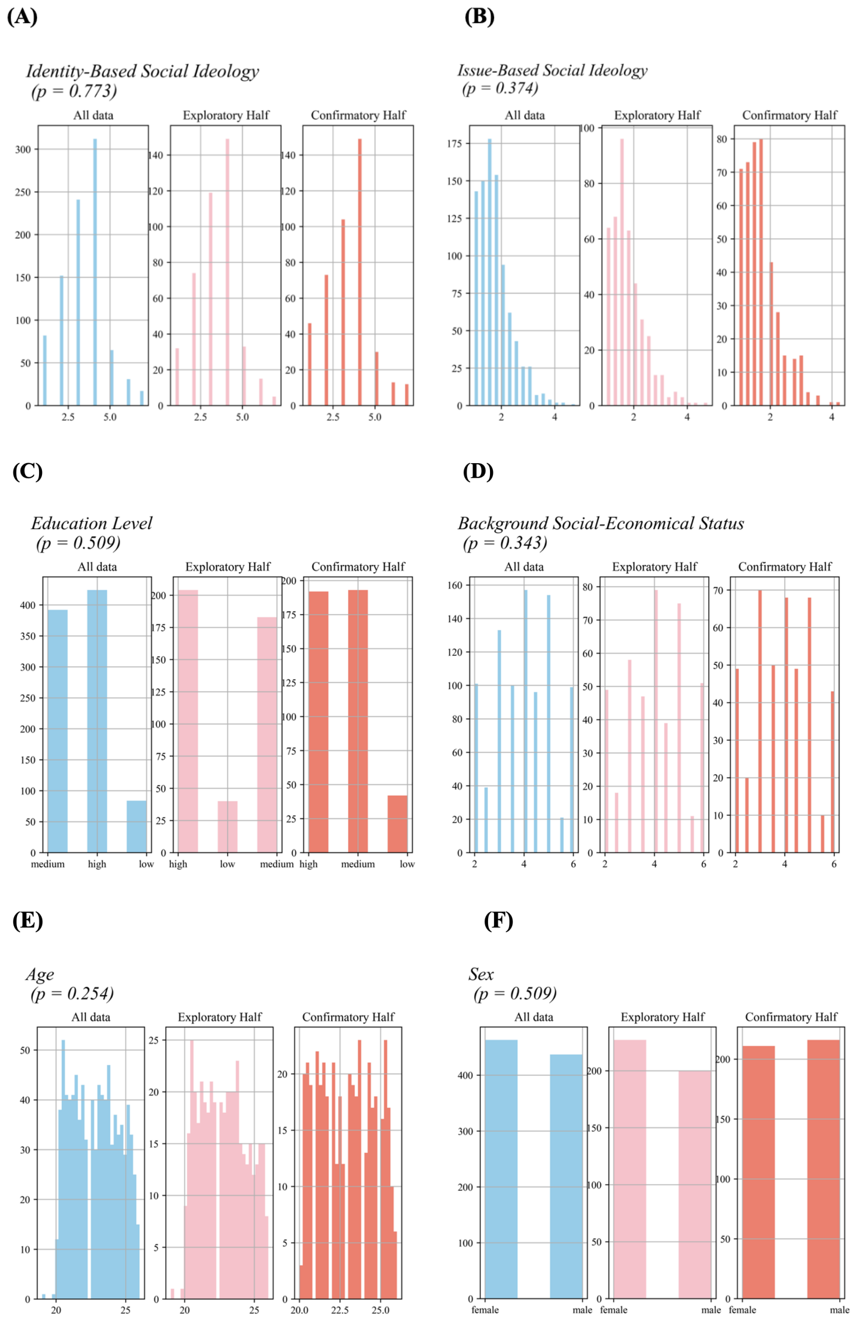


Figure A1. The figure visualizes the results of splitting the full data set into an exploratory half and a confirmatory half. The six histograms outline the distributions of the various variables, along with the p-value of the appropriate statistical test which was performed to ensure that the two samples are not significantly different.

Appendix B

ISC Table

Table B1

ISC Highest Synchrony Values

Node Number (Shen Atlas)	Brain Region	ISC	Significance
75	BA 19 (Occipital Cortex)	0.22	.002
212	BA 18 (Occipital Cortex)	0.21	.002
132	Brainstem	0.20	.002
95	BA 36 (Parahippocampus)	0.19	.002
96	BA 36 (Parahippocampus)	0.19	.002
103	Cerebellum	0.19	.002
130	Brainstem	0.19	.002
251	Cerebellum	0.17	.002
133	Brainstem	0.17	.002
265	Brainstem	0.17	.002

Note. This table shows the ten regions with the highest inter-subject correlation in the exploratory sample (N = 427), ranked by ISC value. This means that these regions exhibited the most similar patterns between participants. Note that multiple nodes may correspond to different sub-regions of the specified Brodmann Areas. The ISC for the confirmatory sample yielded similar results and is therefore not included here.

