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Investigating the effects of context on semantic representations in the brain and mapping social representations in the brain

By

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Abstract

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Context is an important part of understanding the meaning of natural language, but most neuroimaging studies of meaning use isolated words and isolated sentences with little context. Because the brain may process natural language differently from how it processes simplified stimuli, it is unclear whether prior results on word meaning generalize to natural language. In Chapter 1, I present a neuroimaging experiment that examines whether the results of neuroimaging studies that use stimuli with little context generalize to natural language. Results show that context both affects the quality of neuroimaging data and changes where and how semantic information is represented in the brain. This suggests that findings from studies using stimuli with little context do not generalize to natural language.

In Chapters 2 and 3, I present two neuroimaging experiments that map representations of social information in the brain. Relationships are an integral part of life, and people store extensive knowledge about themselves, other individuals, and their dynamics to maintain these relationships. Many prior neuroimaging studies have investigated where different types of social information are represented in the brain. However, because of methodological limitations in these studies, the representation of social information in the brain remains unclear. In Chapter 2, I present a neuroimaging experiment that simultaneously maps the representation of five types of social information that have been investigated in prior studies. Results show that only three of these five types of social information are represented in the brain, and that individual brain regions each represent one type of social information. In Chapter 3, I present a neuroimaging experiment that maps the representation of the self and six different types of other people. Preliminary results from this experiment suggest that the brain represents the self and different types of others in distinct brain regions. These data also reveal three possible axes along which the brain may organize information about the self and others.

Contents

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Chapter 1

Semantic representations during language comprehension are affected by context

1.1 Introduction

Language is our main means of communication and an integral part of daily life. Natural language comprehension requires extracting meaning from words that are embedded in context. However, most neuroimaging studies of word meaning use simplified stimuli consisting of isolated words or sentences (Price, 2012). Natural language differs from isolated words and sentences in several ways. Natural language contains phonological and orthographic patterns, lexical semantics, syntactic structure, and compositional- and discourse-level semantics embedded in social context (Hagoort, 2019). In contrast, isolated words and sentences only contain a few of these components (e.g., lexical meaning, local syntactic structure). (For concision, this paper will refer to all differences between natural language and isolated words/sentences as differences in "context.")

Neuroimaging studies that use isolated words and sentences implicitly assume that their results will generalize to natural language. However, because the brain is a highly nonlinear dynamical system (Breakspear, 2017; Wu et al., 2006), the representation of semantic information may change depending on context (Hagoort, 2019; Hamilton & Huth, 2020; Poeppel et al., 2012). Indeed, contextual effects have been demonstrated clearly in other domains. For example, many neurons in the visual system respond differently to simplified stimuli compared to naturalistic stimuli (David et al., 2004; Ringach et al., 2002; Simoncelli & Olshausen, 2001; Touryan et al., 2005). However, few studies have examined whether insights about semantic representation from studies using simplified stimuli will generalize to natural language.

Results from past studies suggest that context has a large effect on semantic representation. Several natural language studies from our lab reported that semantic information is represented independently of the presentation modality in a large, distributed network of brain regions including bilateral temporal, parietal, and prefrontal cortices (Deniz et al., 2019; Huth et al., 2016). In contrast, studies that used isolated words or sentences as stimuli independently identified only a few brain regions that represent semantic information. These studies have separately identified angular gyrus, left inferior frontal gyrus, left ventromedial prefrontal cortex, left dorsolateral prefrontal cortex, anterior temporal lobe, lateral-, ventral-, and inferotemporal cortex, posterior cingulate gyrus, and posterior parietal cortex (for reviews see (Binder et al., 2009; Price, 2010, 2012).

One way that context might affect neuroimaging results is by affecting the signal-to-noise ratio (SNR) of evoked brain responses (i.e., affecting the metabolic activity of the brain such that the repeatability of the recorded BOLD response is affected). Although no language studies have explicitly looked at evoked BOLD SNR, several converging lines of evidence suggest that context does affect evoked SNR in language studies. (Lerner et al., 2011) examined how language context affects cross-subject correlations in brain responses, and they reported that as the amount of context increased, the number of voxels that were correlated across subjects also increased. In addition, several contrast-based fMRI language studies reported that increasing context evoked larger and more widespread patterns of brain activity (Jobard et al., 2007; Mazoyer et al., 1993; Xu et al., 2005). Finally, most subjects are more attentive when reading natural stories than when reading isolated words, and attention affects BOLD SNR (Bressler & Silver, 2010).

Another more interesting way that context might affect neuroimaging results is by directly changing semantic representations in the brain (i.e., changing which voxels represent semantic information and/or the semantic tuning of those voxels). Context can change the way that subjects attend to semantic information, and semantic representations in many brain areas shift toward attended semantic categories (Çukur et al., 2013; Nastase et al., 2017; Sprague et al., 2015). Context also changes the statistical structure of language stimuli, and these statistical changes can affect cognitive processes and representations in a variety of ways (Breakspear, 2017; Dahmen et al., 2010; Wu et al., 2006).

To test the hypotheses that context affects evoked SNR and semantic representations, we used fMRI and a voxelwise encoding model approach to directly compare four stimulus conditions that vary in context: Narratives, Sentences, Semantic Blocks, and Single Words (Figure 1). The Narratives condition consisted of four narrative stories used in our previous studies (Deniz et al., 2019; Huth et al., 2016; Popham et al., 2021). The other three conditions used sentences, blocks of semantically similar words, and individual words sampled from the narratives in Huth et al. (2016), Deniz et al. (2019), and Popham et al. (2021).

1.2 Materials and Methods

Subjects

Functional data were collected from two male subjects, one female subject, and one non-binary subject assigned female at birth: S1 (male, age 31), S2 (male, age 24), S3 (female, age 24), S4 (non-binary, age 23). All subjects were healthy and had normal

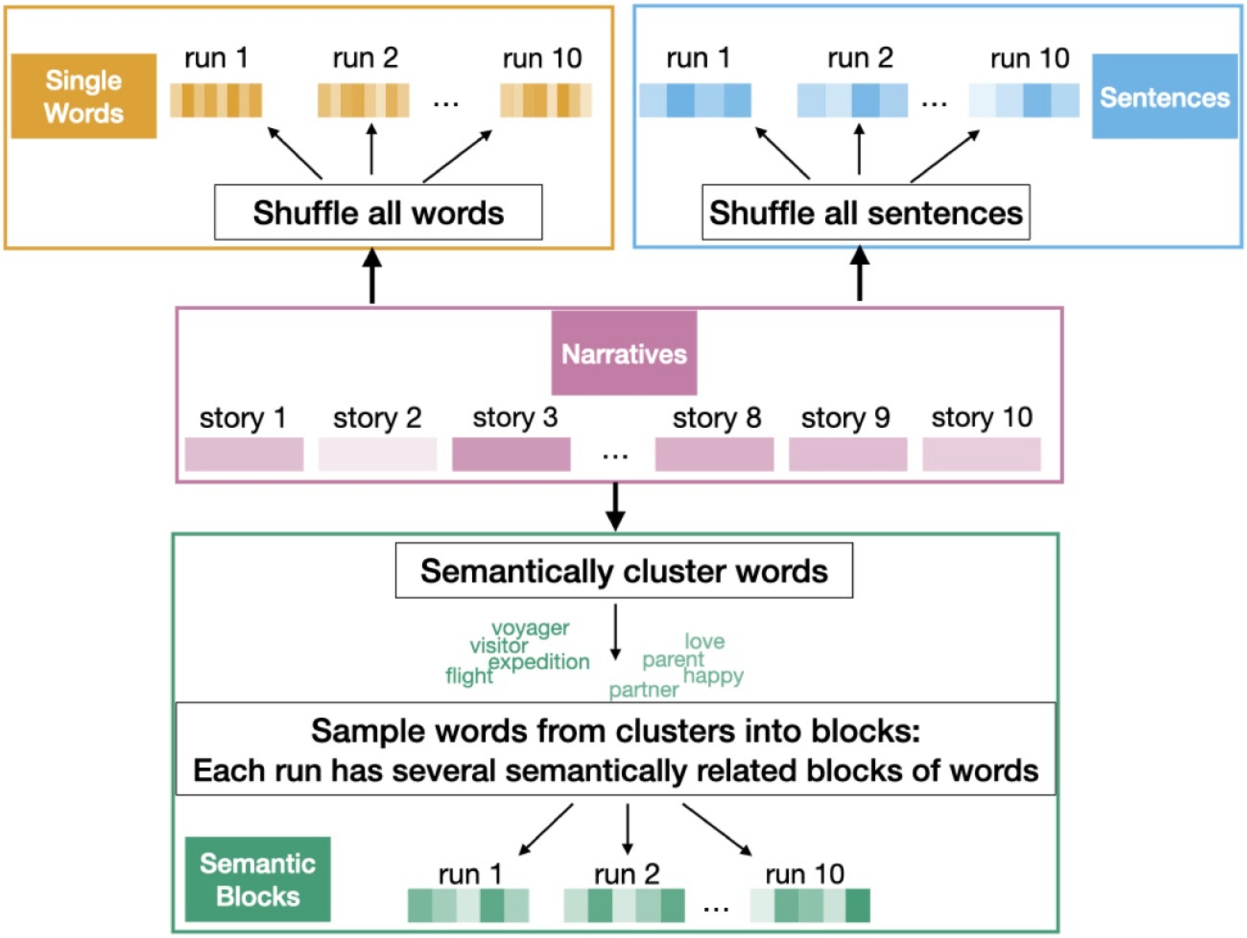


Figure 1: Stimulus conditions. The experiment contained four stimulus conditions that were based on the ten narratives used in Huth et al. (2016). The Single Words condition consisted of words sampled randomly from the ten narratives. The Semantic Blocks condition consisted of blocks of words sampled from clusters of semantically similar words from the ten narratives. There were 12 distinct clusters of semantically similar words, and blocks of words were created by randomly sampling 114 words from one word cluster for each block. The Sentences condition consisted of sentences sampled randomly from the ten narratives. Finally, the Narratives condition consisted of the ten original narratives.

hearing, and normal or corrected-to-normal vision. All subjects were right handed according to the Edinburgh handedness inventory (Oldfield, 1971). Laterality scores were +70 (decile R.3) for S1, +95 (decile R.9) for S2, +90 (decile R.7) for S3, +80 (decile R.5) for S4.

MRI data collection

MRI data were collected on a 3T Siemens TIM Trio scanner with a 32-channel Siemens volume coil, located at the UC Berkeley Brain Imaging Center. Functional scans were collected using gradient echo EPI with repetition time (TR) = 2.0045s, echo time (TE) =

31ms, flip angle = 70 degrees, voxel size = 2.24 x 2.24 x 4.1 mm (slice thickness = 3.5 mm with 18% slice gap), matrix size = 100 x 100, and field of view = 224 x 224 mm. Thirty axial slices were prescribed to cover the entire cortex and were scanned in interleaved order. A custom-modified bipolar water excitation radiofrequency (RF) pulse was used to avoid signal from fat. Anatomical data were collected using a T1-weighted multi-echo MP-RAGE sequence on the same 3T scanner. Approximately 3.5 hours (214.85 minutes) of fMRI data was collected for each subject.

fMRI data pre-processing

The FMRIB Linear Image Registration Tool (FLIRT) from FSL 5.0 (Jenkinson et al., 2002; Jenkinson & Smith, 2001) was used to motion-correct each functional run. A high-quality template volume was then created for each run by averaging all volumes in the run across time. FLIRT was used to automatically align the template volume for each run to an overall template, which was chosen to be the temporal average of the first functional run for each subject. These automatic alignments were manually checked and adjusted as necessary to improve accuracy. The cross-run transformation matrix was then concatenated to the motion-correction transformation matrices obtained using MCFLIRT, and the concatenated transformation was used to resample the original data directly into the overall template space.

A 3rd order Savitsky-Golay filter with a 121-TR window was used to identify low-frequency voxel response drift. This drift was subtracted from the signal before further processing. Responses for each run were z-scored separately before voxelwise modeling. In addition, 10 TRs were discarded from the beginning and the end (20 TRs total) of each run.

Cortical surface reconstruction and visualization

Freesurfer (Dale et al., 1999) was used to generate cortical surface meshes from the T1-weighted anatomical scans. Before surface reconstruction, Blender and pycortex (http://pycortex.org; (Gao et al., 2015)) were used to carefully hand-check and correct anatomical surface segmentations. To aid in cortical flattening, Blender and pycortex were used to remove the surface crossing the corpus callosum and relaxation cuts were made into the surface of each hemisphere. The calcarine sulcus cut was made at the horizontal meridian in V1 as identified from retinotopic mapping data.

Pycortex (Gao et al., 2015) was used to align functional images to the cortical surface. The line-nearest scheme in pycortex was used to project functional data onto the surface for visualization and subsequent analysis. The line-nearest scheme samples the functional data at 64 evenly-spaced intervals between the inner (white matter) and outer (pial) surfaces of the cortex and averages the samples. Samples are taken using nearest-neighbor interpolation, in which each sample is given the value of its enclosing voxel.

Stimuli

Stimuli for all four conditions were generated from ten spoken stories from The Moth Radio Hour (used previously in (Huth et al., 2016)). In each story, a speaker tells an autobiographical story in front of a live audience. The ten selected stories are 10-15 min long, cover a wide range of topics, and are highly engaging. Transcriptions of these stories were used to generate the stimuli.

Story transcription

Each story was manually transcribed by one listener, and this transcription was checked by a second listener. Certain sounds (e.g., laughter, lip-smacking, and breathing) were also transcribed in order to improve the accuracy of the automated alignment. The audio of each story was downsampled to 11.5 kHz and the Penn Phonetics Lab Forced Aligner (P2FA; (Yuan & Liberman, 2008)) was used to automatically align the audio to the transcript. P2FA uses a phonetic hidden Markov model to find the temporal onset and offset of each word and phoneme. The Carnegie Mellon University pronouncing dictionary was used to guess the pronunciation of each word. The Arpabet phonetic notation was used when necessary to manually add words and word fragments that appeared in the transcript but not in the pronouncing dictionary.

After automatic alignment was complete, Praat (Boersman & Weenink, 2014) was used to manually check and correct each aligned transcript. The corrected, aligned transcript was then spot-checked for accuracy by a different listener. Finally, Praat's TextGrid object was used to convert the aligned transcripts into word representations. The word representation of each story is a list of pairs (W, t), where W is a word and t is the time in seconds.

Stimulus Conditions

To evaluate the effect of context on evoked SNR and semantic representation in the brain, four stimulus conditions with different amounts of context were created. These four conditions were Narratives, Sentences, Semantic Blocks, and Single Words.

The Narratives condition consisted of four narratives from The Moth Radio Hour ("undertheinfluence", "souls", "life", “wheretheressmoke”). These four narratives were chosen from the ten narratives used in (Huth et al., 2016). Each narrative was presented in a separate ~10-minute scanning run. One narrative (“wheretheressmoke”) was used as the model validation stimulus, and it was presented twice for each subject.

The Sentences condition consisted of sentences randomly sampled from the ten narratives used in (Huth et al., 2016). Sentence boundaries were marked manually, resulting in 1450 sentences with a median sentence length of 13 words (min=5 words, max=40 words). Sentences were presented in four unique ~10-minute scanning runs. One run was used as the model validation stimulus, and it was presented twice for each subject.

The Semantic Blocks condition consisted of blocks of semantically clustered words from the ten narratives used in (Huth et al., 2016). The motivation for this condition was to mimic the timescale on which semantic topics change in natural language without including grammatical and syntactic components. The semantic word clusters were designed to elicit maximally different voxel responses. To create the clusters, each word was first transformed into its semantic model representation (see Voxelwise model fitting below). The semantic model representation for each word was then projected onto the first ten principal components of the semantic model weights estimated in (Huth et al., 2016). Finally, the projections were clustered with k-means clustering (k=12) to create 12 word clusters. During each scanning run, subjects saw 12 different blocks of 114 words each. The words in each block were sampled from one of the word clusters, and eight different word clusters were sampled in each run. The frequency with which each cluster was sampled was matched to the frequency with which words from that cluster appeared in the ten narratives. Blocks were presented in four unique ~10-minute long runs. One run was used as the model validation stimulus, and it was presented twice for each subject.

The Single Words condition consisted of words randomly sampled without replacement from the ten narratives used in (Huth et al., 2016). There were 21743 appearances of 2868 unique words across the narratives, and each appearance was sampled uniformly. Words were presented in four unique 10-minute scanning runs. One run was used as the model validation stimulus, and it was presented twice for each subject.

For the Sentences, Semantic Blocks, and Single Words conditions, text descriptions of auditory sounds (e.g., laughter and applause) in the ten narratives were removed. In addition, obvious transcription errors were removed from the list of narrative words for the Semantic Blocks and Single Words conditions. Words that did not make sense by themselves (e.g., “tai”, “chi”) were also removed. There were five such words: “tai”, “chi”, “deja”, “vu”, and “sub.”

Stimulus presentation

In all conditions, words were presented individually at the center of the screen using Rapid Serial Visual Presentation (RSVP) (Buchweitz et al., 2009; Forster, 1970). Words in the Narratives and Sentences conditions were presented with the same timing and duration as in the original spoken stories. Words in the Semantic Blocks and Single Words conditions were presented for a baseline of 400 ms with an additional 10 ms for every character. For example, the word “apple” would be presented for 400 ms + 10 ms/character * (5 characters) = 450 ms.

For subjects S1, S2, and S4, the four conditions were presented in 15 runs over two scanning sessions. Each condition was presented in a separate run, and the runs were interleaved in each session. In the first session, the conditions were presented in the order: Single Words, Semantic Blocks (validation stimulus), Sentences, Single Words (validation stimulus), Semantic Blocks, Sentences (validation stimulus), Semantic Blocks, Sentences. In the second session, the conditions were presented in the order: Sentences, Single Words (validation stimulus), Semantic Blocks, Single Words, Semantic Blocks (validation stimulus), Single Words, Sentences (validation stimulus). Conditions were presented in the same order for subjects S1, S2, and S4. For subject S3, the four conditions were presented in four scanning sessions. Each condition was presented in a separate scanning session, and each session contained 8 runs (including two repetitions of the validation stimulus). The stimuli used for this paper was a subset of the total stimuli presented in the four sessions. Although the stimuli were presented differently for subject S3, the results for subject S3 are consistent with the other three subjects. This suggests that our results hold across different stimulus presentation methods.

The pygame library in Python was used to display black text on a gray background at 34 horizontal and 27 vertical degrees of visual angle. Letters were presented at average 6 (min=1, max=16) horizontal and 3 vertical degrees of visual angle. A white fixation cross was present at the center of the display. Subjects were asked to fixate while reading the text. Eye movements were monitored at 60 Hz throughout the scanning sessions using a custom-built camera system equipped with an infrared source (Avotec) and the ViewPoint EyeTracker software suite (Arrington Research). The eye tracker was calibrated before each session of data acquisition.

Explainable variance (EV)

To measure the functional SNR of each stimulus condition, we computed the explainable variance (EV). EV was computed as the amount of variance in the response of a voxel that can be explained by the mean response of the voxel across multiple repetitions of the same stimulus. Formally, if the responses of a voxel to a repeated stimulus is expressed as a matrix Y with dimensions (# of TRs in each repetition, # of stimulus repetitions), then EV is given by

$$EV = EV' - [(1 - EV') / \text{\# of stimulus repetitions} - 1)],$$
$$\text{where } EV' = 1 - [\text{variance}(Y - \text{mean}(Y, \text{axis}=1)) / \text{variance}(Y)].$$

Note that this is the same as the coefficient of determination (R^2) where the model prediction is the mean response across stimulus repetitions. For each condition, EV was computed from the two repeated validation runs.

Voxelwise model fitting and validation

To identify voxels that represent semantic information, a linearized finite impulse response (FIR) encoding model (Huth et al., 2012, 2016; Nishimoto et al., 2011) was fit to every cortical voxel in each subject's brain. The linearized FIR encoding model consisted of one feature space designed to represent semantic information in the stimuli (the semantic model), and four feature spaces designed to represent low-level linguistic information. In the semantic feature space, the semantic content of each word was represented by the word's co-occurrence statistics with the 985 words in Wikipedia's List of 1000 basic words (Huth et al., 2016). Thus, each word was represented by a 985-long vector in the semantic feature space. The co-occurrence statistics were computed over a large text corpus that included the ten narrative stories used in Huth et al. (2016), several books from Project Gutenberg, a wide variety of Wikipedia pages, and a broad selection of reddit.com user comments (Huth et al., 2016). The four low-level feature spaces were word rate (1 parameter), number of letters (1 parameter), letters (26 parameters), and word length variation per TR (1 parameter). Together, the five feature spaces had 1014 features.

The features passed through three additional preprocessing steps before being fit to BOLD responses. First, to account for the hemodynamic response, a separate linear temporal filter with four delays was fit for each of the 1014 features, resulting in 4056 final features. This was accomplished by concatenating copies of the features delayed by 1, 2, 3, and 4 TRs (approximately 2, 4, 6, and 8 seconds). Taking the dot product of this concatenated feature space with a set of linear weights is functionally equivalent to convolving the undelayed features with a linear temporal kernel that has non-zero entries for 1-, 2-, 3-, and 4-time point delays. Second, 10 TRs were discarded from the beginning and the end (20 TRs total) of each run. Third, each feature was z-scored separately within each run. This was done so that the features would be on the same scale as the BOLD responses, which were also z-scored within each run.

A single joint model consisting of the 4056 features was fit to BOLD responses using banded ridge regression (Nunez-Elizalde et al., 2019) and the himalaya Python package (Dupré la Tour et al., 2022). A separate model was fit for every voxel in every subject and condition. For every model, a regularization parameter was estimated for each of the five feature spaces using a random search. In the random search, 1000 normalized hyperparameter candidates were sampled from a Dirichlet distribution and scaled by 30 log-spaced values ranging from 10^{-5} to 10^{20}. The best normalized hyperparameter candidate and scaling were selected for each feature space for each voxel. Finally, models were fit again on the BOLD responses with the selected hyperparameters.

To validate the models, estimated feature weights were used to predict responses to a separate, held-out validation dataset. Validation stimuli for the Narratives condition consisted of two repeated presentations of the narrative "wheretheressmoke" (Huth et al., 2016). Validation stimuli for the Sentences, Semantic Blocks, and Single Words conditions consisted of two repeated presentations of one run for each condition. Prediction accuracy was then computed as Pearson's correlation coefficient between the model-predicted BOLD response and the average BOLD response across the two validation runs. To estimate the contribution of each feature space to the prediction accuracy score, the prediction accuracy was split using the "correlation_score_split" function in the himalaya Python package (see also (St-Yves & Naselaris, 2018), "Feature map contribution to the prediction accuracy"). The contribution from the semantic model is shown as semantic model prediction accuracy in Figures 4 and 5.