Appendix C

RDMs Examples

In **Figure C1** we visualize the differences between RDMs of different brain regions, while in **Figure C2**, we visualize the differences between using different distance metrics.

Figure C1

Examples of Similarity Matrices for Nodes 33 and 267

(A) **(B)**

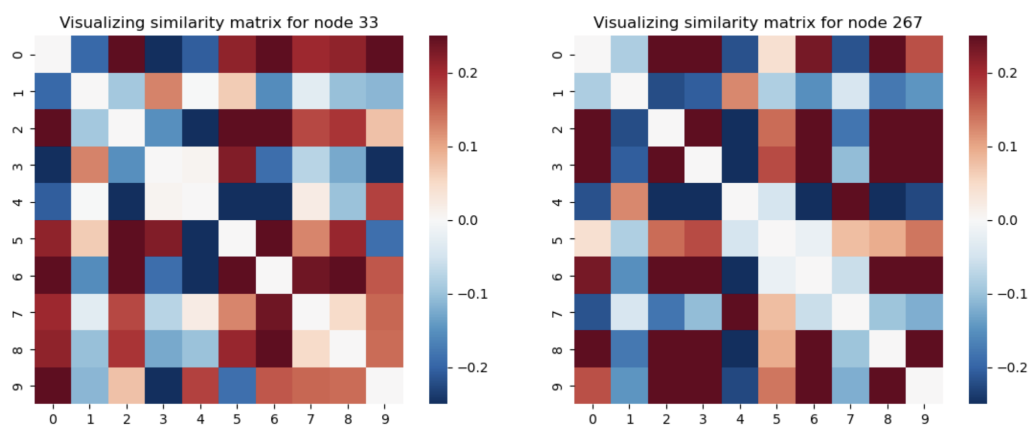
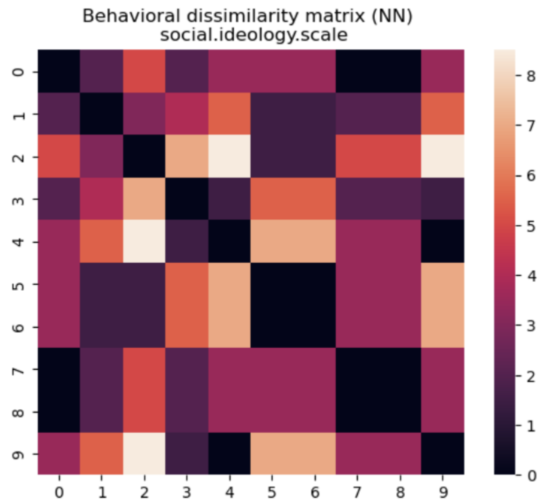


Figure C1. This figure shows the representational similarity matrices for nodes 33 and 267, corresponding to sub-regions of the insula and the brain stem, respectively. This demonstrates how different regions can have very different matrices. Note that for visualization purposes, these matrices were generated using the data of only a few participants from the exploratory sample ($N = 10$).