Statistical significance for each condition was computed with permutation testing. A null distribution was generated by permuting 10-TR blocks of the average validation BOLD response 5000 times and computing the prediction accuracy for each permutation (10 TRs were blocked to account for temporal autocorrelations in the BOLD signal). Resulting p values were corrected for multiple comparisons within each subject using the false discovery rate (FDR) procedure (Benjamini & Hochberg, 1995).

Tuning shifts

To determine how semantic tuning changes between the Sentences and Narratives conditions, we looked at the difference between the estimated semantic model weights in the two conditions. First, temporal information was removed from the semantic model weights by averaging across the four delays for each semantic feature. Semantic model weights were then normalized by their L2-norm for each voxel, subject, and condition separately. This was done to ensure that the semantic model weights in both conditions are on the same numerical scale. Finally, the normalized semantic model weights estimated in the Sentences condition were subtracted from the normalized semantic model weights estimated in the Narratives condition.

To interpret the resulting difference vectors, we used principal components analysis (PCA) to recover a low-dimensional subspace. The difference vector for each voxel in each subject was scaled by the voxel's minimum semantic model prediction accuracy between the Sentences and Narratives conditions. This was done to avoid including noise from voxels that were poorly predicted in either condition. We then applied PCA to the scaled difference vectors, yielding 985 PCs per subject. Partial scree plots showing the proportion of variance explained by the PCs in each subject are shown in Extended Data Figure 8-1. We projected each subject's difference vectors onto the first three PCs for interpretation and visualization.

Cross-condition voxelwise model fitting

Estimated semantic model weights from the Sentences condition were used to predict voxel responses in the Narratives condition. Prediction accuracy was computed as Pearson's correlation coefficient between the predicted BOLD response using semantic model weights from the Sentences condition and the average BOLD response across the two validation runs in the Narratives condition.

All model fitting and analysis was performed using custom software written in Python, making heavy use of NumPy (Harris et al., 2020) and SciPy (Virtanen et al., 2020). Analysis and visualizations were developed using iPython (Perez & Granger, 2007), and the interactive programming and visualization environment jupyter notebook (Kluyver et al., 2016).

Code Accessibility

The himalaya package (Dupré la Tour et al., 2022) is publicly available on GitHub (https://github.com/gallantlab/himalaya).

1.3 Results

The goal of this study was to understand whether context affects evoked SNR and semantic representations in the brain. Previous studies suggest that both evoked SNR and semantic representations will differ across the four experimental conditions (Single

Words, Semantic Blocks, Sentences, and Narratives). Here, we analyzed evoked SNR and semantic representations for each of the four conditions in individual subjects.

To estimate evoked SNR, we computed the reliability of voxel responses across repetitions of the same stimulus. Several different sources of noise can influence the variability of voxel responses across stimulus repetitions: magnetic inhomogeneity, voxel response variability, and variability in subject attention or vigilance. Because these sources are independent across stimulus repetitions, pooling voxel responses across repetitions averages out the noise and provides a good estimate of the evoked SNR. In this study, we used explainable variance (EV) as a measure of reliability and computed the EV for two repetitions of one run in each condition to estimate evoked SNR (see Methods).

Figure 2 shows EV for the four conditions in one typical subject (S1) (see Extended Data Figure 2-1 for voxels with significant EV; see Extended Data Figure 2-2 for unthresholded EV for subjects 2-4). In the Single Words condition, appreciable EV is only found in a few scattered voxels located in bilateral primary visual cortex, STS, and inferior frontal gyrus (IFG) (Figure 2a). The number of voxels with significant EV ($p<0.05$, FDR-corrected) in the Single Words condition is 256, 1198, 0, and 0 for subjects 1-4, respectively. A similar pattern is seen in the Semantic Blocks condition, where appreciable EV is only found in a few scattered voxels located in bilateral primary visual cortex, STS, and IFG (Figure 2b). The number of voxels with significant EV ($p<0.05$, FDR-corrected) in the Semantic Blocks condition is 324, 1613, 1201, and 0 for subjects 1-4, respectively. In contrast, both the Sentences and Narratives conditions produce high EV in many voxels located in bilateral visual, parietal, temporal, and prefrontal cortices (Figures 2c and 2d). The number of voxels with significant EV ($p<0.05$, FDR-corrected) in the Sentences condition is 4225, 11697, 2359, and 7251 for subjects 1-4, respectively. The number of voxels with significant EV ($p<0.05$, FDR-corrected) in the Narratives condition is 7622, 8062, 7059, and 2931 for subjects 1-4, respectively. Together, these results show that increasing context increases evoked SNR in bilateral visual, temporal, parietal, and prefrontal cortices.

To quantify semantic representation, we used a voxelwise encoding model (VM) procedure and a semantic feature space to identify voxels that represent semantic information in each condition (Figure 3). We first extracted semantic features from the stimulus words in each condition separately (see Methods). We then used banded ridge regression (Nunez-Elizalde et al., 2019) to fit a separate semantic encoding model for each voxel, subject, and condition. Here we refer to voxels that were predicted significantly by the semantic model (see Methods) as “semantically selective voxels.”

Figure 4 shows semantic model prediction accuracy for semantically selective voxels for the four conditions in one typical subject (S1) (see Extended Data Figure 4-1 for additional subjects; see Extended Data Figure 4-2 for unthresholded semantic model prediction accuracy for all subjects). In the Single Words condition, no voxels are semantically selective in any of the four subjects (Figure 4a, $p<0.05$, FDR corrected). In

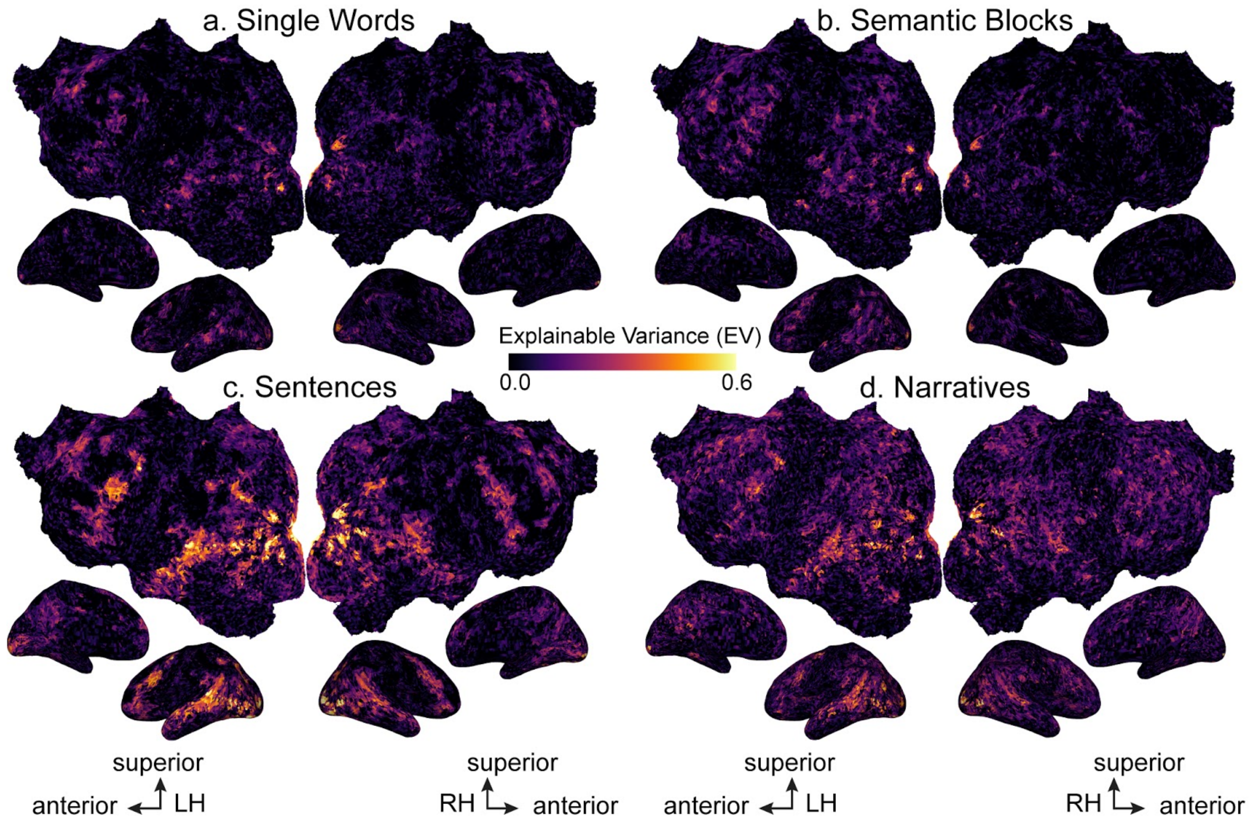


Figure 2. Explainable variance (EV) for the four conditions across the cortical surface. EV for the four conditions is shown for one subject (S1) on the subject's flattened cortical surface. EV was computed as an estimate of the evoked signal-to-noise ratio (SNR). Here EV is given by the color scale shown in the middle, and voxels that have high EV (i.e., high evoked SNR) appear yellow. (LH: Left Hemisphere, RH: Right Hemisphere) The format is the same in all panels. **a.** EV was computed for the Single Words condition and is shown on the flattened cortical surface of subject S1. Scattered voxels in bilateral primary visual cortex, superior temporal sulcus (STS), and inferior frontal gyrus (IFG) have high EV. **b.** EV was computed for the Semantic Blocks condition. Similar to the Single Words condition, scattered voxels in bilateral primary visual cortex, STS, and IFG have high EV. **c.** EV was computed for the Sentences condition. Many voxels in bilateral visual, parietal, temporal, and prefrontal cortices have high EV. **d.** EV was computed for the Narratives condition. Similar to the Sentences condition, voxels in bilateral visual, parietal, temporal, and prefrontal cortices have high EV. Together, these results show that increasing context increases evoked SNR in bilateral visual, temporal, parietal, and prefrontal cortices. (See Extended Data Figure 3-1 for significant EV voxels for subject S1 and Extended Data Figure 3-2 for EV for all subjects.)

the Semantic Blocks condition, scattered voxels along the left STS and left IFG are semantically selective (Figure 4b, $p<0.05$, FDR corrected). The number of semantically selective voxels ($p<0.05$, FDR corrected) in the Semantic Blocks condition is 708, 0, 0, and 0 for subjects 1-4, respectively. In the Sentences condition, voxels in the left angular gyrus, left STG, bilateral STS, bilateral ventral precuneus, bilateral ventral premotor speech area (sPMv), bilateral superior frontal sulcus (SFS), and left superior frontal

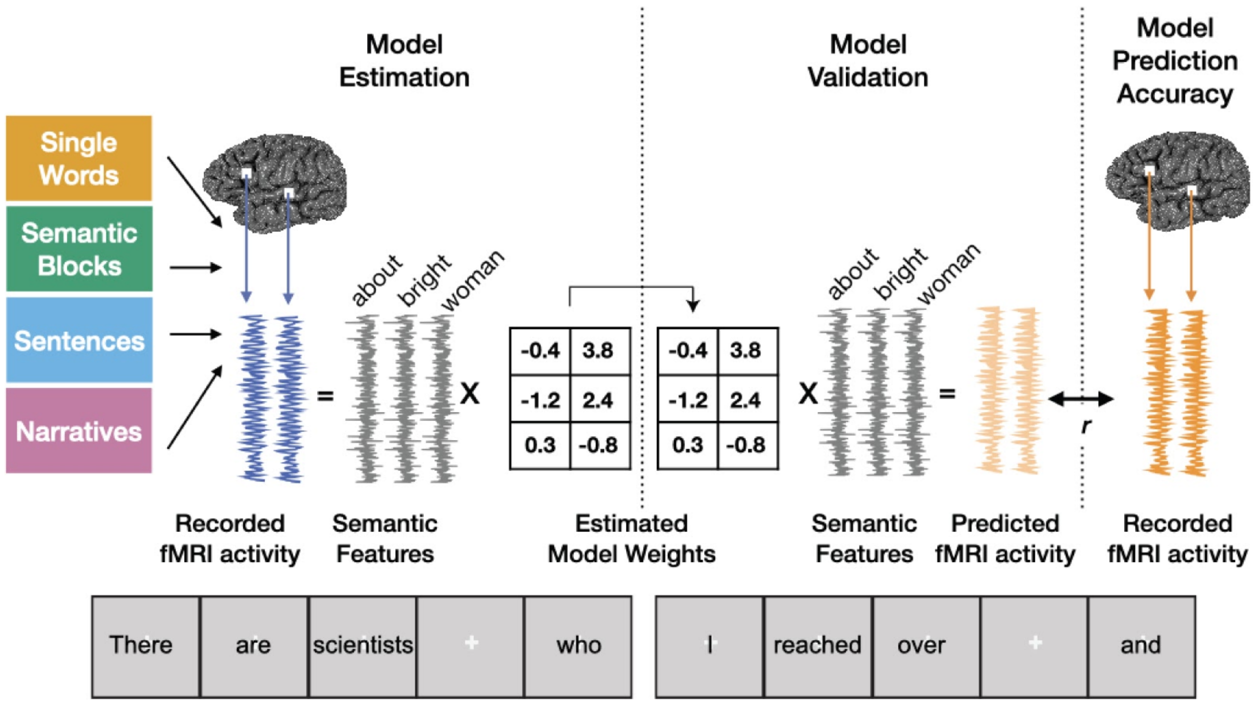


Figure 3: Voxelwise Modeling. Four subjects read words from the four stimulus conditions while BOLD responses were recorded. Each stimulus word was projected into a 985-dimensional word embedding space that was independently constructed using word co-occurrence statistics from a large corpus (Semantic Features). A finite impulse response (FIR) regularized regression model was estimated separately for each voxel in every subject and condition using banded ridge regression (Nunez-Elizalde et al. 2019). The estimated model weights were then used to predict BOLD responses to a separate, held-out validation stimulus. Model prediction accuracy was quantified as the correlation (r) between the predicted and recorded BOLD responses to the validation stimulus.

gyrus (SFG) are semantically selective (Figure 4c, $p<0.05$, FDR corrected). The number of semantically selective voxels ($p<0.05$, FDR-corrected) in the Sentences condition is 1566, 2581, 0, and 0 for subjects 1-4, respectively. Finally, in the Narratives condition, voxels in bilateral angular gyrus, bilateral STS, bilateral STG, bilateral temporal parietal junction (TPJ), bilateral sPMv, bilateral ventral precuneus, bilateral SFS, bilateral SFG, bilateral IFG, left inferior parietal lobule (IPL), and left posterior cingulate gyrus are semantically selective (Figure 4d, $p<0.05$, FDR corrected). The number of semantically selective voxels ($p<0.05$, FDR-corrected) in the Narratives condition is 4745, 7355, 7786, and 1757 for subjects 1-4, respectively. Together, these results suggest that increasing context increases the representation of semantic information in bilateral temporal, parietal, and prefrontal cortices. These results also suggest that this effect is highly variable in individual subjects for non-natural language stimuli (Semantic Blocks, Sentences) but not for natural language stimuli (Narratives).

The results presented in Figure 4 were obtained in each subject's native brain space. To determine how the representation of semantic information varies across subjects for the

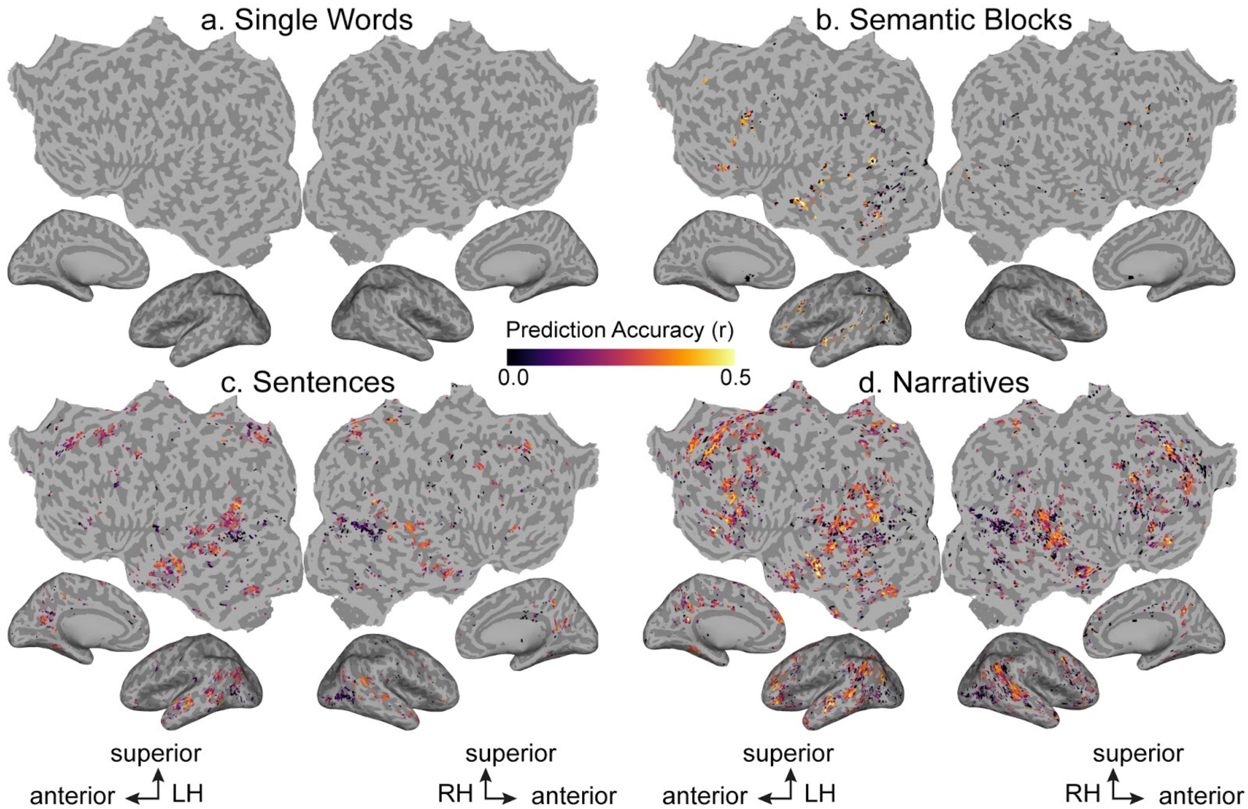


Figure 4. Semantic model prediction accuracy for the four conditions across the cortical surface. Semantic model prediction accuracy in the four conditions is shown on the flattened cortical surface of one subject (S1; see Extended Data Figure 4-1 and 4-2 for all subjects). Voxelwise modeling was first used to estimate semantic model weights in the four conditions. Semantic model prediction accuracy was then computed as the correlation (r) between the subject's recorded BOLD activity to the held-out validation stimulus and the BOLD activity predicted by the semantic model. In each panel, only voxels with significant semantic model prediction accuracy ($p<0.05$, FDR corrected) are shown. Prediction accuracy is given by the color scale in the middle, and voxels that have a high prediction accuracy appear yellow. Voxels for which the semantic model prediction accuracy is not statistically significant are shown in gray. (LH: Left Hemisphere, RH: Right Hemisphere) **a.** Semantic model prediction accuracy was computed for the Single Words condition. No voxels are significantly predicted in the Single Words condition. **b.** Semantic model prediction accuracy was computed for the Semantic Blocks condition. The format is the same as panel **a**. Voxels in left STS and IFG are significantly predicted. **c.** Semantic model prediction accuracy was computed for the Sentences condition. The format is the same as panel **a**. Voxels in left angular gyrus, left STG, bilateral STS, bilateral ventral precuneus, bilateral ventral premotor speech area (sPMv), bilateral superior frontal sulcus (SFS), and left superior frontal gyrus (SFG) are significantly predicted. **d.** Semantic model prediction accuracy was computed for the Narratives condition. The format is the same as panel **a.** Voxels in bilateral angular gyrus, bilateral STS, bilateral STG, bilateral temporal parietal junction (TPJ), bilateral sPMv, bilateral ventral precuneus, bilateral SFS, bilateral SFG, bilateral IFG, left inferior parietal lobule (IPL), and left posterior cingulate gyrus are significantly predicted. Together, these results suggest that increasing context increases the representation of semantic information in bilateral temporal, parietal, and prefrontal cortices.

four conditions, we transformed the semantic encoding model results obtained for each subject into the standard MNI brain space (Deniz et al., 2019). Figure 5 shows the mean unthresholded model prediction accuracy across subjects (Figure 5a-d) and the number of subjects for which each voxel is semantically selective (Figure 5e-h) for each condition. In the Single Words condition, no voxels are semantically selective in any of the four subjects (Figure 5a and 5e, $p<0.05$, FDR corrected). In the Semantic Blocks condition, scattered voxels in left STS are semantically selective in two out of four subjects (Figure 5b and 5f, $p<0.05$, FDR corrected). In the Sentences condition, voxels in the bilateral STS, left STG, bilateral ventral precuneus, bilateral angular gyrus, bilateral SFS, and bilateral premotor cortex are semantically selective in two out of four subjects (Figure 5c and 5g, $p<0.05$, FDR corrected). Finally, in the Narratives condition, voxels in bilateral angular gyrus, bilateral STS, right STG, right anterior temporal lobe, bilateral SFS and SFG, left IFG, left IPL, bilateral ventral precuneus, and bilateral posterior cingulate gyrus are semantically selective in all subjects (Figure 5d and 5h, $p<0.05$, FDR corrected), and voxels in left STG and right IFG are semantically selective in three out of four subjects (Figure 5d and 5h, $p<0.05$, FDR corrected). These results are consistent with those in Figure 4, and they suggest that increasing stimulus context increases the representation of semantic information across the cortical surface at the group level. In addition, this effect is inconsistent across individual subjects for non-natural stimuli (Semantic Blocks, Sentences) but not natural stimuli (Narratives).

Because the Narratives condition contains more contextual information than the other three conditions, we hypothesized that we would find more semantically selective voxels in the Narratives condition than in the other three conditions. To test this, we calculated the difference in the number of semantically selective voxels between the Narratives condition and each of the other three conditions. The difference between the Narratives and Single Words conditions is 4745, 7355, 7786, and 1757 voxels for subjects 1-4, respectively ($p<0.05$ for all subjects). The difference between the Narratives and Semantic Blocks conditions is 4037, 7355, 7786, and 1757 voxels for subjects 1-4, respectively ($p<0.05$ for all subjects). Finally, the difference between the Narratives and Sentences conditions is 3179, 4774, 7786, and 1757 voxels for subjects 1-4, respectively ($p<0.05$ for all subjects). The difference between the Narratives and Single Words conditions partly reflects the fact that most voxels have low evoked SNR in the Single Words condition and high evoked SNR in the Narratives condition (Figure 3). Because it is impossible to model noise, differences in evoked SNR across conditions directly affect the number of voxels that achieve a significant model fit. The difference between the Narratives and Semantic Blocks conditions also partly reflects differences in evoked SNR -- for most voxels, evoked SNR is low in the Semantic Blocks condition and high for the Narratives condition (Figure 3). In contrast, the evoked SNR is high for many voxels in both the Narratives and the Sentences conditions (Figure 3), so the difference in the number of semantically selective voxels is unlikely to be due to differences in evoked SNR. Instead, this result suggests that semantic information is represented more widely across the cortical surface in the Narratives condition than in the Sentences condition.