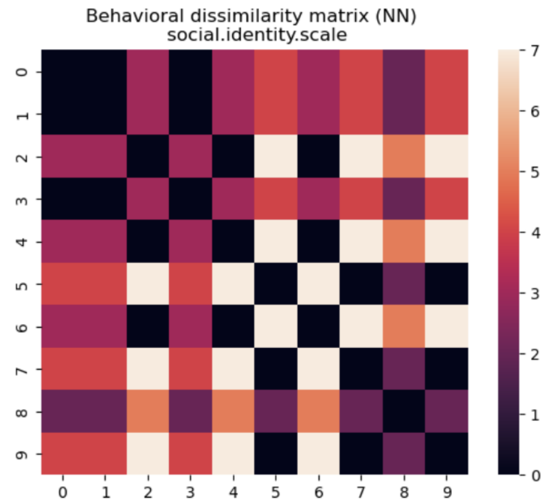
Figure C2

Examples of Dissimilarity Matrices Computed Using Different Distance Metrics

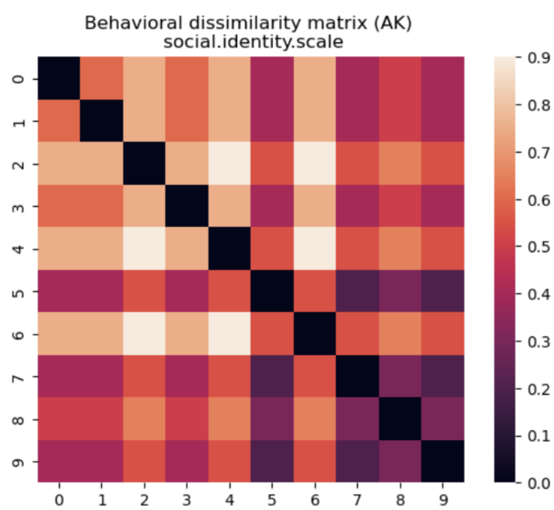
(A)



(B)



(C)



(D)

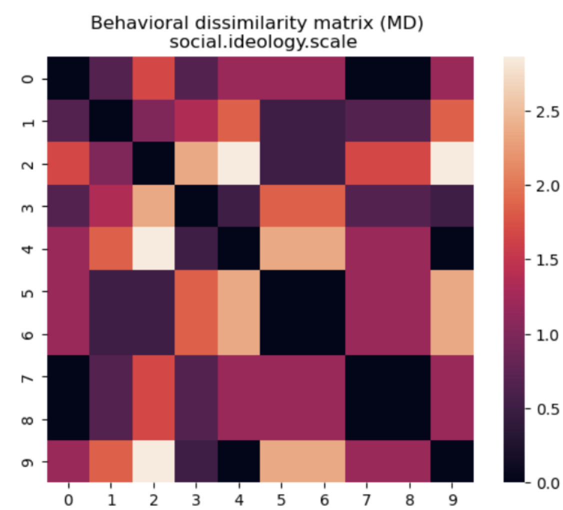


Figure C2. (A) and (B) demonstrate how for different variables (identity- and issue-based social ideology) there should be different matrices even when using the same distance metric (NN). (A), (C) and (D) show that issue-based social ideology can have different matrices when calculating distance in different way. Note that for visualization purposes, these matrices were generated using the data of only a few participants from the exploratory sample ($N = 10$).

Appendix D

Non-Normality

The following two tables exhibit that the data in each half-sample was not distributed normally, due to its accurate representation of the Dutch population.

Table D1

Exploratory Sample Normality Violations

Variable	Shapiro-Wilk Statistic	Significance
Issue-based Social Ideology	0.89	$< .001$
Identity-based Social Ideology	0.93	$< .001$
Education level	0.75	$< .001$
Background SES	0.94	$< .001$
Sex	0.64	$< .001$

Note. Results of the Shapiro-Wilk test which was performed on the exploratory data set to test whether the variables are distributed normally.

Table D2

Confirmatory Sample Normality Violations

Variable	Shapiro-Wilk Statistic	Significance
Issue-based Social Ideology	0.90	$< .001$
Identity-based Social Ideology	0.92	$< .001$
Education level	0.76	$< .001$
Background SES	0.95	$< .001$
Sex	0.64	$< .001$

Note. Results of the Shapiro-Wilk test which was performed on the confirmatory data set to test whether the variables are distributed normally.

Appendix E

Exploratory to Confirmatory

Table E1

Nodes Tested in Confirmatory Sample

Variable	Model	Ten Most Significant	Remained Significant
Issue-based social identity	NN	98, 102, 103, 105, 163, 164, 188, 189, 212, 213	34, 102, 103, 168, 188, 189
Issue-based social identity	AK	71, 72, 73, 74, 75, 76, 77, 78, 79, 185	-
Issue-based social ideology	NN	106, 115, 117, 128, 130, 142, 225, 235, 236, 266	-
Issue-based social ideology	AK	88, 90, 178, 180, 181, 182, 183, 184, 185, 191	-
Background SES	NN	72, 73, 74, 75, 76, 77, 78, 79, 157, 208	-
Background SES	AK	98, 102, 103, 105, 106, 107, 109, 110, 189, 201	102, 213
Education Level	NN	107, 109, 110, 111, 112, 113, 114, 116, 237, 239	-
Education Level	AK	102, 114, 116, 127, 129, 141, 145, 213, 224, 265	102, 103, 189
Sex	NN	103, 127, 129, 132, 141, 224, 234, 235, 237, 265	103
Sex	AK	98, 102, 103, 105, 181, 182, 183, 184, 208, 237	102, 103