To determine which semantic concepts are represented in voxels that are semantically

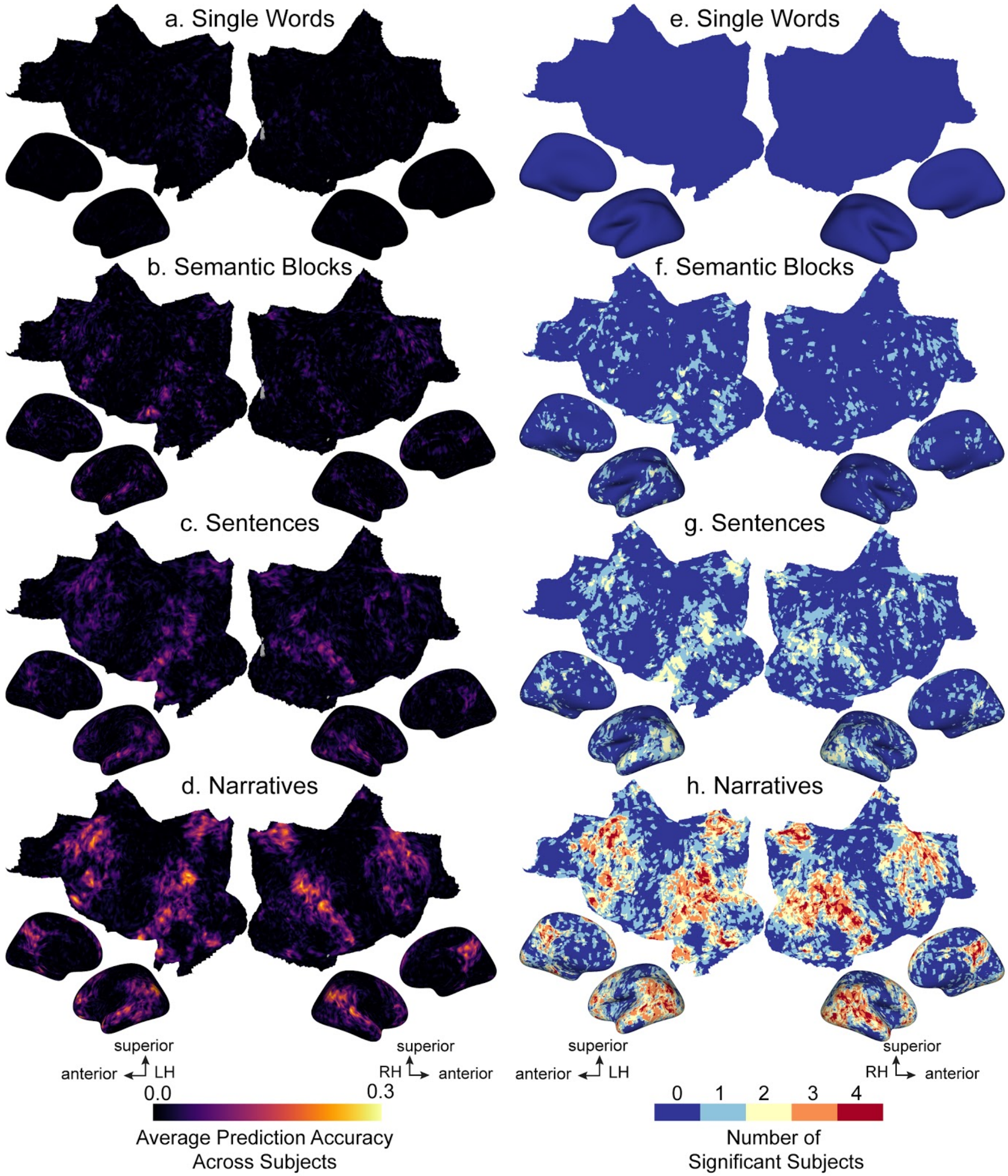


Figure 5. Semantic model prediction accuracy across all subjects for the four conditions in standard brain space. Semantic model prediction accuracy was first computed for each subject and for each condition as described in **Figure 4**. These individualized predictions were then projected into the standard MNI brain space. **a.-d.** Average prediction accuracy across the four subjects is computed for each MNI voxel and shown for each condition on the cortical surface of the MNI brain. Average prediction accuracy is given by the color scale, and voxels with higher prediction accuracy appear brighter. **a.** In the Single Words

condition, average prediction accuracy is low across the cortical surface. **b.** In the Semantic Blocks condition, average prediction accuracy is high in voxels in left anterior STS. **c.** In the Sentences condition, average prediction accuracy is high in bilateral STS, STG, anterior temporal lobe, angular gyrus, ventral precuneus, SFS, and SFG. **d.** In the Narratives condition, average prediction accuracy is very high in bilateral STS, STG, MTG, anterior temporal lobe, angular gyrus, IPL, ventral precuneus, posterior cingulate gyrus, Broca's area, IFG, SFS, SFG, and left posterior inferior temporal sulcus. **e.-h.** For each condition, statistical significance of prediction accuracies was determined in each subject's native brain space and then projected into the MNI brain space. The number of subjects with significant prediction accuracy is shown for each voxel on the cortical surface of the MNI brain. The number of significant subjects is given by the color scale shown at bottom. Dark red voxels are significantly predicted in all subjects, and dark blue voxels are not significantly predicted in any subjects. **e.** In the Single Words condition, no voxels are semantically selective for any subjects. **f.** In the Semantic Blocks condition, scattered voxels in left STS are semantically selective in two out of four subjects. **g.** In the Sentences condition, voxels in the bilateral STS, STG, angular gyrus, ventral precuneus, and SFS are semantically selective in two out of four subjects. **h.** In the Narratives condition, voxels in bilateral angular gyrus, bilateral STS, anterior temporal lobe, SFS, SFG, IFG, ventral precuneus, posterior cingulate gyrus, and right STG are semantically selective in all four subjects. The results shown here are consistent with those in **Figure 4**, and they suggest that increasing context increases the representation of semantic information across the cortical surface at the group level but not for individual subjects.

selective in the Narratives condition but not in the Sentences condition, we looked at the semantic tuning of such voxels. The semantic tuning of each voxel is given by its 985-dimensional vector of estimated semantic model weights, one weight for each of the 985 semantic model features (see Methods). Since the semantic model has 985 features, it is difficult and impractical to interpret the semantic tuning of a voxel by looking at each individual semantic feature directly. Instead, we projected each voxel's estimated semantic model weights into a low-dimensional subspace of the semantic model, and interpreted semantic tuning based on how the semantic weights projected into this subspace. This low-dimensional subspace was created by applying principal component analysis (PCA) to the aggregated estimated semantic model weights of seven subjects in Huth et al. 2016. Applying PCA to the aggregated semantic model weights returns principal components (PCs) that are ordered by how much variance they explain in the aggregated semantic model weights. The low-dimensional subspace was defined as the first three PCs of the aggregated semantic model weights.

To visualize semantic tuning, we projected the estimated Narratives semantic model weights for each voxel onto the three PCs, and then we colored each voxel with an RGB color scheme. For each voxel, the red value indicates the projection onto the first PC, the green value indicates the projection onto the second PC, and the blue value indicates the projection onto the third PC. Figure 6 shows the estimated Narratives semantic model weights projected onto the three PCs for two subjects (S1 and S2, this analysis was not performed for S3 and S4 because they did not have any semantically selective voxels in the Sentences condition). In both subjects, most voxels that are semantically selective in

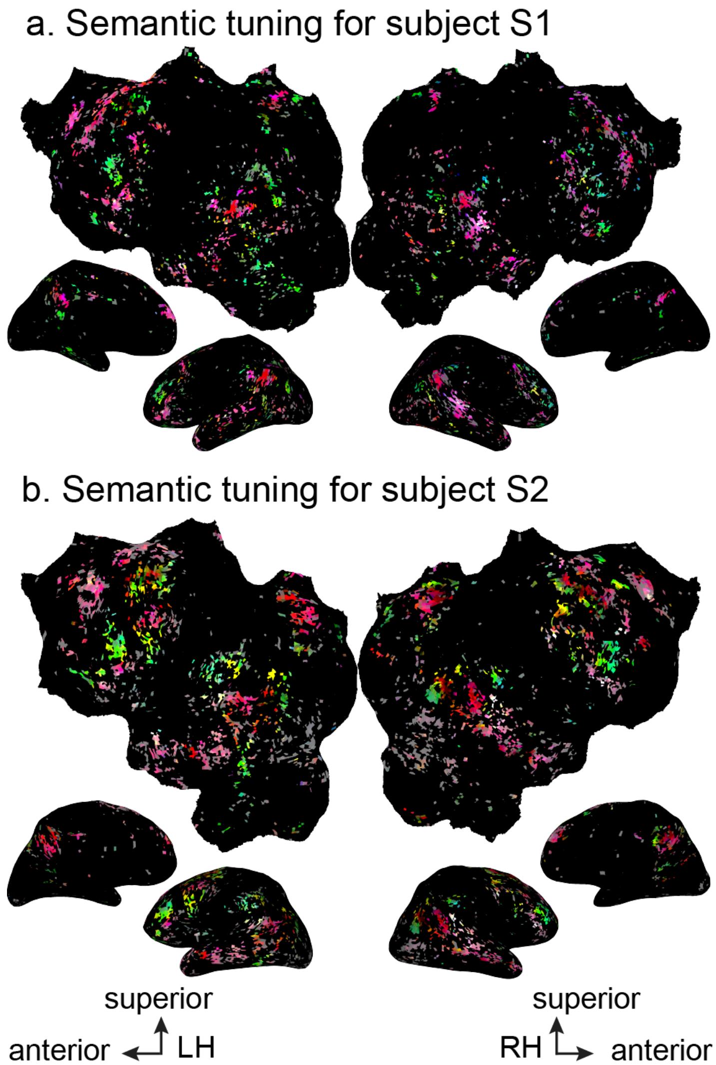


Figure 6. Semantic tuning of voxels that are semantically selective in the Narratives condition but not the Sentences condition. Semantic tuning is shown on the flattened cortical surface of two subjects (S1 and S2) for voxels that are semantically selective in the Narratives condition but not in the Sentences condition. These voxels are in the bilateral superior temporal sulcus, middle temporal gyrus, precuneus, inferior frontal gyrus, and ventrolateral and dorsolateral prefrontal cortex. Semantic model weights estimated in the Narratives condition were projected into a low-dimensional subspace created by performing principal components analysis (PCA) on semantic model weights estimated in Huth et al. 2016. Each voxel is colored according to the projection of its Narratives semantic model weights onto the first (red), second (green), and third (blue) PCs. The color wheel legend shows the semantic concepts associated with different colors. Most voxels in both subjects have a high red value or a high green value. A high red value corresponds to tuning for concepts related to humans and social relationships, and a high green value corresponds to tuning for concepts related to materials and measurements.

the Narratives condition but not in the Sentences condition have either a high red value or a high green value. A high red value corresponds to tuning for concepts related to humans and social relationships, and a high green value corresponds to tuning for concepts related to materials and measurements. These two semantic categories are represented in voxels that are semantically selective in the Narratives condition but not in the Sentences condition.

Differences in semantic representation between the Sentences and Narratives conditions could be limited to a difference in the number of voxels recruited to represent semantic information in each condition. However, because the brain is a highly nonlinear dynamical system, we hypothesized that differences in contextual information between the two conditions could lead to differences in semantic tuning. To test this hypothesis, the semantic model weights estimated in the Sentences condition were correlated with the semantic model weights estimated in the Narratives condition for voxels that are semantically selective in both conditions. Figure 7 shows Pearson's correlation coefficient between the semantic model weights estimated in the Sentences condition and the Narratives condition mapped onto the cortical surface of two subjects (S1 and S2). In both subjects, semantic model weights for the Sentences and Narratives conditions are weakly to moderately correlated (S1 correlation min=-0.319, max=0.817, mean=0.344; S2 correlation min=-0.271, max=0.725, mean=0.316). This result shows that the semantic model weights for the Sentences and Narratives conditions point in different directions in the semantic space, and that semantic tuning shifts between the Sentences and Narratives conditions.

To determine how semantic tuning shifts between the Sentences and Narratives conditions, we looked at how estimated semantic model weights differ between the two conditions. For every voxel that is semantically selective in both conditions, we subtracted its semantic model weights estimated in the Sentences condition from its semantic model weights estimated in the Narratives condition (see Methods). The resulting semantic difference vector describes the semantic concept that changes between the voxel's semantic tuning in the Sentences and Narratives conditions. The difference vector resides in the same 985-dimensional semantic space as the semantic model weights, so we projected the difference vector into a low-dimensional semantic subspace to interpret its semantic tuning. This subspace was created by applying PCA to the difference vectors for each subject separately. The first five PCs explained 47.1% of the variance in subject S1 and 48.2% of the variance in subject S2 (see Extended Data Figure 8-1 for partial scree plots), indicating that the semantic tuning shifts can be described by a relatively low number of dimensions. Figure 8 shows the projection of the difference vectors onto the first three PCs for one subject (S1; see Extended Data Figure 8-2 for subject S2). Each voxel is colored according to how positively (red) or negatively (blue) its difference vector projects onto each of the three PCs. For the first PC, voxels in bilateral STS and bilateral SFG have a strong positive projection while voxels in bilateral angular gyrus have a strong negative projection in both subjects. For the second PC, voxels in bilateral angular gyrus and superior STS have a strong positive projection in both subjects. No voxels have a strong negative projection in either subject. For the third PC, voxels in right STS have a strong positive projection in both subjects. No voxels have

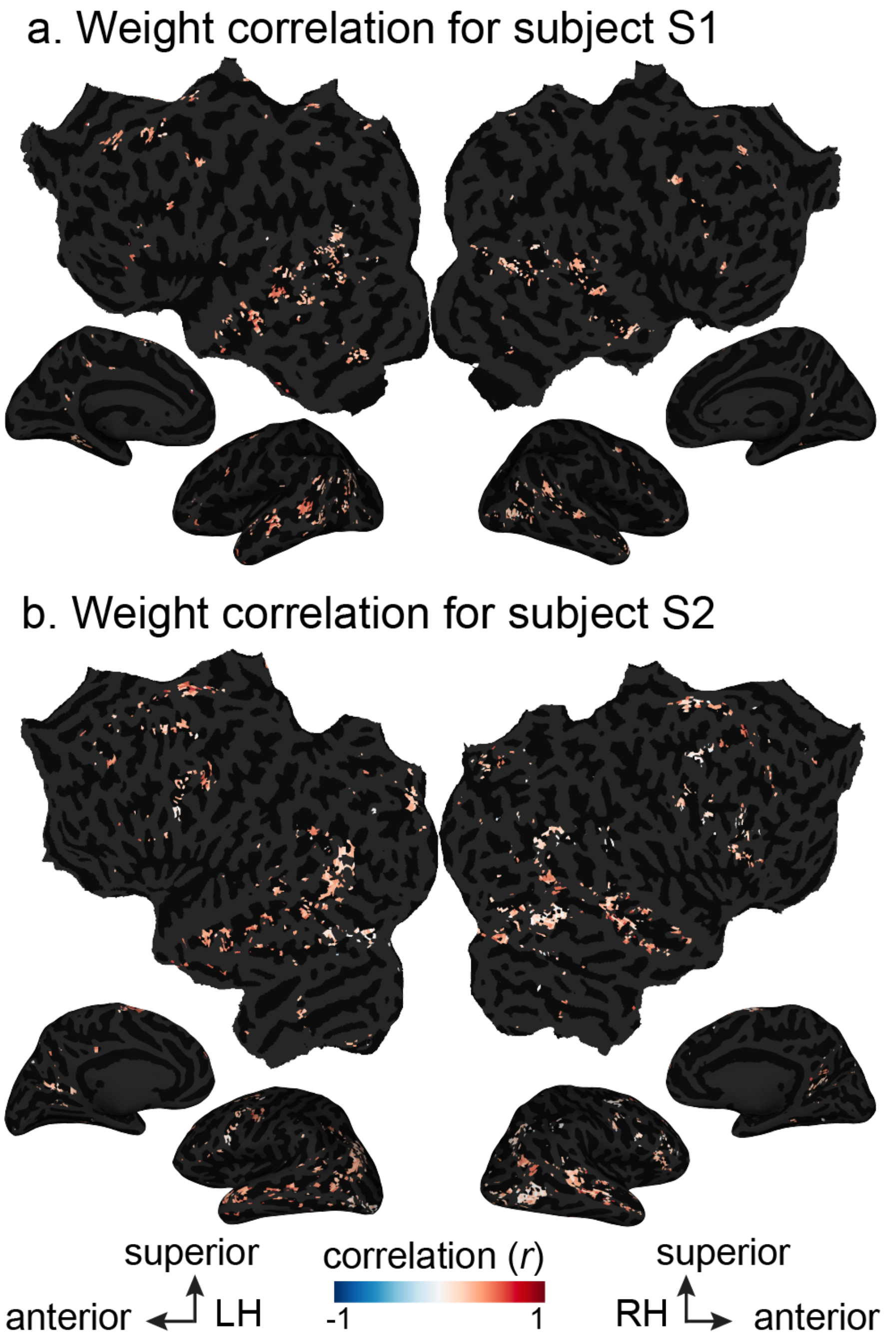


Figure 7. Correlation of semantic model weights estimated in the Sentences and Narratives conditions. Pearson's correlation coefficient between semantic model weights estimated in the Sentences condition and semantic model weights estimated in the Narratives conditions is plotted on the flattened cortical surface of two subjects (S1 and S2). Only voxels that are semantically selective in both conditions are shown. These include voxels in the superior temporal sulcus and prefrontal cortex in both hemispheres and in both subjects. These voxels are weakly to moderately correlated between these two conditions, indicating that the semantic model weights estimated in the Sentences and Narratives conditions point in different directions in the semantic space. This shows that semantic tuning changes between the Sentences and Narratives conditions.

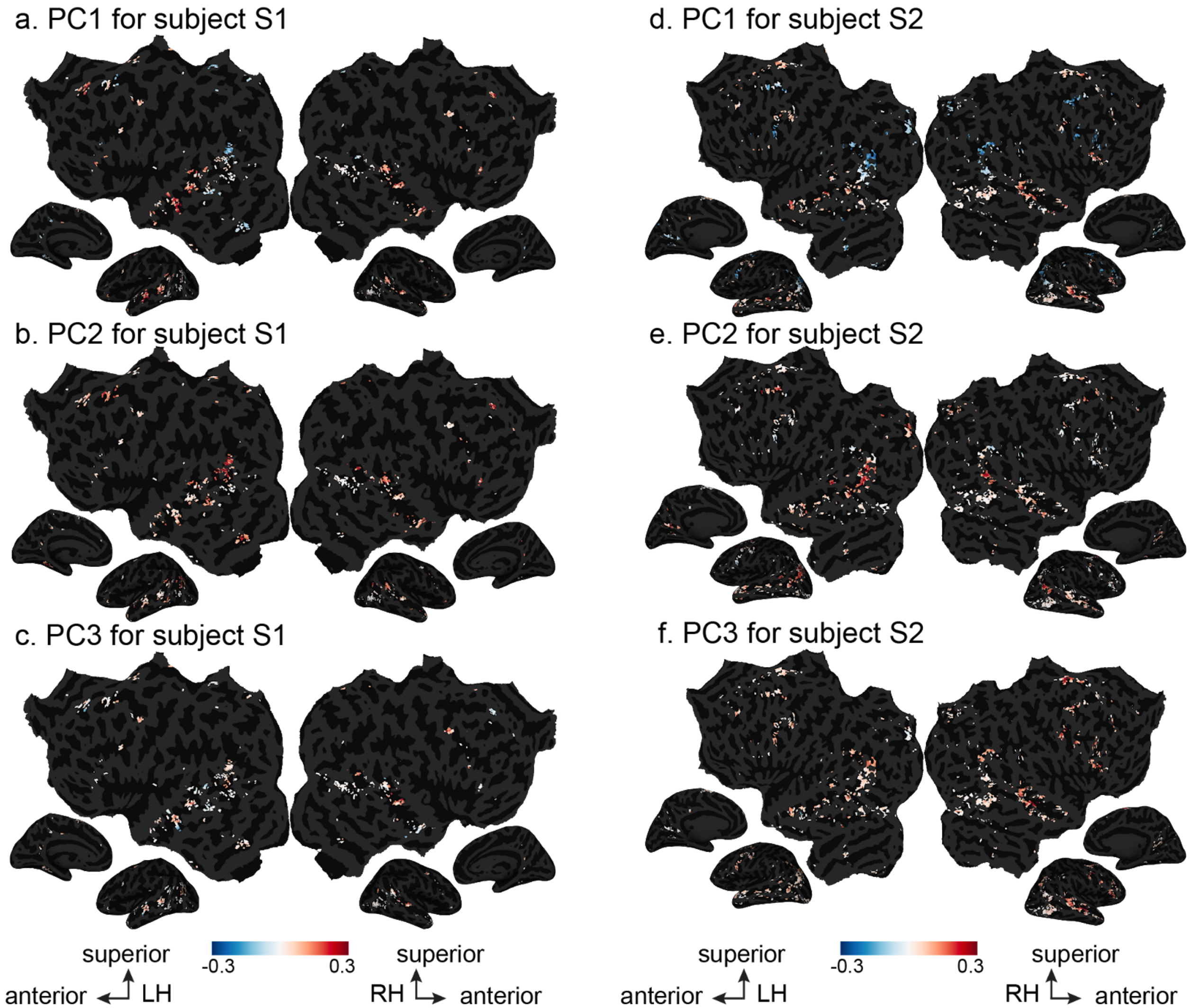


Figure 8. Semantic tuning shifts between the Sentences and Narratives conditions. Semantic model weights estimated in the Sentences condition were subtracted from semantic model weights estimated in the Narratives condition. PCA was then applied to the resulting difference vectors for each subject separately. The projection of the difference vectors onto the first three PCs is shown on the flattened cortical surface of two subjects (S1 and S2). Only voxels that are semantically selective in both conditions are shown. Projection strength is given by the color scales, and the ends of the color scales are labeled with the corresponding semantic concepts for each PC. Voxels that project onto one end of a PC appear red, while voxels that project onto the opposite end of the same PC appear blue. For the first PC, voxels in bilateral STS and bilateral SFG are red while voxels in bilateral angular gyrus are blue in both subjects. For the second PC, voxels in bilateral angular gyrus and superior STS are red while no voxels are blue in both subjects. For the third PC, voxels in right STS are red while no voxels are blue in both subjects. This result shows that semantic tuning shifts between the Sentences and Narratives conditions are spatially organized across cortex.

a strong negative projection in either subject. These results suggest that semantic tuning shifts between the Sentences and Narratives conditions are spatially organized across cortex.

To interpret the PCs of the semantic difference vectors, we looked at the words in the semantic model that were correlated with each PC (see Extended Data Table 8-1 for the ten most correlated and least correlated words for each PC for each subject). For subject S1, the first PC is high on words related to interviewing and interrogation and low on words related to building and investing. The second PC is high on words related to packages and deliveries and low on words related to athletics. The third PC is high on words related to measurement and low on words related to family. For subject S2, the first PC is high on words related to visualization and low on words related to time and numbers. The second PC is high on words related to travel and deliveries and low on words related to body parts and actions. The third PC is high on function words and words related to numbers and low on informal words and interjections. The first three PCs for subject S1 are only moderately correlated to the first three PCs for subject S2: the correlation for the first PC is 0.3144, the correlation for the second PC is 0.5996, and the correlation for the third PC is 0.2351. This suggests that semantic tuning shifts between the Sentences and Narratives conditions are subject-dependent. However, additional analysis using a larger subject pool is needed to determine the individual differences in semantic tuning.

So far, we have shown that semantic information is represented more widely across the cortical surface in the Narratives condition compared to the Sentences condition (Figures 4, 5, 6), and that semantic tuning shifts between the two conditions (Figures 6, 7, 8). These results suggest that the voxelwise models trained in the Sentences condition will not generalize to the Narratives condition. To test this hypothesis, we used the semantic model weights estimated in the Sentences condition to predict brain activity in the Narratives condition. Figure 9 shows the results of this analysis in subject S1 and S2. In both subjects S1 and S2, voxels in bilateral angular gyrus, bilateral STS, bilateral TPJ, bilateral sPMv, bilateral ventral precuneus, bilateral SFG, bilateral IFG, and left SFS are semantically selective ($p<0.05$, FDR corrected). However, when semantic model weights estimated in the Narratives condition are used to predict the same brain activity, additional voxels in left IPL, right SFS, bilateral STG, right anterior temporal lobe, and bilateral posterior cingulate gyrus are semantically selective ($p<0.05$, FDR corrected) in subjects S1 and S2 (see Figure 4 and Extended Data Figure 4-1). The semantic model weights estimated in the Sentences condition predict brain activity in the Narratives condition worse than the semantic model weights estimated in the Narratives condition. This result shows that the voxelwise models fit in the Sentences condition do not generalize to the Narratives condition.

1.4 Discussion

The aim of this study was to determine whether and how context affects semantic representations in the human brain. Our results show that both evoked SNR and semantic representations are affected by the amount of context in the stimulus. First, stimuli with relatively more context (Narratives, Sentences) evoke brain responses with

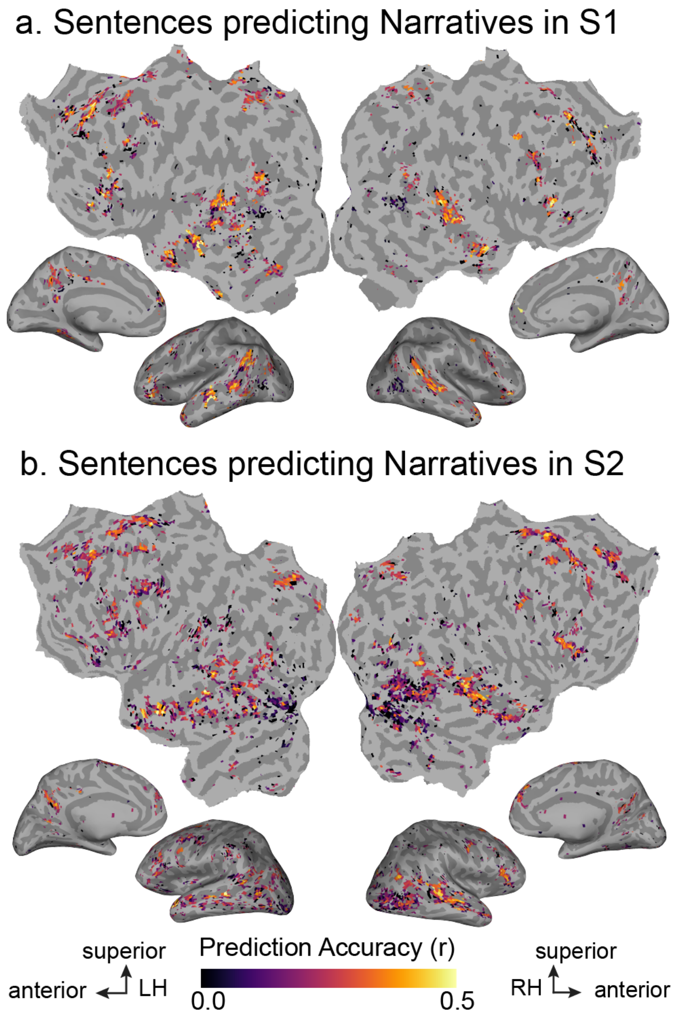


Figure 9. Prediction accuracy of semantic model weights estimated in the Sentences condition predicting data in the Narratives condition. Semantic model weights estimated in the Sentences condition were used to predict BOLD activity for the held-out validation stimulus in the Narratives condition. The resulting semantic model prediction accuracy is shown on the flattened cortical surface of two subjects (S1 and S2). Only voxels with significant model prediction accuracy ($p<0.05$, FDR corrected) are shown. Prediction accuracy is given by the color scale in the middle, and voxels that have a high prediction accuracy appear yellow. Voxels for which the semantic model prediction accuracy is not statistically significant are shown in gray. (LH: Left Hemisphere, RH: Right Hemisphere) Voxels in bilateral angular gyrus, bilateral STS, bilateral TPJ, bilateral sPMv, bilateral ventral precuneus, bilateral SFG, bilateral IFG, and left SFS are semantically selective ($p<0.05$, FDR corrected). When semantic model weights estimated in the Narratives condition are used to predict the same BOLD data, additional voxels in left IPL, right SFS, bilateral STG, right anterior temporal lobe, and bilateral posterior cingulate gyrus are semantically selective (Figure 4). This result shows that the semantic model weights estimated in the Sentences condition do not generalize to the Narratives condition.

higher SNR compared to stimuli with relatively less context (Semantic Blocks, Single Words) (Figure 3). Second, increasing the amount of context increases the representation of semantic information across the cortical surface at the group level (Figures 4, 5). However, in individual subjects, only the Narratives condition consistently increased the representation of semantic information compared to the Single Words condition (Figures 4, 5). Third, increasing the amount of context changes the semantic tuning of semantically selective voxels across the cortical surface (Figures 6, 7, 8). These results strongly imply that neuroimaging studies that use isolated words or sentences do not fully map the functional brain representations that underlie natural language comprehension (Figure 9).

Our observations that increasing context increases both the evoked SNR and the cortical representation of semantic information at the group level are fully consistent with results from previous neuroimaging studies. Several previous studies found that stimuli with more context evoke larger, more widespread patterns of brain activity (Jobard et al., 2007; Mazoyer et al., 1993; Xu et al., 2005), that brain activity evoked for individual words is modulated by context (Just et al., 2017), and that brain activity evoked by stimuli with more context are more reliable than those evoked by stimuli with less context (Lerner et al. 2011). Furthermore, previous studies that used narrative stimuli (Deniz et al., 2019; C.-T. Hsu et al., 2019; Huth et al., 2016; Pereira et al., 2018; Popham et al., 2021; Wehbe et al., 2014) identified many more voxels involved in semantic processing than studies that used isolated words or sentences (for reviews see (Binder et al., 2009; Price, 2010, 2012). Our results are also consistent with the hierarchical process memory framework, which suggests that all cortical regions accumulate and integrate temporal information in a spatially organized manner [CITE]. Specifically, the framework predicts that stimuli with intermediate temporal dependencies (e.g., Single Words) are processed in superior temporal gyrus, and that stimuli with long temporal dependencies (e.g., Sentences and Narratives) are processed in higher-level regions such as angular gyrus, precuneus, and prefrontal cortex. These predictions are reflected in our results.

However, there are several important differences between the results we reported here and those reported in previous neuroimaging studies. First, past studies that used isolated sentences found left IFG involved in semantic processing (Constable et al., 2004; Humphries et al., 2007; Rodd et al., 2005). In contrast, we only found a couple of semantically selective voxels scattered in left IFG in two out of four subjects in the Sentences condition (Figures 4 and 5). Second, past studies that used isolated words found bilateral STS, bilateral lateral sulcus, left IFG, left MTG, and left ITG involved in semantic processing (Booth et al., 2002; Jobard et al., 2007; Lerner et al., 2011; Mazoyer et al., 1993; Xu et al., 2005). In contrast, we did not find any semantically selective voxels in the Single Words condition (Figures 4 and 5). Finally, one previous study looked at brain activity evoked by a stimulus conceptually similar to Semantic Blocks (Mollica et al., 2020). In the study, Mollica et al. (2020) used sentences that were scrambled such that nearby words could be combined into meaningful phrases. They found that the brain activity evoked by scrambled sentences was similar to the brain activity evoked by unscrambled sentences in left IFG, left middle frontal gyrus, left temporal lobe, and left angular gyrus. In contrast, we only found voxels that were semantically selective in both the Semantic Blocks and Sentences conditions in left STS (Figures 4 and 5).

The inconsistencies between this study and past studies most likely stem from five major methodological differences between this study and those earlier studies. First, we avoided smoothing our data before performing analyses. We performed our analyses for each subject in their native brain space, and we did not perform any spatial smoothing across voxels. In contrast, most previous studies performed normalization procedures to transform their data into a standard brain space and applied a spatial smoothing operation across voxels (Carp, 2012; Lindquist, 2008). Spatial smoothing and normalization procedures can incorrectly assign signal to voxels and average away meaningful signal and individual variability in language processing (Deniz et al., 2019; Fedorenko et al., 2012; Fedorenko & Kanwisher, 2009; Huth et al., 2016; Steinmetz & Seitz, 1991). Thus, brain regions identified by past studies may be more relevant at the group level than in individual subjects. These smoothing procedures likely contribute to the inconsistencies observed between past studies and this study.

Second, we used an explicit computational model to identify semantically selective voxels. In contrast, most previous studies identified semantic brain regions by contrasting different experimental conditions (Binder et al., 2008, 2009; Price, 2012). Although past studies designed their experimental conditions to isolate brain activity involved in semantic processing (Binder et al., 2008, 2009), there could be unexpected differences unrelated to semantic processing between the conditions. For example, experiments that contrast a semantic task with a phonological task (Binder et al., 2008, 2009) may have task difficulty as a confound. As a result, it is possible that some semantic brain areas identified by past studies are actually involved in processing the unexpected differences rather than semantics. We would likely not have identified such brain areas in this study, since our semantic model only contains information about semantics.

Third, we evaluated semantic model prediction accuracy on a separate, held-out validation dataset. In contrast, most previous studies drew inferences from analyses performed on only one dataset without a validation dataset (Binder et al., 2009). Performing analyses on only one dataset can lead to inflated results that are overfit to the dataset (Soch et al., 2016). Thus, some semantic brain areas identified by past studies may only be relevant for the specific stimuli, experimental design, or data used in those studies. Such study-specific brain areas would not generalize to other studies, such as this study.

Fourth, we collected a relatively large amount of fMRI data per subject from four subjects. In contrast, most previous studies collected a small amount of fMRI data per subject from many (15-30) subjects. Because fMRI data is noisy, most previous studies either averaged their data across subjects and/or smoothed their data to observe the effects of interest. However, as discussed earlier, smoothing and averaging fMRI data can lead to erroneous conclusions about language processing in the brain (Steinmetz and Seitz, 1991; Fedorenko and Kanwisher, 2009; Fedorenko et al., 2012; Huth et al., 2016; Deniz et al., 2019). In this study, we avoided averaging across subjects and smoothing procedures by collecting a relatively large amount of data per subject. Moreover, each subject provided a complete replication of all analyses because each subject had their own model fitting and validation data. Thus, even though there are fewer subjects in this study than in previous studies, it is likely that our findings will generalize to new subjects.

Finally, subjects in our study passively read the stimulus words, which allowed us to directly compare the Narratives condition with the other three conditions. In contrast, many past studies of semantic processing used active tasks involving lexical decisions (Binder et al., 2003), matching (Vandenberghe et al., 1996), or monitoring (Démonet et al., 1992). Active tasks are thought to increase subject engagement, which can increase evoked BOLD SNR. Thus, if we had used an active task, the effect of context on evoked SNR might have been even larger than the differences that we report here. In addition, different active tasks can affect semantic processing differently in the brain (Toneva et al., 2020). Therefore, task effects likely contributed to the inconsistencies observed between past studies and this study.

To our knowledge, no previous language neuroimaging studies have looked at whether stimulus context affects semantic tuning. One interesting aspect of our results is that the semantic tuning shifts are different for subjects S1 and S2. Since both subjects saw the same stimuli in the Sentences and Narratives conditions, the difference in tuning shifts is most likely due to individual differences in attention rather than differences in the stimuli. This is consistent with a previous study from our lab showing that many voxels across cortex shift their tuning towards attended semantic categories (Çukur et al., 2013).

Many language neuroimaging studies use isolated sentences to localize the language network (e.g., (Fedorenko et al., 2010; Scott et al., 2017; Wilson et al., 2017)). These localizers contrast isolated sentences with non-words (i.e., sentences > non-words) to identify regions of interest (ROIs) in the brain involved in language processing. The identified ROIs often include left IFG, left middle frontal gyrus, left temporal lobe, left angular gyrus, and right temporal lobe. Consistent with these localizers, many voxels in the listed ROIs have high EV in the Sentences condition. In fact, the raw EV value in the Sentences condition is higher than the raw EV value in the Narratives condition in many voxels, suggesting that the Sentences condition engages more of the language network than the Narratives condition. However, we find fewer semantically selective voxels in the Sentences condition than in the Narratives condition in all subjects (Figure XX). Instead, we find that out of the five feature spaces we used in this study, the “number of letters” feature space has the highest prediction accuracy in the Sentences condition in all subjects (Figure XX). This suggests that a substantial portion of brain activations evoked by isolated sentences reflects the number of letters in the stimulus. However, the explainable variance in the Sentences condition could also be explained by a different feature space that we did not include in our analyses for this paper.

Our study used a semantic model to determine whether and how semantic representations change across the four conditions. Although our semantic model is able to capture many of the semantic properties of individual words, it nonetheless has several limitations. First, because this model likely captures some narrative information that is correlated with word-level semantic information, some of the brain activity predicted by our semantic model may therefore reflect higher-level linguistic or domain-general representations (Blank & Fedorenko, 2017; Fedorenko et al., 2012). Second, our semantic model may not predict brain activity optimally in the Single Words, Semantic Blocks, and Sentences conditions. This is because our semantic model was trained with a context window size of 15 words (see Methods), but there is limited contextual information available in those three conditions. It is possible that a semantic model trained with a smaller context window size may better predict brain activity in those three conditions. However, using our semantic model to identify semantically selectivity voxels does not unfairly bias our results against the Single Words, Semantic Blocks, and Sentences conditions. Because we want to understand how the brain processes natural language rather than simplified language stimuli, a semantic model that captures a more naturalistic amount of contextual information is more appropriate. Finally, our semantic model has one vector representation for each word, and it does not differentiate between different word senses or different contexts in which a word may appear. Because contextual information is not preserved across the four conditions, our semantic model may not predict voxel activity as well as other models that integrate contextual semantic information differently (Jain & Huth, 2018; Toneva & Wehbe, 2019), especially in the Sentences and Narratives conditions. The voxelwise modeling framework provides a straightforward method for evaluating alternative semantic models directly by construction of appropriate feature spaces. Therefore, a valuable direction for future research would be to examine other semantic models, and to include language models that explicitly account for factors such as narrative structure, metaphor, and humor.

In conclusion, our results show that increasing the amount of stimulus context increases the SNR of evoked brain responses, increases the representation of semantic information in the brain, and changes the semantic tuning of semantically selective voxels. These results imply that neuroimaging studies that use isolated words or sentences to study semantic processing or to localize the language network (Fedorenko et al., 2010) may provide a misleading picture of semantic language comprehension in daily life. Although natural language stimuli are much more complex than isolated words and sentences, the development and validation of the voxelwise encoding model framework for language processing (de Heer et al., 2017; Deniz et al., 2019; Huth et al., 2016; Popham et al., 2021) has made it possible to rigorously test hypotheses about semantic processing with natural language stimuli. To ensure that the results of neuroimaging study generalize to natural language processing, we suggest that future studies of semantic processing should use more naturalistic stimuli.

1.5 Extended Data Figures and Tables

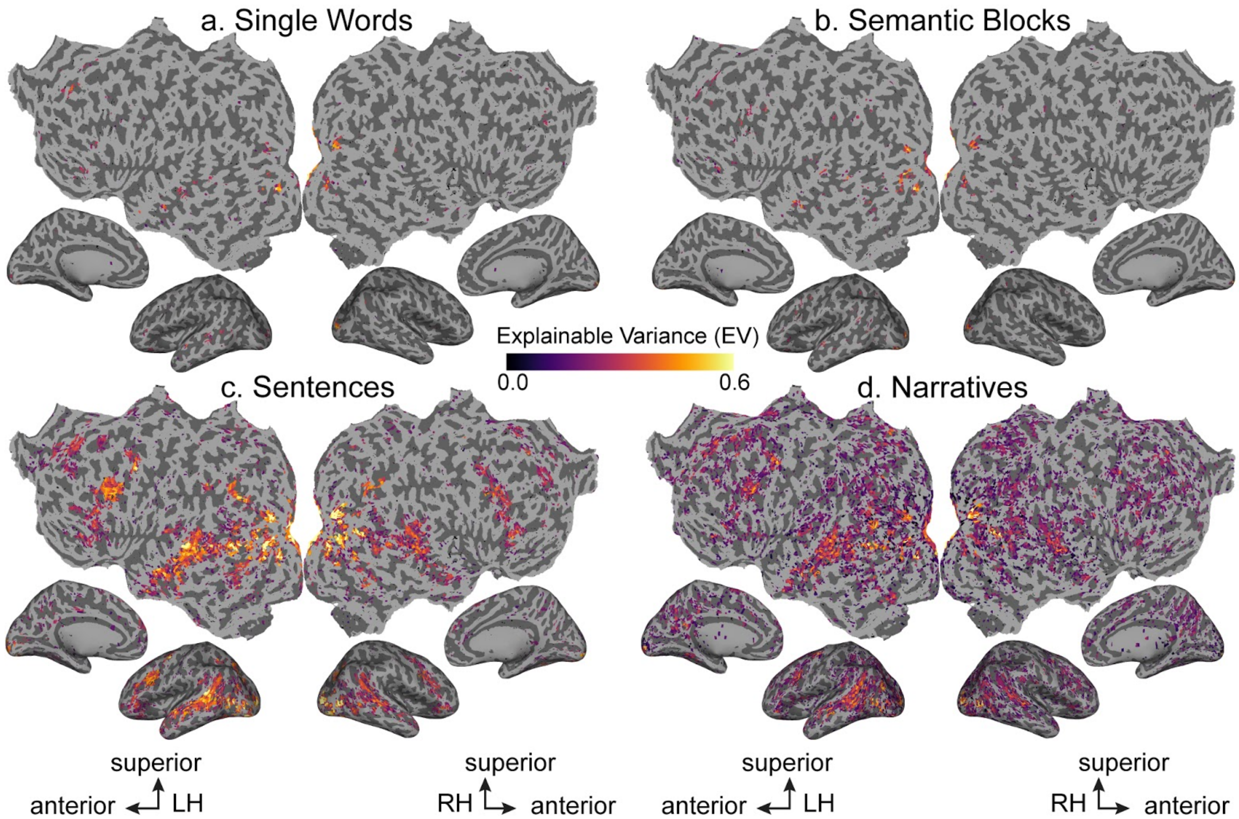


Figure 2-1. Significant explainable variance (EV) for the four conditions across the cortical surface. EV is shown for the four conditions on the flattened cortical surface of one subject (S1). EV was computed as an estimate of the evoked signal-to-noise ratio (SNR). Only voxels with significant EV ($p<0.05$, FDR corrected) are shown. EV is given by the color scale shown in the middle, and voxels that have high EV appear yellow. Voxels with EV values that are not statistically significant are shown in gray. (LH: Left Hemisphere, RH: Right Hemisphere) **a.** EV was computed for the Single Words condition, and significant voxels are shown on the flattened cortical surface of subject S1. Scattered voxels in bilateral primary visual cortex, left STS, and left IFG have significant EV. **b.** Same as panel **a**. but for the Semantic Blocks condition. Similar to the Single Words condition, scattered voxels in bilateral primary visual cortex, left STS, and left IFG have significant EV. **c.** Same as panel **a**. but for the Sentences condition. Many voxels in bilateral visual, parietal, temporal, and prefrontal cortices have significant EV. **d.** Same as panel **a**. but for the Narratives condition. Similar to the Sentences condition, voxels in bilateral visual, parietal, temporal, and prefrontal cortices have high EV.

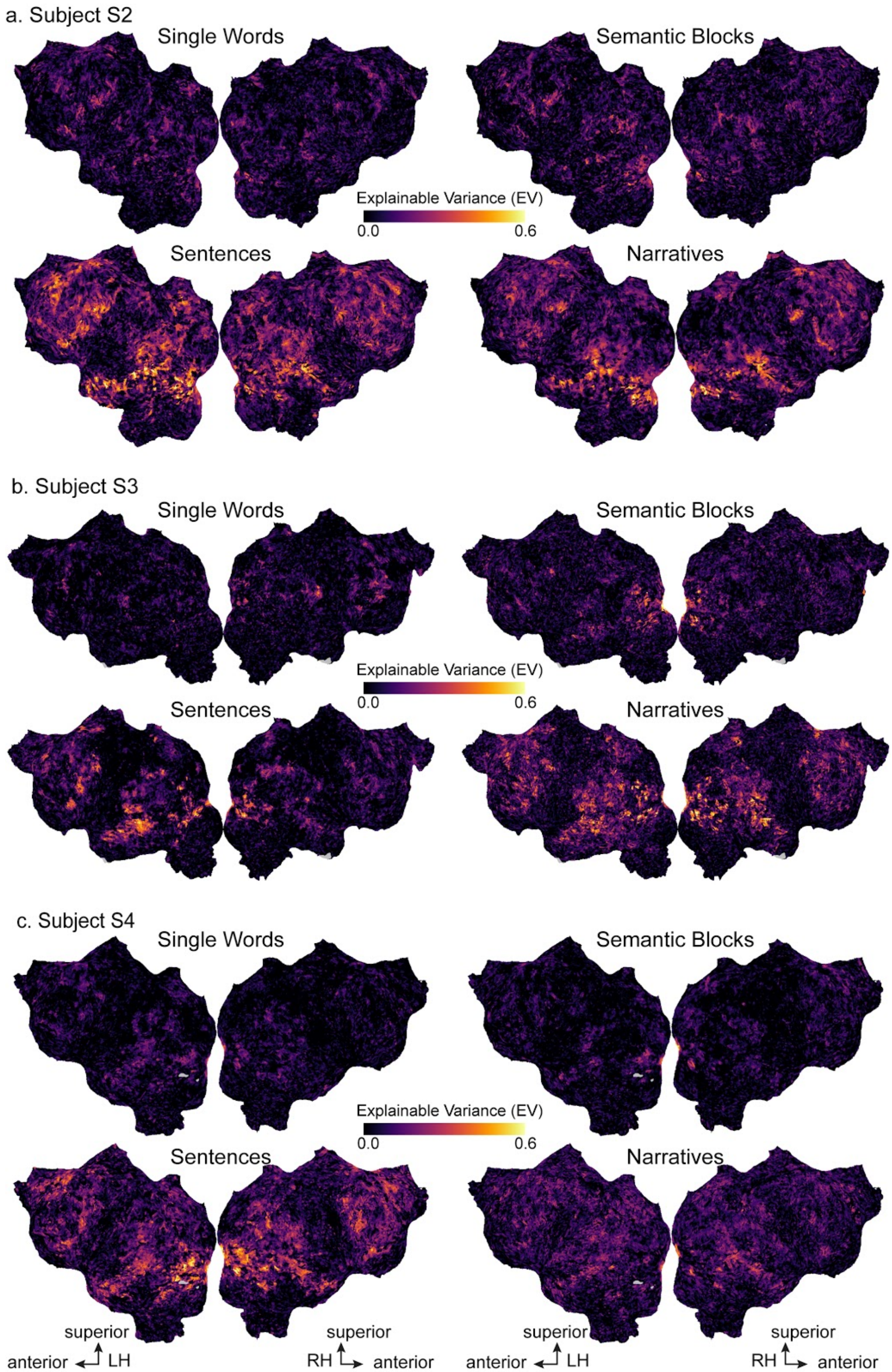

a. Subject S2
Single Words
Semantic Blocks
Explainable Variance (EV)
0.0
0.6
Sentences
Narratives
b. Subject S3
Single Words
Semantic Blocks
Explainable Variance (EV)
0.0
0.6
Sentences
Narratives
c. Subject S4
Single Words
Semantic Blocks
Explainable Variance (EV)
0.0
0.6
Sentences
Narratives
superior
anterior
LH
superior
RH
anterior
superior
anterior
LH
superior
RH
anterior

Figure 2-2. Explainable variance (EV) for the four conditions across the cortical surface for subjects S2, S3, and S4. EV is shown for the four conditions on the flattened cortical surface of subjects S2, S3, and S4. The format is the same as **Figure 3**. EV was computed as an estimate of the evoked signal-to-noise ratio (SNR). EV is given by the color scale shown in the middle, and voxels that have high EV (i.e., high evoked SNR) appear yellow. (LH: Left Hemisphere, RH: Right Hemisphere) Across all subjects, EV is low across most of the cortical surface in the Single Words and Semantic Blocks conditions. In contrast, EV is high for many voxels in bilateral visual, parietal, temporal, and prefrontal cortices in the Sentences and Narratives conditions.

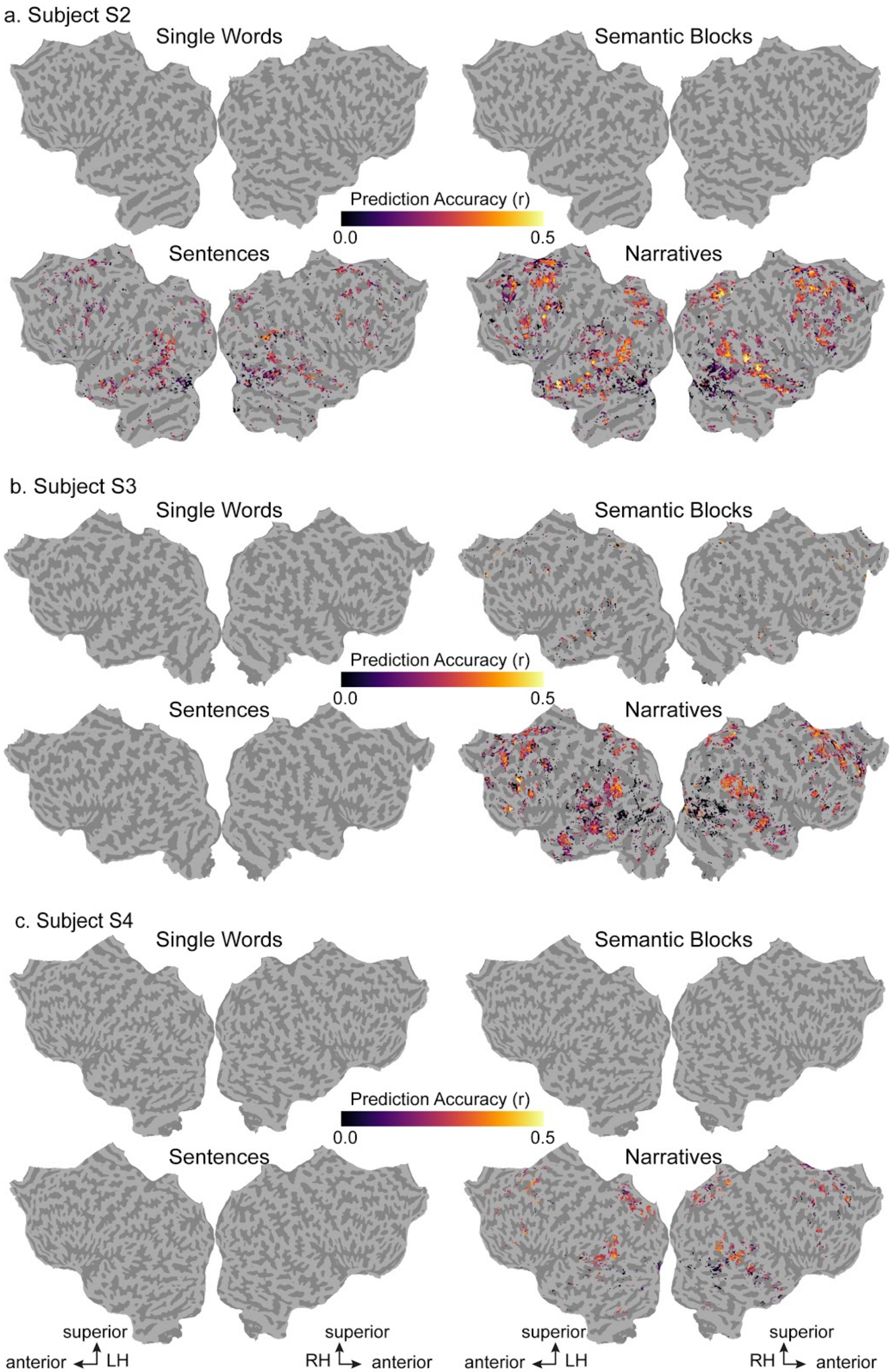

a. Subject S2
Single Words
Semantic Blocks
Prediction Accuracy (r)
0.0
0.5
Sentences
Narratives
b. Subject S3
Single Words
Semantic Blocks
Prediction Accuracy (r)
0.0
0.5
Sentences
Narratives
c. Subject S4
Single Words
Semantic Blocks
Prediction Accuracy (r)
0.0
0.5
Sentences
Narratives
superior
anterior
LH
superior
RH
anterior
superior
anterior
LH
superior
RH
anterior

Figure 4-1. Semantic model prediction accuracy for the four conditions across the cortical surface for subjects S2, S3, and S4. Semantic model prediction accuracy in the four conditions is shown on the flattened cortical surface of subjects S2, S3 and S4. The format is the same as **Figure 4**. Voxelwise modeling was first used to estimate semantic model weights in the four conditions. Semantic model prediction accuracy was then computed as the correlation (r) between the subject's recorded BOLD activity to the held-out validation story and the BOLD activity predicted by the semantic model. In each panel, only voxels with significant semantic model prediction accuracy ($p<0.05$, FDR corrected) are shown. Prediction accuracy is given by the color scale in the middle, and voxels that have a high prediction accuracy appear yellow. Voxels with semantic model prediction accuracies that are not statistically significant are shown in gray. (LH: Left Hemisphere, RH: Right Hemisphere) In the Single Words condition, no voxels are significantly predicted in all subjects. In the Semantic Blocks condition, scattered voxels in left STS, left angular gyrus, left sPMv, and bilateral SFS are significantly predicted in subject S3. In the Sentences condition, voxels in bilateral STS, bilateral STG, bilateral angular gyrus, bilateral ventral precuneus, bilateral SFS and SFG, bilateral IFG, and bilateral sPMv are significantly predicted in subject S2. In the Narratives condition, voxels in bilateral angular gyrus, bilateral ventral precuneus, bilateral SFS and SFG, and right STS are significantly predicted in all three subjects. In addition, bilateral STG, left STS, bilateral Broca's area and IFG, and bilateral sPMv are significantly predicted in subjects S2 and S3.

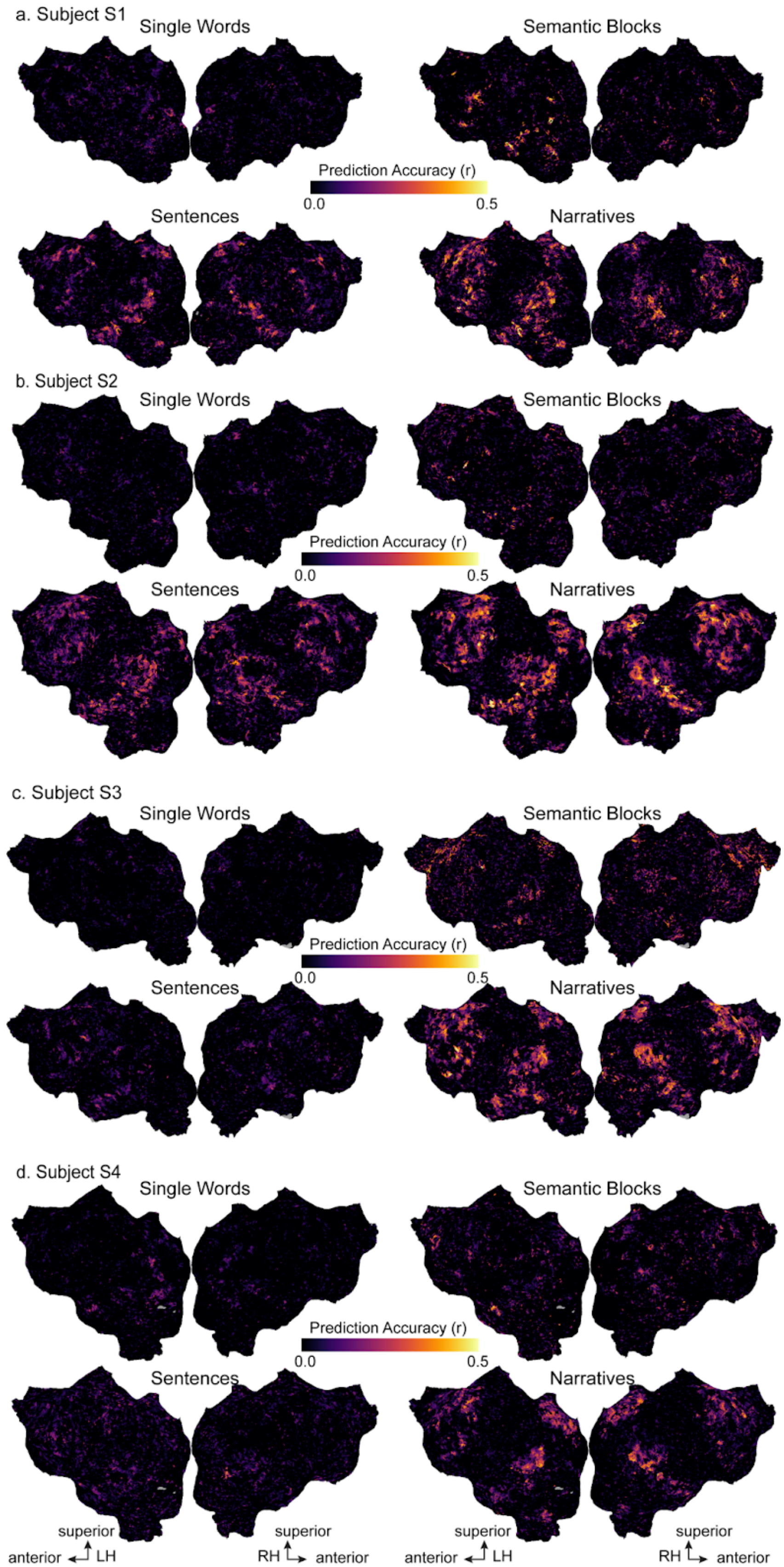

a. Subject S1
Single Words
Semantic Blocks
Prediction Accuracy (r)
0.0
0.5
Sentences
Narratives
b. Subject S2
Single Words
Semantic Blocks
Prediction Accuracy (r)
0.0
0.5
Sentences
Narratives
c. Subject S3
Single Words
Semantic Blocks
Prediction Accuracy (r)
0.0
0.5
Sentences
Narratives
d. Subject S4
Single Words
Semantic Blocks
Prediction Accuracy (r)
0.0
0.5
Sentences
Narratives
superior
anterior
LH
superior
RH
anterior
superior
anterior
LH
superior
RH
anterior

Figure 4-2. Un-thresholded semantic model prediction accuracy for the four conditions across the cortical surface for all subjects. Un-thresholded semantic model prediction accuracy in the four conditions is shown for all subjects on each subject's flattened cortical surface. Voxelwise modeling was first used to estimate semantic model weights in the four conditions. Semantic model prediction accuracy was then computed as the correlation (r) between the subject's recorded BOLD activity to the held-out validation story and the BOLD activity predicted by the semantic model. Prediction accuracy is given by the color scale in the middle, and voxels that have a high prediction accuracy appear yellow. (LH: Left Hemisphere, RH: Right Hemisphere) In the Single Words condition, prediction accuracy is high in scattered voxels in primary visual cortex in subjects S1 and S4. In the Semantic Blocks condition, prediction accuracy is high in voxels in left STS and left angular gyrus in subjects S1 and S3. In addition, prediction accuracy is high in voxels in left Broca's area and IFG in subject S1, and prediction accuracy is high in voxels in bilateral SFS, SFG, and ventral precuneus in subject S3. In the Sentences condition, prediction accuracy is high in voxels in bilateral angular gyrus, STS, STG, MTG, anterior temporal lobe, IFG, sPMv, SFS, SFG, and ventral precuneus in subjects S1 and S2. In the Narratives condition, prediction accuracy is high in voxels in bilateral angular gyrus, STS, STG, MTG, anterior temporal lobe, Broca's area and IFG, sPMv, SFS, SFG, ventral precuneus, and posterior cingulate gyrus in all subjects.

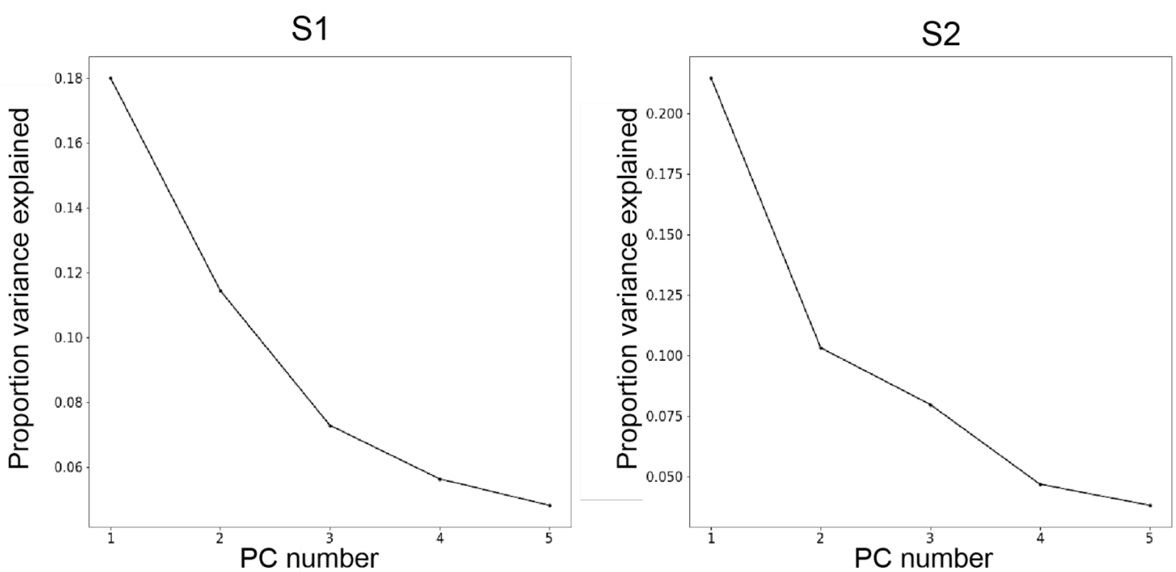


Figure 8-1. Proportion of variance explained by PCs of semantic difference vectors. Semantic model weights estimated in the Sentences condition were subtracted from semantic model weights estimated in the Narratives condition. PCA was then applied to the resulting difference vectors for each subject separately. The amount of variance explained by each of the first five PCs is plotted for each subject. The first five PCs explain 47.1% of the variance in subject S1 and 48.2% of the variance in subject S2.

Subject	PC	Top 10 most correlated words	Top 10 least correlated words

S1	1	'appointment', 'interview', 'accused', 'detective', 'interviews', 'inspector., 'spoke', 'officer', 'secretary', 'detention'	'propel', 'build', 'upwards', 'diversify', 'allows', 'high', 'float', 'enables', 'market', 'speeds'
	2	'contents', 'package', 'processed', 'packages', 'discovery', 'boxes', 'delivery', 'delivered', 'deliver', 'discover'	'athletic', 'athletics', 'volleyball', 'soccer', 'scoring', 'tournaments', 'professional', 'players', 'football', 'team'
	3	'meters', 'diameter', 'density', 'mm', 'surface', 'larger', 'boundary', 'ranges', 'large', 'thermal'	'wished', 'wanted', 'fellow', 'wife', 'father', 'sister', 'husband', 'mother', 'asked', 'loved'
S2	1	'imagery', 'presence', 'refer', 'portrayed', 'depicted', 'resembles', 'resemblance', 'closely', 'voiced', 'fictional'	'month', 'week', 'hours', 'weeks', 'year', 'months', 'hour', 'dollars', 'cents', 'semester'
	2	'destination', 'taxi', 'travel', 'mail', 'rental', 'via', 'delivery', 'visit', 'cancel', 'deliver'	'with', 'face', 'against', 'as', 'hands', 'chin', 'hitter', 'his', 'he', 'fingers'
	3	'which', 'by', 'has', 'number', 'according', 'may', 'several', 'citation', 'were', 's'	'everytime, 'goddamn', 'yea', 'cuz', 'wanna', 'sucks', 'freaking', 'sucked', 'awesome', 'idk'

Table 8-1. Most and least correlated words for each PC. The first three PCs of the difference vectors were correlated with words in the semantic model. The ten most correlated words and the ten least correlated words are shown for each PC for each subject.

Chapter 2

Mapping the representation of social information in the brain

2.1 Introduction

The groups and communities that people belong to form an integral part of their lives. To help maintain these complex social relationships, people have extensive knowledge about the individuals and the dynamics in these groups. Many previous neuroimaging studies have tried to identify where social knowledge is represented in the brain. These studies found a small number of cortical regions that may represent different types of social information, including individual traits (Thornton & Mitchell, 2017; Van Overwalle & Heleven, 2021), interpersonal relationships (Courtney & Meyer, 2020), social groups (Delplanque et al., 2019; Kobayashi et al., 2022), and social networks (Parkinson et al., 2017). However, these studies suffer from two major limitations that make it difficult to interpret their results.

First, prior neuroimaging studies of social knowledge representation only focused on one type of social information, and they only reported statistical significance for their results. It is difficult to compare statistically significant results reported across independent studies for two reasons. First, statistical significance and p-values do not generally translate to effect size. Thus, even if a brain region is only significant in one study, it does not mean that the effect (e.g., mean BOLD response) observed in that study was significantly larger than the effect observed in any other study. Second, statistical significance indicates that an effect was unlikely to happen under the null hypothesis, but it does not provide a measure of how well the alternative hypothesis actually describes the data. Thus, even if a brain region is significant in a study, it does not mean that the alternative hypothesis in the study (e.g, precuneus represents individual traits) best describes that brain region. Thus, it is unclear how significant results from prior studies should be interpreted with respect to one another, and it is also unclear which types of social information are actually represented in the brain regions identified in those studies. To answer these questions, an experiment that probes multiple types of social information simultaneously is needed.

Second, results in most prior neuroimaging studies of social representation are potentially confounded by non-social information. This is because most prior studies did not account for non-social information in their experiments that could have explained variance in the recorded BOLD responses. Since non-social information is often correlated with the social information of interest, brain regions reported to represent social information may actually represent correlated non-social information. Moreover, brain regions may be reported to represent social information more strongly than they would if non-social information had been accounted for. As an example, Parkinson et al. (2017) had participants view short clips of different people in a social network, but they did not account for visual information in their analysis. Prior studies have shown that both low-level visual models and visual semantic models explain a large proportion of the BOLD response during movie watching (Huth et al., 2012; Nishimoto et al., 2011). Thus, brain areas that Parkinson et al. (2017) identified as representing information about social networks (e.g., extrastriate visual cortex represents eigenvector centrality) might instead represent visual information in the clips that is correlated with social network information. To avoid this confound, non-social information needs to be explicitly modeled and accounted for during data analysis.

To address these two limitations, we simultaneously mapped the cortical representations of five types of social information in individual participants while accounting for non-social information. In the experiment, participants answered questions about five types of social information for a fictional social network while blood oxygen level-dependent (BOLD) responses were recorded by functional magnetic resonance imaging (fMRI). The five types of social information were: individual character traits ("individual traits"), relationships between two characters ("character relationships"), social groups ("social groups"), questions based on social network analysis metrics ("social network"), and questions that asked the participant to relate to characters and groups ("subjective judgment"). We then used a voxelwise encoding model approach (VM) to map the representation of each type of social information across the cortical surface while accounting for non-social information.

2.2 Materials and Methods

Participants

Functional data were collected from three male participants, two female participants, and one non-binary participant assigned female at birth: S1 (female, age 27), S2 (male, age 28), S3 (male, age 29), S4 (male, age 35), S5 (non-binary, age 26), S6 (female, age 30). All participants were healthy and had normal hearing, and normal or corrected-to-normal vision.

MRI data collection

MRI data were collected on a 3T Siemens TIM Trio scanner with a 32-channel Siemens volume coil, located at the UC Berkeley Brain Imaging Center. Functional scans were collected using gradient echo EPI with repetition time (TR) = 2.0045s, echo time (TE) = 31ms, flip angle = 70 degrees, voxel size = 2.24 x 2.24 x 4.1 mm (slice thickness = 3.5 mm with 18% slice gap), matrix size = 100 x 100, and field of view = 224 x 224 mm. Thirty axial slices were prescribed to cover the entire cortex and were scanned in interleaved order. A custom-modified bipolar water excitation radiofrequency (RF) pulse was used to avoid signal from fat. Anatomical data were collected using a T1-weighted multi-echo MP-RAGE sequence on the same 3T scanner. On average, 83 min of fMRI data was collected for each participant.

fMRI data pre-processing

The FMRIB Linear Image Registration Tool (FLIRT) from FSL 5.0 (Jenkinson et al., 2002; Jenkinson & Smith, 2001) was used to motion-correct each functional run. A high-quality template volume was then created for each run by averaging all volumes in the run across time. FLIRT was used to automatically align the template volume for each run to an overall template, which was chosen to be the temporal average of the first functional run for each participant. These automatic alignments were manually checked and adjusted as necessary to improve accuracy. The cross-run transformation matrix was then concatenated to the motion-correction transformation matrices obtained using MCFLIRT, and the concatenated transformation was used to resample the original data directly into the overall template space.

White matter detrending (Behzadi et al., 2007) was used to identify low-frequency voxel response drift. This drift was subtracted from the signal before further processing. Responses for each run were z-scored separately before voxelwise modeling. In addition, 5 TRs were discarded from the beginning and the end (10 TRs total) of each run.

Cortical surface reconstruction and visualization

Freesurfer (Dale et al., 1999) was used to generate cortical surface meshes from the T1-weighted anatomical scans. Before surface reconstruction, Blender (https://www.blender.org/) and pycortex (http://pycortex.org; (Gao et al., 2015)) were used to carefully hand-check and correct anatomical surface segmentations. To aid in cortical flattening, Blender and pycortex were used to remove the surface crossing the corpus callosum and relaxation cuts were made into the surface of each hemisphere. The calcarine sulcus cut was made at the horizontal meridian in V1 as identified from retinotopic mapping data.

Pycortex (Gao et al., 2015) was used to align functional images to the cortical surface. The line-nearest scheme in pycortex was used to project functional data onto the surface for visualization and subsequent analysis. The line-nearest scheme samples the functional data at 64 evenly-spaced intervals between the inner (white matter) and outer (pial) surfaces of the cortex and averages the samples. Samples are taken using nearest-neighbor interpolation, in which each sample is given the value of its enclosing voxel.

Experimental design

Six participants watched the first two Harry Potter movies (*Harry Potter and the Sorcerer's Stone*, *Harry Potter and the Chamber of Secrets*) prior to the fMRI experiment. Before watching the movies, participants were given a list of movie characters to pay attention to while watching the movies. The list contained characters that would appear during the fMRI experiment. Participants were asked to be familiar with the listed characters before the fMRI experiment.

During the fMRI experiment, participants answered questions (see Stimulus questions) about the movie characters, their relationships, and their social groups. Questions were presented in individual trials. At the start of each trial, a trial marker "--------" was shown at the center of the screen for 380 ms. Then, the question was presented as text and shown one word at a time at the center of the screen using Rapid Serial Visual Presentation (RSVP) (Buchweitz et al., 2009; Forster, 1970). Words were presented for a baseline of 300 ms with an additional 10 ms for every character. For example, the word "apple" would be presented for 300 ms + 10 ms/character * (5 characters) = 350 ms. These parameters were determined after extensive pilot testing, and they provide a good balance between readability and keeping subject engagement. All questions ended with a question mark, which was presented for 200 ms. Participants responded to each question by pressing 1-5 on a five-button button box, where 1=low/disagree and 5=high/agree. All participants pressed buttons with their right hand. The next trial started immediately after the participant's response. If a participant didn't respond within an answering period of 3-5 seconds (jittered across trials), the next trial automatically started after the answering period. Missed trials were not repeated. On average, participants completed 98.9% of the presented trials.

Five out of six participants completed 8 scanning runs, and one participant (S6) completed 7 scanning runs. There were 150 trials in each scanning run, and 140 of the 150 trials were unique. The remaining 10 trials in each run were repeated from the unique trials, and they were used as padding at the beginning (5 trials) and the end (5 trials) of each run. On average, participants took 10.6 minutes to complete each scanning run.

Stimulus questions

In this experiment, each participant answered 1120 unique questions. These questions were designed with two goals in mind. First, we wanted to probe many different aspects of each type of social information. This was so that our results would not be biased towards a specific aspect. Second, we wanted questions about each type of social information to be asked about a wide range of characters and social groups. This was so that our results would not be biased towards a specific character or social group. To satisfy these two goals, we first created a large number of question templates that probe different aspects of the five types of social information. These question templates could be paired with different characters or social groups. For example, one question template is "How much does [character] value wealth?" Then, to optimize pairing question templates with characters and social groups, similar question templates were grouped together and organized hierarchically in a tree (see Question Organization). Finally, mixed-integer linear programming (MILP; (Slivkoff & Gallant, 2021)) was used to find an optimal pairing of question templates and characters/social groups, and to find a balanced distribution of paired questions across scanning runs (see Question and experiment generation).

Question Organization. Question templates were organized hierarchically in a tree. This organization is given by Table 1. At the highest level of the tree, the question templates are organized by which of the five types of social information they probe:

individual character traits ("individual traits"), relationships between two characters ("character relationships"), social groups ("social groups"), questions based on social network analysis metrics ("social network"), or questions that ask the participant to relate to characters and groups ("subjective judgment").

Each of the five large question groups contains smaller subgroups of question templates that focus on different components of each type of social information. For example, the character relations question group contains four question subgroups: family and partners, friends, relationship descriptions, and roles. There are 19 question subgroups.

Each question subgroup contains even smaller sub-subgroups of question templates that ask about different aspects of each question subgroup. For example, the "family and partners" question subgroup contains questions about how frequently a character interacts with their family, whether a character has a close relationship with their family, and whether a character has a partner. Most of these question sub-subgroups contain only one question template, and a small number of question sub-subgroups contain multiple question templates. There are 106 question sub-subgroups and 198 question templates.

Question Sources. Most of the question templates are based on prior literature, and a small subset of the question templates were generated by the authors. The question templates that are based on prior literature are described here. First, question templates about social roles are based on the list of social roles in FrameNet (Ruppenhofer et al., 2016). Second, question templates about character values are taken from the Schwartz Theory of Basic Values (Schwartz, 1992). Third, question templates about the valence of character relationships are based on the Interpersonal Lexicon (De Raad, 1999). Fourth, question templates in the social network question group are based on nine commonly used social network metrics in the social network analysis literature. These include degree centrality, closeness centrality, eigenvector centrality, cross-clique centrality, betweenness centrality, clustering coefficient, brokerage, balancedness, and homophily. With the exception of balancedness and homophily, these social network metrics have standard mathematical definitions. Since computing the numerical values of social network metrics in the experiment is infeasible for most participants, the question templates for each social network metric were designed to ask about the information that each metric captures at a conceptual level. For example, a question for degree centrality was "How many characters does [character] interact with regularly?" Finally, some question templates were taken from the General Social Survey (Smith et al., 2019) and the UC Berkeley Social Networks Study (Fischer, 2018).

Characters and social groups. The question templates were paired with 21 characters and 13 social groups. Of these 21 characters, 20 characters were from the first two Harry Potter movies. The 21st character was the participant, whose first name was used in the experiment. The participant was originally included as a character in the experiment because we were interested in looking at the cortical representations of the self and different types of characters. However, the contribution of the character identity feature space to the joint model prediction accuracy was very small in most participants (see Voxelwise encoding model fitting and validation), so we did not pursue this question in this study. A list of the characters and groups are provided in Table 2.

The 20 characters and 13 social groups were chosen because they played memorable roles in the first two Harry Potter movies. In addition, the characters were chosen such that they would span a range of values for each of the social network metrics that were asked about in the experiment.

To compute social network feature values for each character, we first had to generate a social network for the movies. We obtained copies of the screenplays for the movies from http://www.hogwartsishere.com/library/book/7391/chapter/1/ (*Harry Potter and the Sorcerer's Stone*) and http://www.hogwartsishere.com/library/book/7391/chapter/2/ (*Harry Potter and the Chamber of Secrets*). The screenplays were slightly different from the movies, so the first author manually checked and revised the screenplays to match the movies. We parsed the text in the screenplays to get a list of characters and scenes. Finally, we created a network where each character was a node, and two characters were connected with an edge if they appeared in at least one scene together. Edges were weighted by the number of times the two characters appeared in the same scenes together.

We computed eight social network metrics for each character on the resulting social network: degree centrality, closeness centrality, eigenvector centrality, cross-clique centrality, betweenness centrality, clustering coefficient, brokerage, and homophily (we did not compute balancedness). We used the networkx package (Hagberg et al., 2008) to compute all of the social network metrics except brokerage and homophily. To compute brokerage for a character, we took the mean embeddedness of all the edges that include that character. The embeddedness of an edge e=(v1, v2) was defined as the number of common neighbors shared by v1 and v2 (Easley & Kleinberg, 2010).

To compute homophily, we created a mathematical definition for homophily based on its conceptual definition. Homophily is the principle that people tend to associate more with similar people than dissimilar people (McPherson et al., 2001). People can be similar in many different categories (e.g., age, gender, interests). To create a homophily metric that encompassed a wide range of categories, the first two authors first rated each of the 20 characters on 29 attributes from 1 (low) to 5 (high). These attributes are listed in Table 3 and include interests, group membership, social standing and roles, physical attributes, values, and personality. The scores for each attribute were then averaged between the two authors. Next, the attribute ratings were scaled according to their importance as determined by the first two authors. The scaling factor for each attribute is listed in Table 3. Finally, the homophily between two characters was defined as the Pearson's correlation between the attribute ratings for those two characters. To compute a homophily value for a single character, the mean homophily between that character and their neighbor characters was taken.

Question and experiment generation. The 198 question templates and 21 characters/13 social groups were paired together and distributed across scanning runs using mixed-integer linear programming (MILP, (Slivkoff & Gallant, 2021)). MILP is an optimization tool that allows the incorporation of complex design constraints into an experiment. Here, we imposed several constraints on the experiment. First, we constrained the number of times that question templates from each of the 19 question subgroups would appear throughout the entire experiment. Second, we set a constraint that the number of question templates allocated for each subgroup had to be evenly divided between the question sub-subgroups in the question subgroup. Third, we set a constraint that the 21 characters had to appear approximately the same number of times across the experiment, and the 13 social groups had to appear approximately the same number of times across the experiment. Fourth, we set a constraint that each character and social group would be paired with roughly the same number of question templates for each question subgroup (separately for characters and social groups). Finally, we set a constraint that approximately equal numbers of question templates from each question subgroup had to appear in each scanning run. Table 4 gives the number of question templates from each question subgroup that appeared in the experiment, and the full list of experiment questions is included in the Supplementary Materials.

Voxelwise encoding model fitting and validation

Model fitting. To identify voxels that represent different types of social information, a linearized encoding model (Huth et al., 2012, 2016; Nishimoto et al., 2011) was fit to every cortical voxel in each participant's brain. The linearized encoding model consisted of 14 feature spaces. Five of the feature spaces were designed to represent the five social information question groups. Each of these feature spaces consisted of binary features that corresponded to the question subgroups for each question group. Each binary feature had a value of 1 when a trial contained a question in the question subgroup, and a value of 0 otherwise. The remaining nine feature spaces were designed to capture non-social information, and these included a linguistic semantic feature space (Huth et al., 2016), four feature spaces that reflected low-level linguistic information, and four feature spaces that reflected participant behavior and experimental parameters. There were a total of 1074 features across the 14 feature spaces. A list of the 14 feature spaces and the number of features in each feature space is given in Table 5.

The features passed through three additional preprocessing steps before being fit to BOLD responses. First, to account for the hemodynamic response, a separate finite impulse response (FIR) filter with four delays was fit for each of the 1074 features, resulting in 4296 final features. This was accomplished by concatenating copies of the features delayed by 1, 2, 3, and 4 TRs (approximately 2, 4, 6, and 8 seconds). Taking the dot product of this concatenated feature space with a set of linear weights is functionally equivalent to convolving the undelayed features with a linear temporal kernel that has non-zero entries for 1-, 2-, 3-, and 4-time point delays. Second, 5 TRs were discarded from the beginning and the end (10 TRs total) of each run. Third, each feature was z-scored separately within each run. This was done so that the features would be on the same scale as the BOLD responses, which were also z-scored within each run.

A single joint model consisting of the 4296 features was fit to BOLD responses using banded ridge regression (Nunez-Elizalde et al., 2019) and the himalaya Python package (Dupré la Tour et al., 2022). A separate model was fit for every voxel in every participant and condition. For every model, a regularization parameter was estimated for each of the five feature spaces using a random search. In the random search, 1000 normalized hyperparameter candidates were sampled from a Dirichlet distribution and scaled by 30 log-spaced values ranging from 10^{-5} to 10^{20}. The best normalized hyperparameter candidate and scaling were selected for each feature space for each voxel. Finally, models were fit again on the BOLD responses with the selected hyperparameters.

Model validation. Models were validated using a leave-one-out cross validation (CV) scheme. For every participant, the joint model was trained on seven out of eight runs of BOLD data. (The joint model was trained on six out of seven runs for participant S6.) The estimated model weights were then used to predict responses to the eighth run of BOLD data. This procedure was repeated for every split of seven “training” runs and one “test” run. Prediction accuracy for each cross validation fold was computed as the coefficient of determination (R^2) between the model-predicted BOLD responses and the recorded BOLD responses for the test run. Prediction accuracy values were averaged across the eight CV folds for every voxel in every participant. In this paper, the averaged prediction accuracy values are referred to simply as the “prediction accuracy”.

Significance testing. Statistical significance of the joint model prediction accuracy was computed with permutation testing. For each CV fold, a null distribution was generated by first permuting the timepoints of the predicted BOLD response (y_hat) for the test run, and then computing the prediction accuracy for the permuted y_hat. The permutation was done in blocks of 10 TRs to account for temporal autocorrelations in the BOLD signal. There were 5000 permutations for each CV fold. The 5000 permutations were then averaged across the CV folds to create one null distribution for each voxel. A p-value was computed for each voxel by comparing the joint model prediction accuracy value with the null distribution. P-values were corrected for multiple comparisons within each participant using the false discovery rate (FDR) procedure (Benjamini & Hochberg, 1995).

Contribution of individual feature spaces. To estimate the contribution of each feature space to the joint model prediction accuracy, the joint model prediction accuracy was split using the “r2_score_split_svd” function in the himalaya Python package (Dupré la Tour et al., 2022). This function computes the relative weight (J. W. Johnson, 2000) of each feature space while also accounting for the magnitude of the predictions from each feature space with respect to the other feature spaces. In this paper, the contribution of each feature space to the joint model prediction accuracy is also referred to simply as the feature space’s “contribution”.

Model weight normalization and scaling. To look at the cortical representation of social information in more detail, we visualized the estimated model weights for individual features by projecting them onto the cortical surface of each participant (Figures 11-13). The model weights estimated for each individual voxel went through two preprocessing steps before visualization. First, the estimated weights for each feature space were normalized by dividing the estimated weight for each feature by the L2-norm of the estimated weights for all features in the feature space. This was done because a separate regularization parameter was estimated for each feature space (see

VM), so the estimated weights for features in different feature spaces could have different scales. Second, the normalized estimated model weights for each feature space were scaled by the square root of the contribution for that feature space. This was done so that estimated model weights for feature spaces with a small contribution would have a small value.

Software

All model fitting and analysis was performed using custom software written in Python, making heavy use of NumPy (Harris et al., 2020) and SciPy (Virtanen et al., 2020). Analysis and visualizations were developed using iPython (Perez & Granger, 2007), the interactive programming and visualization environment jupyter notebook (Kluyver et al., 2016), himalaya (Dupré la Tour et al., 2022), Pycortex (Gao et al., 2015), and Matplotlib (Hunter, 2007).

Code Accessibility

The himalaya package (Dupré la Tour et al., 2022) is publicly available on GitHub (https://github.com/gallantlab/himalaya). The pycortex package (Gao et al., 2015) is also publicly available on GitHub (https://github.com/gallantlab/pycortex).

2.3 Results

The goal of this study was to characterize the representations of five types of social information in the brain: individual character traits ("individual traits"), relationships between two characters ("character relationships"), social groups ("social groups"), social network analysis metrics ("social network"), and subjective judgments about characters and groups ("subjective judgment"). To do this, six participants watched the first two Harry Potter movies (*Harry Potter and the Sorcerer's Stone*, *Harry Potter and the Chamber of Secrets*) prior to the experiment to familiarize themselves with the characters, relationships, and social groups in those movies. Then, participants answered questions about the five types of social information for the two movies while BOLD activity was recorded by fMRI (Figure 1).

To identify what information is represented in the BOLD response of each voxel, we fit a linearized encoding model to every cortical voxel in each participant's brain (Huth et al., 2012, 2016; Nishimoto et al., 2011). The linearized encoding model consisted of 14 feature spaces, each of which captured a different kind of information in the experiment. Five of the feature spaces were designed to represent the five types of social information listed above. Each of these feature spaces consisted of binary features that represented question subgroups for each type of social information (see Methods: Stimulus questions). The remaining nine feature spaces were designed to represent non-social information in the experiment, and they captured linguistic information, the participant's behavior, and experimental parameters (see Table X for more details). The linearized encoding model was fit to the recorded BOLD responses for each participant using a leave-one-out cross-validation procedure. In each cross-validation fold, data

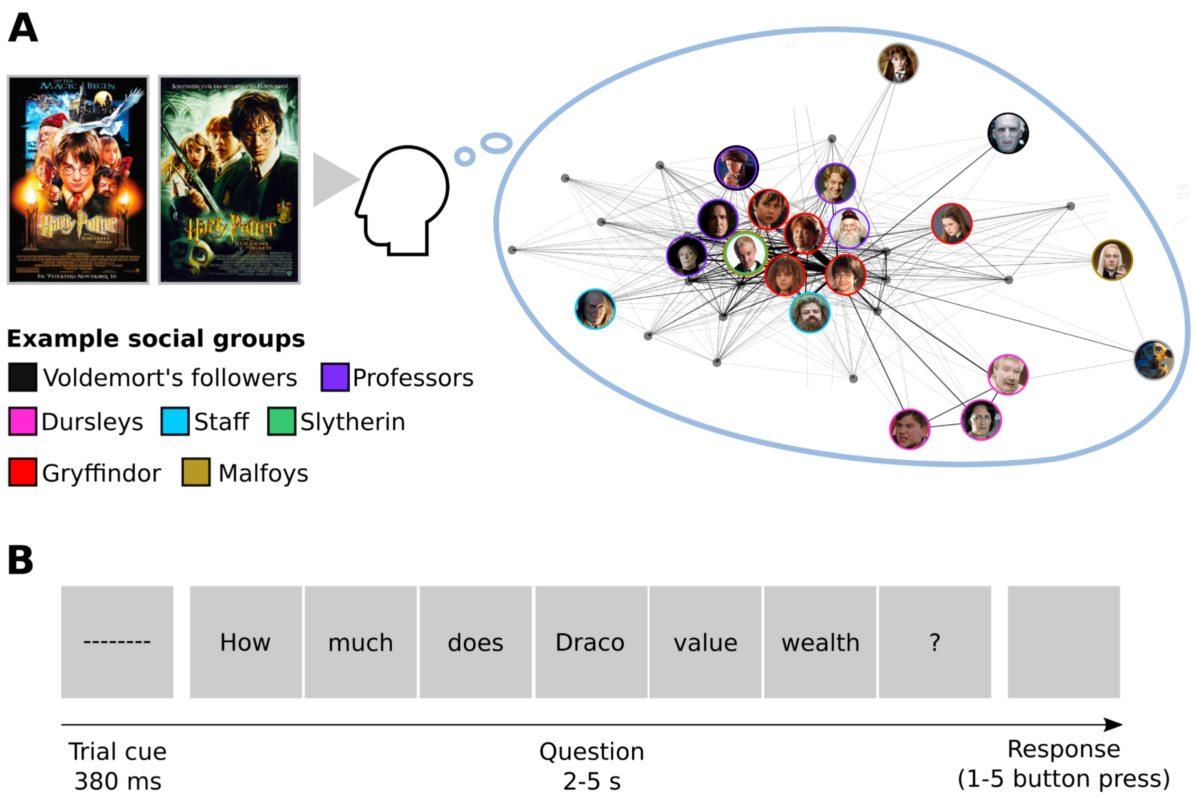


Figure 1. Experimental Design. A. Participants watch the first two Harry Potter movies prior to the fMRI experiment. Participants are asked to pay attention to the movie, and they are given a list of characters that will be asked about during the experiment. **B.** During the fMRI experiment, participants answer questions about individual and network-level social information. In each trial, participants see a short pre-trial cue followed by a question presented in RSVP format. Participants then answer by pressing a button indicating their response from 1-5, where 1 = strongly disagree, few, etc. and 5 = strongly agree, many, etc.

from one scanning run was set aside as the test dataset, and data from the remaining runs comprised the training dataset. We used banded ridge regression (Nunez-Elizalde et al., 2019) to fit the 14 feature spaces as a single joint model to the recorded BOLD responses in the training dataset (Figure 2). To validate that the model was not overfit to the training dataset, the model was then used to predict the recorded BOLD responses in the test dataset. Model goodness of fit was assessed on the test dataset, and it was computed as the amount of variance in the recorded BOLD responses explained by the model-predicted BOLD responses (i.e., the coefficient of determination R^2). In this study, this value is also referred to as the model prediction accuracy. The model fitting and testing procedure was repeated for all possible splits of training and testing datasets, and all subsequent results are an average across cross-validation splits (see Methods for a detailed explanation).

Figure 3 shows the joint model prediction accuracy for all six participants (S1-S6). In all participants, model prediction accuracy is high in many voxels located in bilateral early

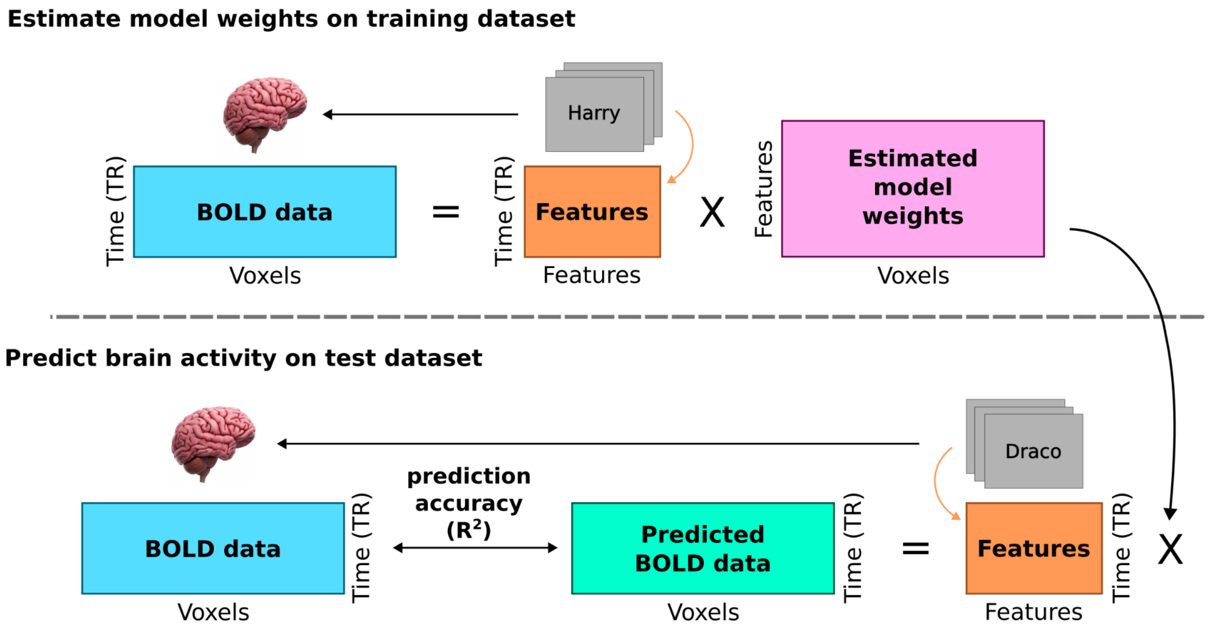


Figure 2. Voxelwise modeling. Participants answered questions presented as text while BOLD responses (blue boxes) were recorded with fMRI. To identify the information represented in each voxel's BOLD response, a linearized encoding model was constructed by extracting features of the stimulus, the participant's behavior, and experimental parameters (orange boxes). These features capture both social information and non-social information. The extracted features were then fit to a subset of the recorded BOLD responses ("training dataset") for every voxel in each participant using banded ridge regression (Nunez-Elizalde et al. 2019). To validate that the resulting estimated model weights (pink box) were not overfit to the training dataset, the estimated model weights were used to predict the remaining "test dataset" BOLD responses (green box). Model prediction accuracy was quantified as the coefficient of determination (R^2) between the predicted and recorded BOLD responses for the test dataset. This procedure was repeated multiple times for different splits of the BOLD responses into training and test datasets (see Methods).

visual cortex, left superior temporal sulcus (STS), left angular gyrus, left inferior parietal lobule (IPL), left primary motor and somatosensory hand areas, bilateral inferior frontal gyrus (IFG), left superior frontal gyrus (SFG) and superior frontal sulcus (SFS), left dorsomedial prefrontal cortex (dmPFC), and bilateral precuneus. The model explained at least 1% of the variance in an average of 27.1% of voxels for participants S1-3, and the model explained at least 0.5% of the variance in an average of 17.5% of voxels for participants S4-6. This result shows that the joint model is able to explain variance in voxels across much of the cortical surface.

To identify voxels that represent each type of social information, we estimated the contribution of each of the five social feature spaces to the joint model prediction accuracy for every voxel in each participant. The contribution of a feature space to the joint model prediction accuracy is the amount of the joint model prediction accuracy

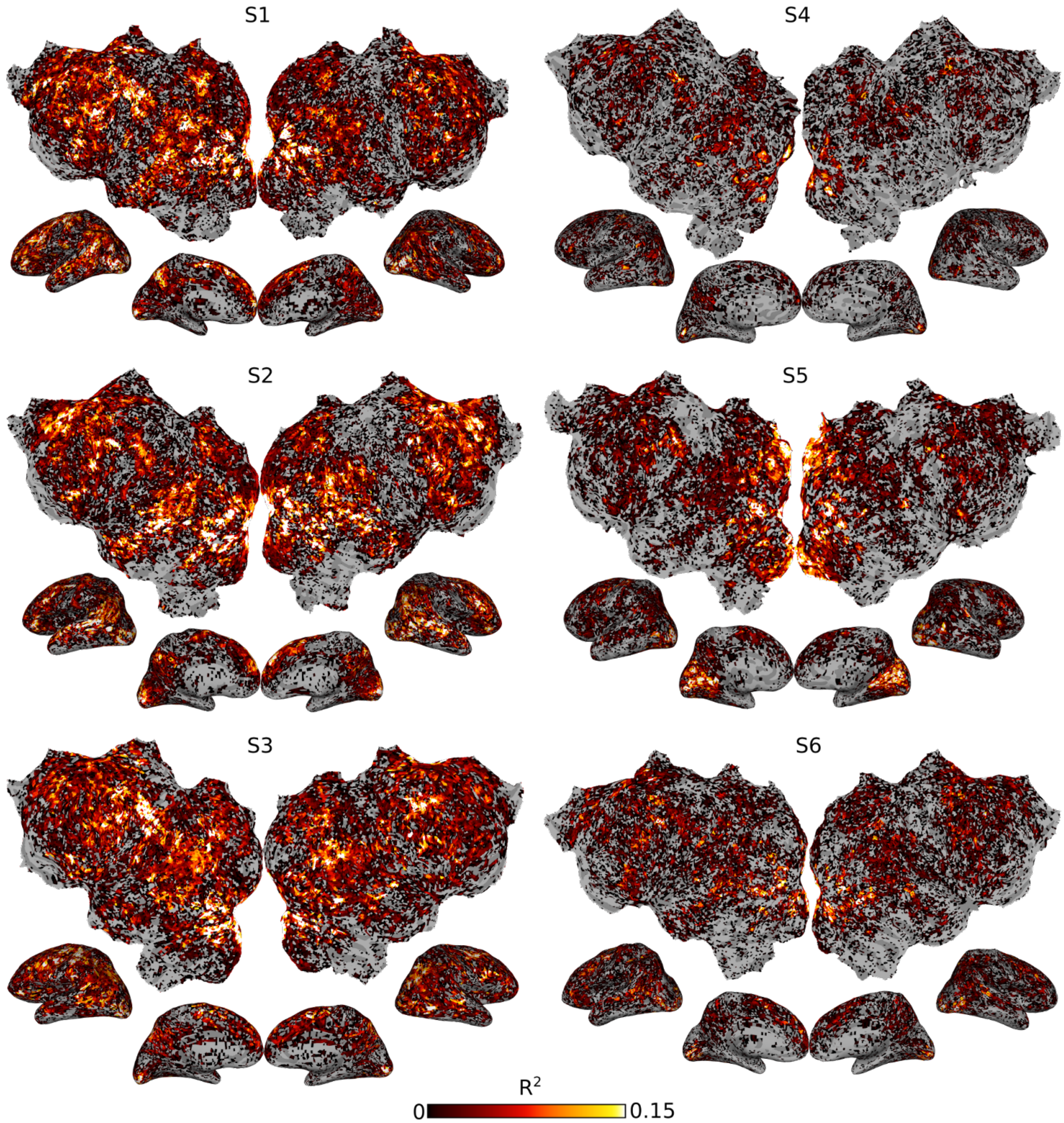


Figure 3. Joint model prediction accuracy across the cortical surface. Joint model prediction accuracy is shown on the flattened cortical surfaces of all six participants. Voxelwise modeling was first used to jointly estimate model weights for all features. Joint model prediction accuracy was then computed as the coefficient of determination (R2) between each subject's recorded BOLD activity and the BOLD activity predicted by the joint model. In each panel, only voxels with significant joint model prediction accuracy ($p<0.05$, FDR-corrected) are shown. Prediction accuracy is given by the color scale at the bottom, and voxels that have a high prediction accuracy appear yellow. Voxels for which the joint model prediction accuracy is not statistically significant are shown with the curvature (gray). In all participants, voxels in bilateral early visual cortex, left STS, left angular gyrus, left IPL, left primary motor and somatosensory hand areas, bilateral IFG, left SFG and SFS, left dmPFC, and bilateral precuneus are

significantly predicted. This result shows that our joint model is able to capture voxel responses across the cortical surface.

that can be attributed to that feature space. This measure takes into account both the direct effect of the feature space as well as its interactions with other feature spaces in the model. Here, the contribution of a feature space to the joint model prediction accuracy is also referred to simply as the “contribution” of the feature space.

The following five figures (Figures 4-8) show the contribution of each of the five social feature spaces for all six participants. Figure 4 shows the contribution of the individual traits feature space. In all participants, the individual traits feature space contributed to the joint model prediction accuracy in voxels in the left TPJ and left SFG/SFS. Additionally, in five out of six participants, the individual traits feature space contributed to the joint model prediction accuracy in voxels in the left precuneus, left dmPFC, and right IPL. Figure 5 shows the contribution of the character relationships feature space. In all participants, the character relationships feature space contributed to the joint model prediction accuracy in voxels in left SFS/SFG, left precuneus, right IPL, right IFS, and right precuneus. In addition, in five out of six participants, the character relationships feature space contributed to the joint model prediction accuracy in voxels in left IPL and left orbital IFG. Figure 6 shows the contribution of the subject judgment feature space. In all participants, the subject judgment feature space contributed to the joint model prediction accuracy in voxels in left SFS/SFG and left dmPFC. Figure 7 shows the contribution of the social network feature space. In five out of six participants, the social network feature space had low to moderate contributions to the joint model prediction accuracy in scattered voxels across the cortical surface. Contributions were seen in four out of these five participants in left orbital IFG, left SFS/SFG, and left dmPFC. In contrast, in participant S2, the social network feature space contributed strongly to the joint model prediction accuracy in localized clusters of voxels. In this participant, the social network feature space contributed to the joint model prediction accuracy in voxels in bilateral STS, left angular gyrus, bilateral IPL, bilateral IFG and IFS, left MFG, bilateral posterior SFS and SFG, right dmPFC, and bilateral precuneus. Finally, Figure 8 shows the contribution of the social groups feature space. In all participants, the social groups feature space contributed very weakly to the joint model prediction accuracy across the cortical surface. Our results in Figures 4-8 show that there is wide variation in both how much and where each social feature space contributes to the joint model prediction accuracy. In particular, our results suggest that information about individual traits, character relationships, and subjective judgments are strongly and consistently represented in the brain. In contrast, information about social groups is weakly represented in the brain, and information about social networks is represented inconsistently in the brain across participants.

To see whether cortical voxels represent one or multiple types of social information, we simultaneously plotted the contributions of the individual traits, character relationships, and subjective judgment feature spaces on the cortical surface. Feature space

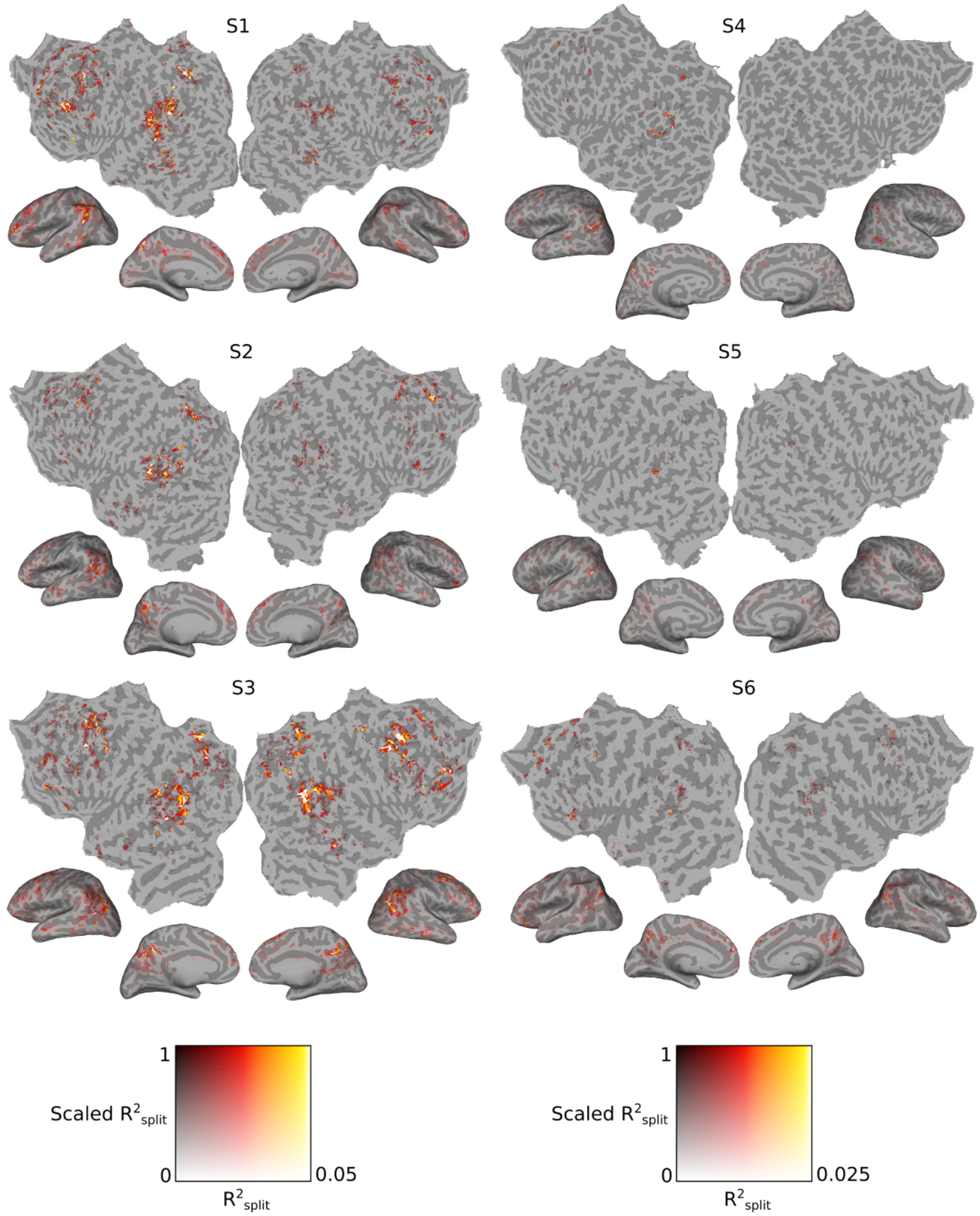


Figure 4. Contribution of the individual traits feature space to the joint model prediction accuracy across the cortical surface. The contribution of the individual traits feature space to the joint model prediction accuracy is shown on the flattened cortical surface of all six participants. The contribution is given by a 2D colormap, and the format is the same as in Figure 4. The vertical axis of the 2D colormap is given by the contribution scaled by 0.025 for participants S1-S3 and by 0.0125 for participants S4-S6. In each panel, only voxels with significant joint model prediction accuracy ($p<0.05$, FDR-corrected) are shown. In all participants, the individual traits feature space contributes to the joint model prediction accuracy in voxels in the left TPJ and left SFG/SFS. In five out of six participants, the individual traits feature space contributes to the joint model prediction accuracy in voxels in the left precuneus, left dmPFC, and right IPL.

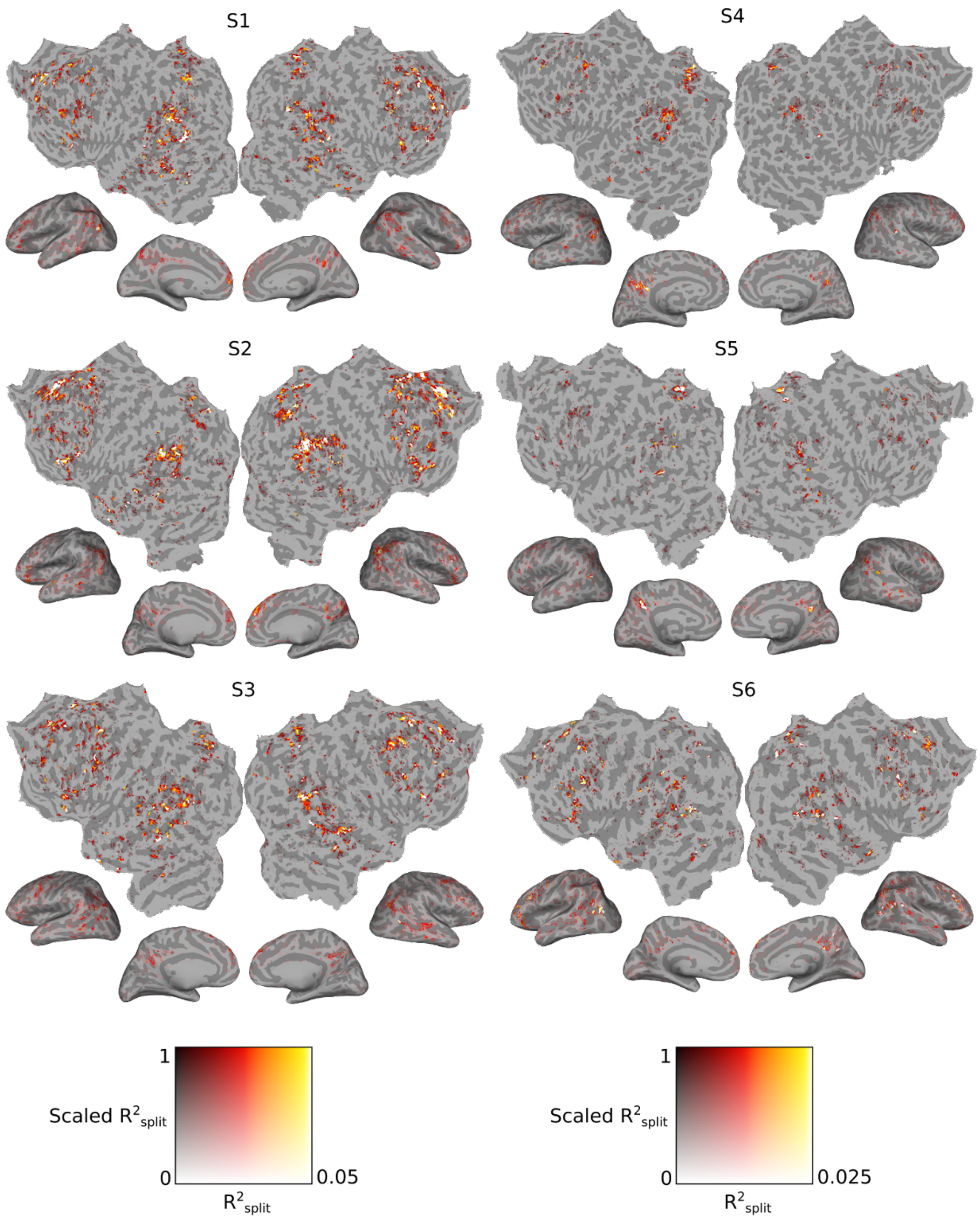


Figure 5. Contribution of the character relationships feature space to the joint model prediction accuracy across the cortical surface. The contribution of the character relationships feature space to the joint model prediction accuracy is shown on the flattened cortical surface of all six participants. The contribution is given by a 2D colormap, and the format is the same as in Figure 4. The vertical axis of the 2D colormap is given by the contribution scaled by 0.025 for participants S1-S3 and by 0.0125 for participants S4-S6. In each panel, only voxels with significant joint model prediction accuracy ($p<0.05$, FDR-corrected) are shown. In all participants, the character relationships feature space contributes to the joint model prediction accuracy in voxels in left SFS/SFG, left precuneus, right IPL, right IFS, and right precuneus. In five out of six participants, the character relationships feature space contributes to the joint model prediction accuracy in voxels in left IPL and left orbital IFG.

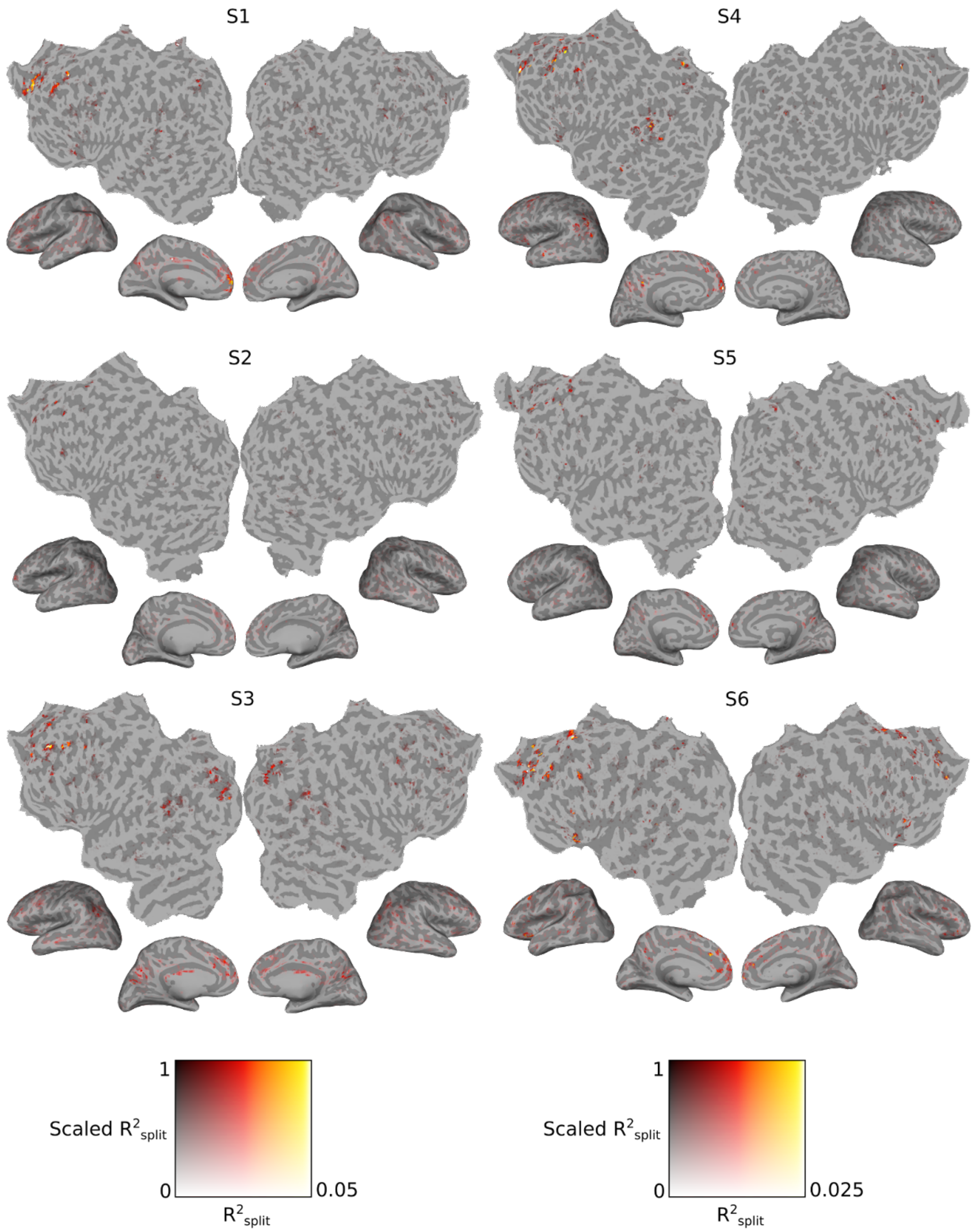


Figure 6. Contribution of the subject judgment feature space to the joint model prediction accuracy across the cortical surface. The contribution of the subject judgment feature space to the joint model prediction accuracy is shown on the flattened cortical surface of all six participants. The contribution is given by a 2D colormap, and the format is the same as in Figure 4. The vertical axis of the 2D colormap is given by the contribution scaled by 0.025 for participants S1-S3 and by 0.0125 for participants S4-S6. In each panel, only voxels with significant joint model prediction accuracy ($p<0.05$, FDR-corrected) are shown. In all participants, the subject judgment feature space contributes to the joint model prediction accuracy in voxels in left SFS/SFG and left dmPFC.

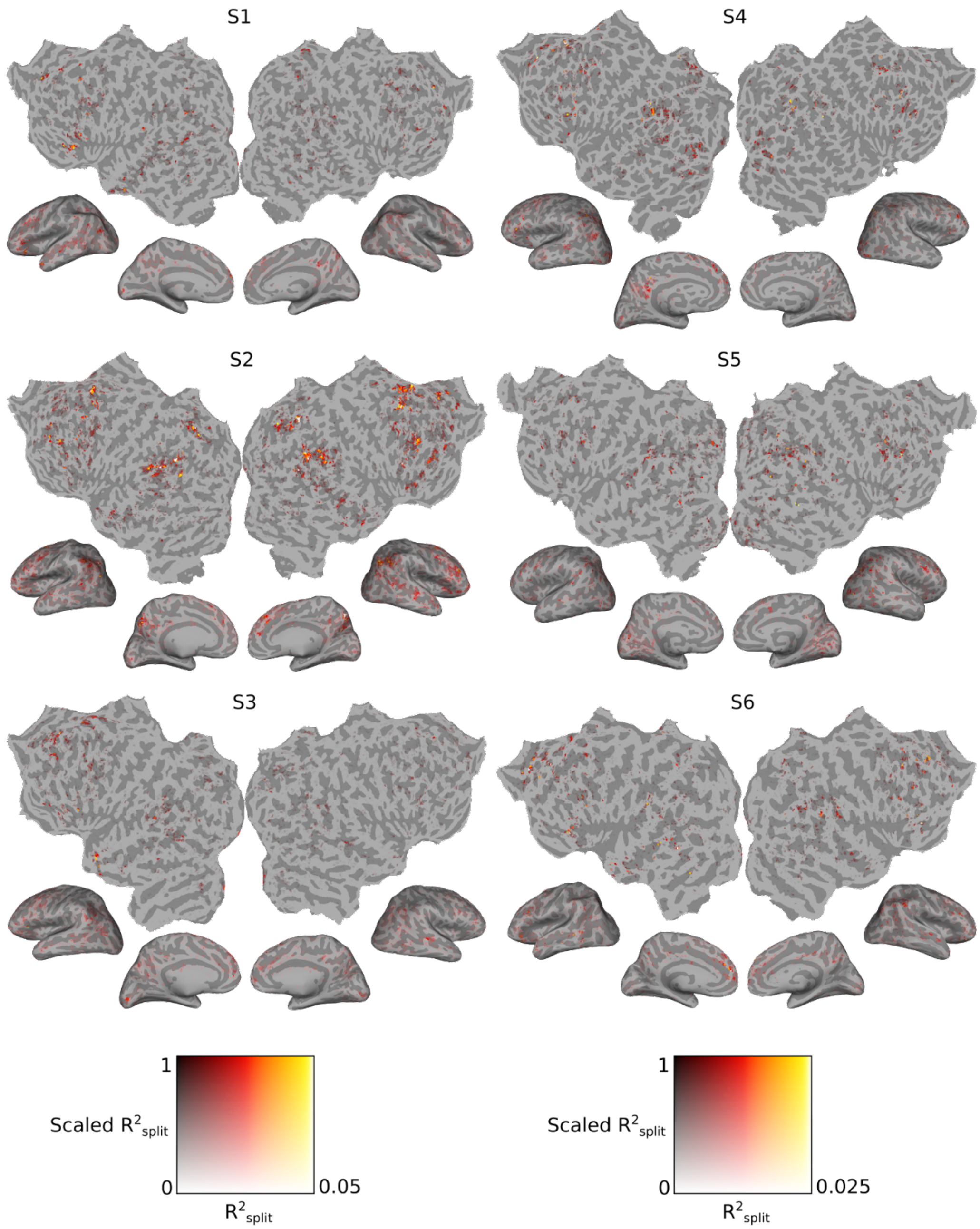


Figure 7. Contribution of the social network feature space to the joint model prediction accuracy across the cortical surface. The contribution of the social network feature space to the joint model prediction accuracy is shown on the flattened cortical surface of all six participants. The contribution is given by a 2D colormap, and the format is the same as in Figure 4. The vertical axis of the 2D colormap is given by the contribution scaled by 0.025 for participants S1-S3 and by 0.0125 for participants S4-S6. In each panel, only voxels with significant joint model prediction accuracy ($p<0.05$, FDR-corrected) are shown. In five out of six participants, the social network feature space has low to moderate contributions to the joint model prediction accuracy in scattered voxels across the cortical surface. In contrast, in subject S2, the social network feature space contributes to the joint model prediction accuracy in voxels in bilateral STS, left angular gyrus, bilateral IPL, bilateral IFG and IFS, left MFG, bilateral

posterior SFS and SFG, right dmPFC, and bilateral precuneus. These results show that the cortical representation of social network information is widely variable across individual participants.

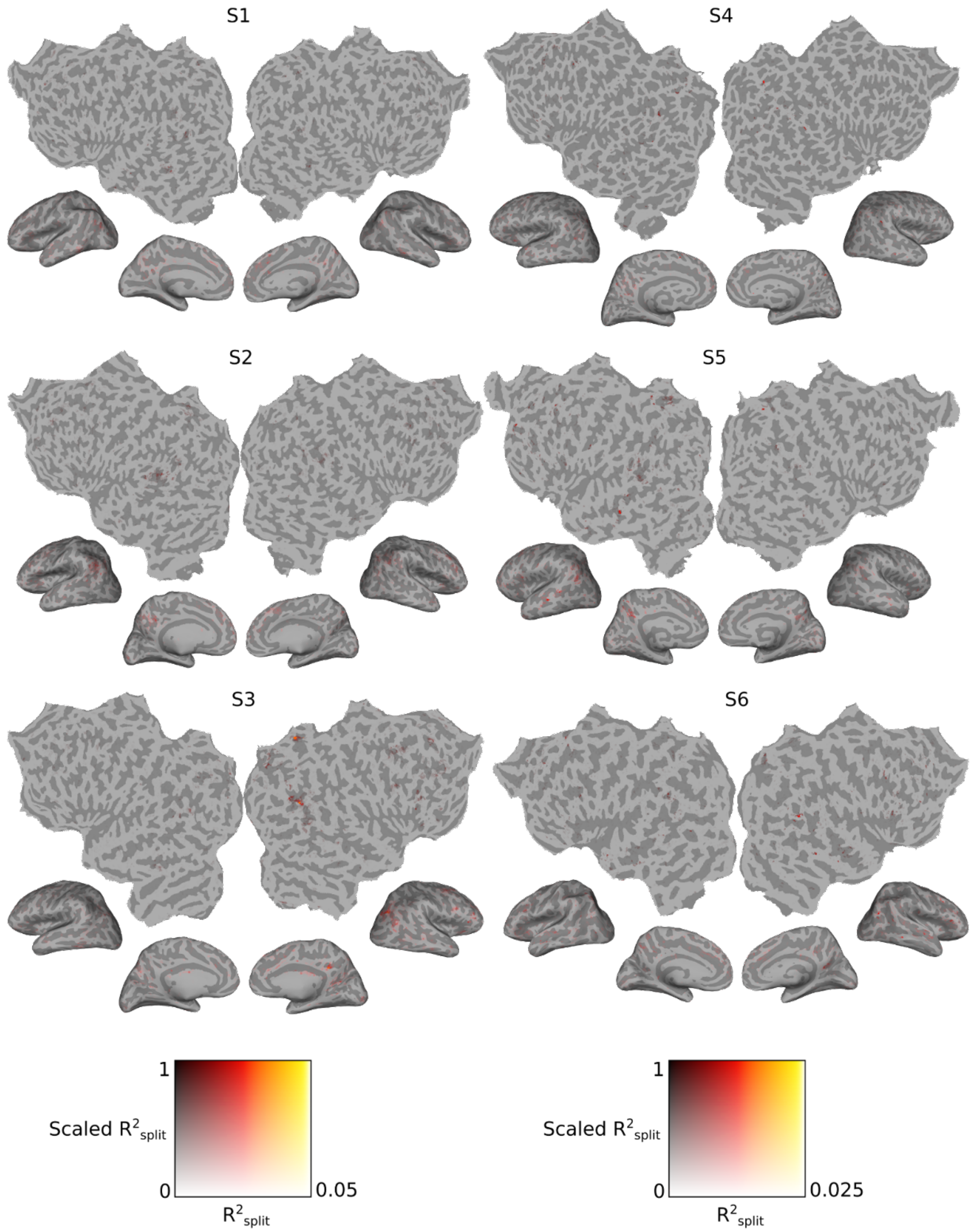


Figure 8. Contribution of the social groups feature space to the joint model prediction accuracy across the cortical surface. The contribution of the social groups feature space to the joint model prediction accuracy is shown on the flattened cortical surface of all six participants. The contribution is given by a 2D colormap, and the format is the same as in Figure 4. The vertical axis of the 2D colormap is given by the contribution scaled by 0.025 for participants S1-S3 and by 0.0125 for participants S4-S6. In each panel, only voxels with

significant joint model prediction accuracy ($p<0.05$, FDR-corrected) are shown. In all participants, the social groups feature space contributed very weakly to the joint model prediction accuracy across the cortical surface.

contributions were visualized with an RGB color scheme, and each voxel was colored according to the contributions of the individual traits (red), character relationships (green), and subjective judgments (blue) feature spaces (see Methods). Figure 9 shows this visualization for the six participants. In all participants, only one of the three feature spaces contributes to the joint model prediction accuracy in the vast majority of voxels (red, green, and blue voxels). There are very few voxels for which multiple feature spaces have comparable contributions to the joint prediction accuracy (yellow, magenta, cyan, or white voxels). The red, green, and blue voxels form distinct, localized clusters across the cortex, and these clusters subdivide many brain regions often associated with social cognition (e.g., TPJ, medial PFC). Moreover, although each feature space contributes to the joint model prediction accuracy in the same general brain regions across participants, the fine-grained pattern of feature space contributions within brain regions is different for each participant. Together, these results suggest that most cortical voxels represent only one type of social information, and these results reveal a complex map of the representation of social information that is unique to each participant.

So far, we have looked at the cortical representation of five types of social information: individual traits, character relationships, social groups, social networks, and subjective judgements. However, these five types of social information are broad, and each type of social information can be broken down into more specific subtypes of information. To get a more fine-grained view of where different types of social information are represented across the cortex, we visualized the estimated model weights of individual features across the cortical surface. We only considered features in the individual traits and character relationships feature spaces. We did not consider features in the social network and social groups feature spaces because they had very small feature space contributions in most participants, and we did not consider the subjective judgment feature space because it consists of only one feature. There were a total of seven individual features across the individual traits and character relationships feature spaces. Of the seven features, three features had estimated weights with clear patterns of selectivity across the cortical surface that were also consistent across participants. These three features were physical traits (individual traits feature space), character values (individual traits feature space), and relationship descriptions (character relationships feature space).

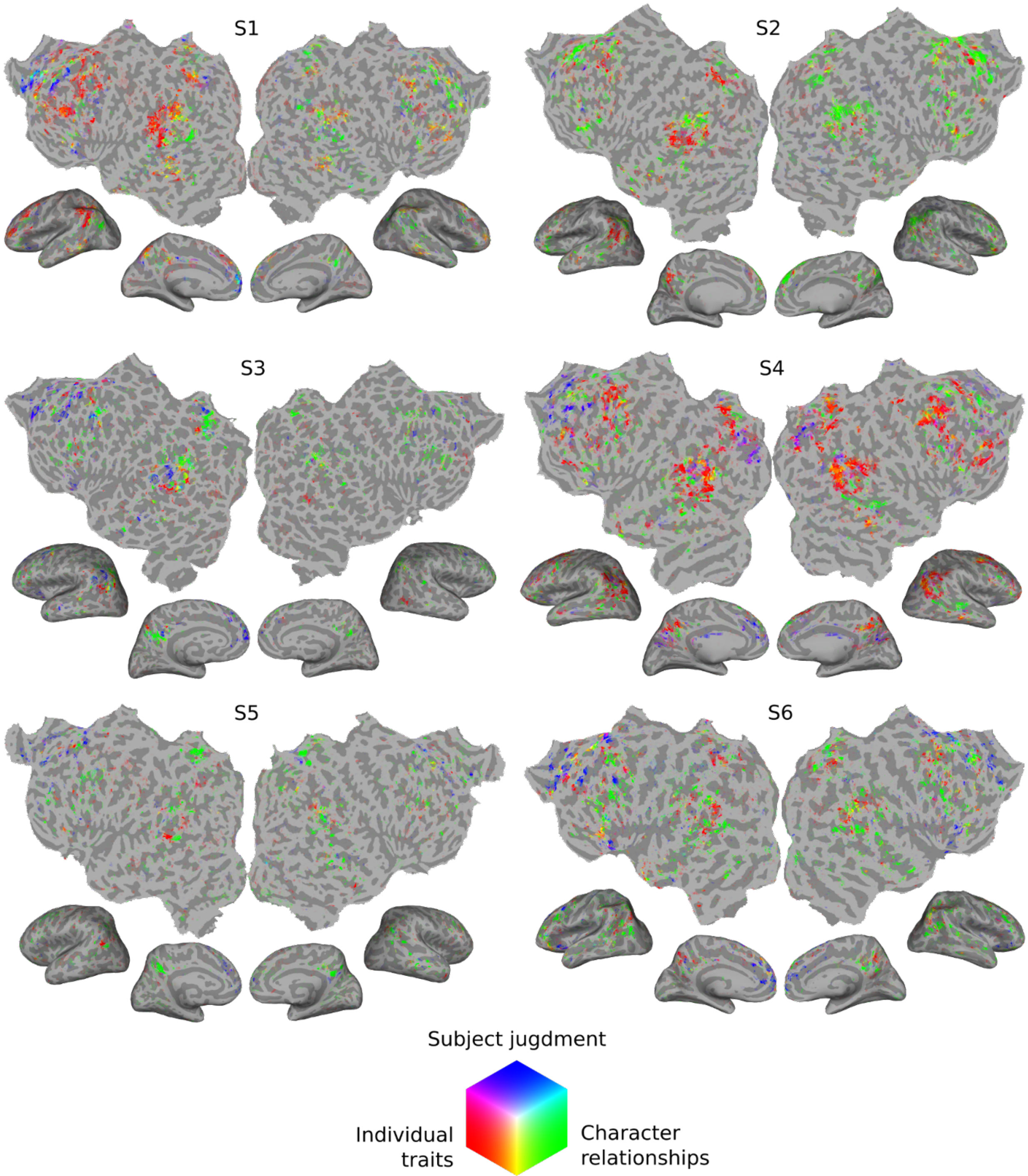


Figure 9. Visualization of the contributions of the individual traits, character relationships, and subject judgment feature spaces to the joint model prediction accuracy across the cortical surface. The contributions of the individual traits, character relationships, and subject judgment feature spaces to the joint model prediction accuracy are visualized together on the flattened cortical surfaces of all six participants. Feature space contribution is shown using an RGB color scheme, and each voxel is colored according to the contributions of the individual traits (red), character relationships (green), and subject judgment (blue) feature spaces. The opacity of the color is given by first taking the maximum of

the three feature space contributions, and then scaling that value by 0.025 for participants S1-S3 and by 0.0125 for participants S4-S6. The vast majority of voxels are colored red, green, or blue in all participants. This result shows that most cortical voxels only represent one type of social information.

The following three figures (Figures 10-12) show the estimated weights for these three features for all six participants. For each voxel, a positive estimated weight indicates that the BOLD response to the feature is above the average observed BOLD response in that voxel. In contrast, a negative weight indicates that the voxel's BOLD response to the feature is below the average observed BOLD response in that voxel. Figure 10 shows the estimated model weights for the physical traits feature for all six participants. In all participants, voxels in left IPS, left IFS and IFG, and left SFS and SFG had positive estimated weights; and voxels in left TPJ had negative estimated weights. In addition, in five out of six participants, voxels in right IFS and right dmPFC had positive estimated weights; and voxels in left SFS and SFG had negative estimated weights. Figure 11 shows the estimated model weights for the character values feature for all six participants. In all participants, voxels in left dmPFC and left IFG have positive estimated weights; and voxels in right dmPFC have negative estimated weights. In addition, in five out of six participants, a small cluster of voxels in left TPJ have positive estimated weights; and voxels in right SFG have negative estimated weights. Figure 12 shows the estimated model weights for the relationship descriptions feature for all six participants. In all participants, voxels in left STS, left IFG, left SFS and SFG, left dmPFC, bilateral TPJ, and bilateral precuneus have positive estimated weights; and voxels in left SFS and SFG, right precuneus, bilateral IPL, and bilateral IFS have negative estimated weights. In addition, in five out of six participants, voxels in right STS and right SFS and SFG have positive estimated weights; and voxels in left ITS and ITG and right MFG have negative estimated weights. Together, the results in Figures 10-12 provide a more fine-grained map of the representation of different types of social information in individual participants. For example, the individual traits feature space contributes to the joint model prediction accuracy in bilateral precuneus in participant S3. However, the physical traits feature does not have positive weights in bilateral precuneus for participant S3. This suggests that voxels in bilateral precuneus represent a different type of information about individual traits.

One of the key advantages of our study over prior studies is that we account for non-social information in our analysis. Accounting for non-social information is important because non-social information can be correlated with social information. Analyses that do not account for non-social information may mistakenly conclude that social information is represented in brain regions that actually represent non-social information. In addition, analyses that do not account for non-social information may overestimate how strongly a brain region represents social information relative to non-social information.

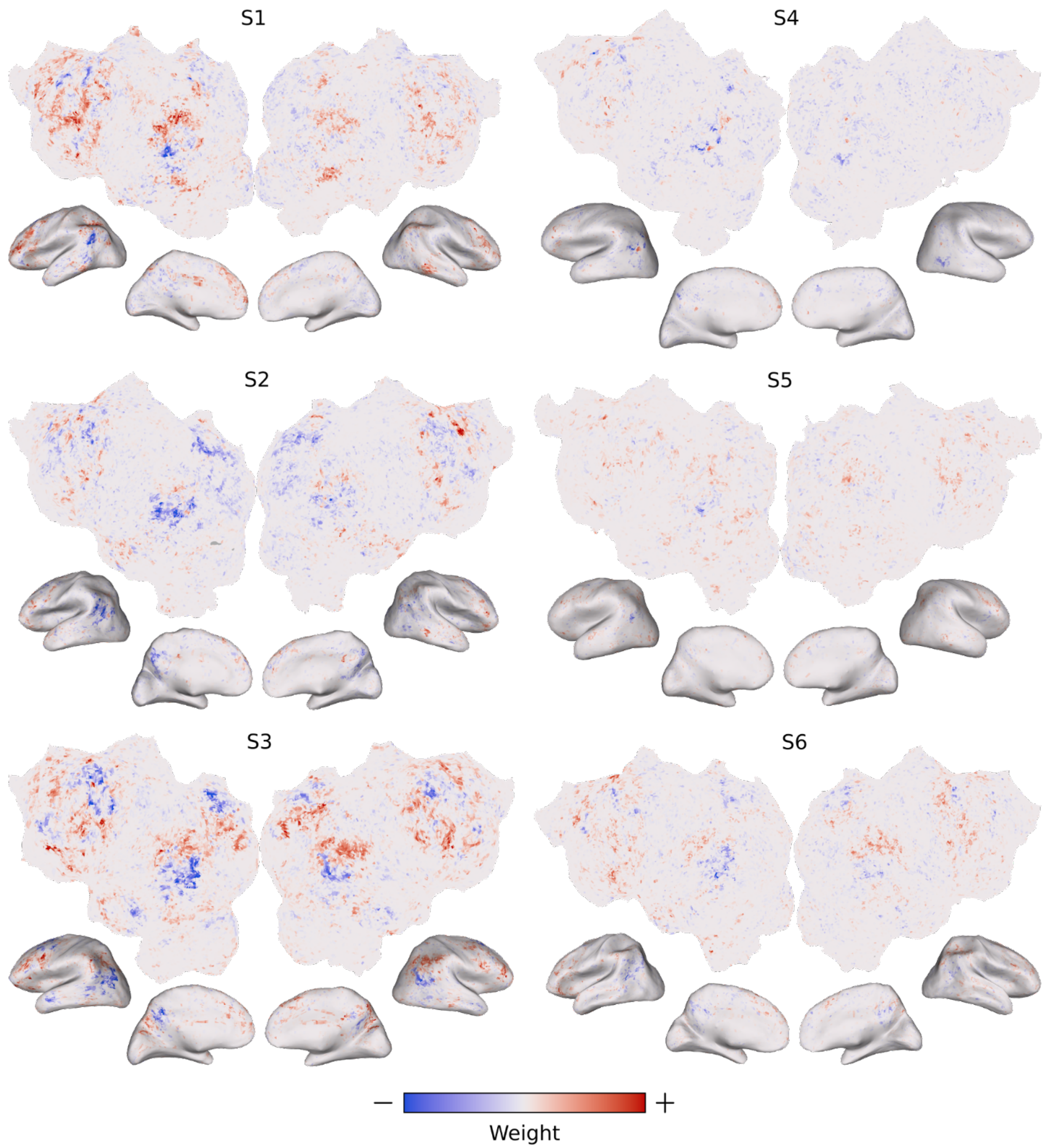


Figure 10. Estimated model weights for the physical traits feature across the cortical surface. Estimated model weights for the physical traits feature is shown on the flattened cortical surface of all six participants. The weight value is given by the color scale at the bottom. In all participants, voxels in left IPS, left IFS and IFG, and left SFS and SFG had positive estimated weights; and voxels in left TPJ had negative estimated weights. In five out of six participants, voxels in right IFS and right dmPFC had positive estimated weights; and voxels in left SFS and SFG had negative estimated weights.

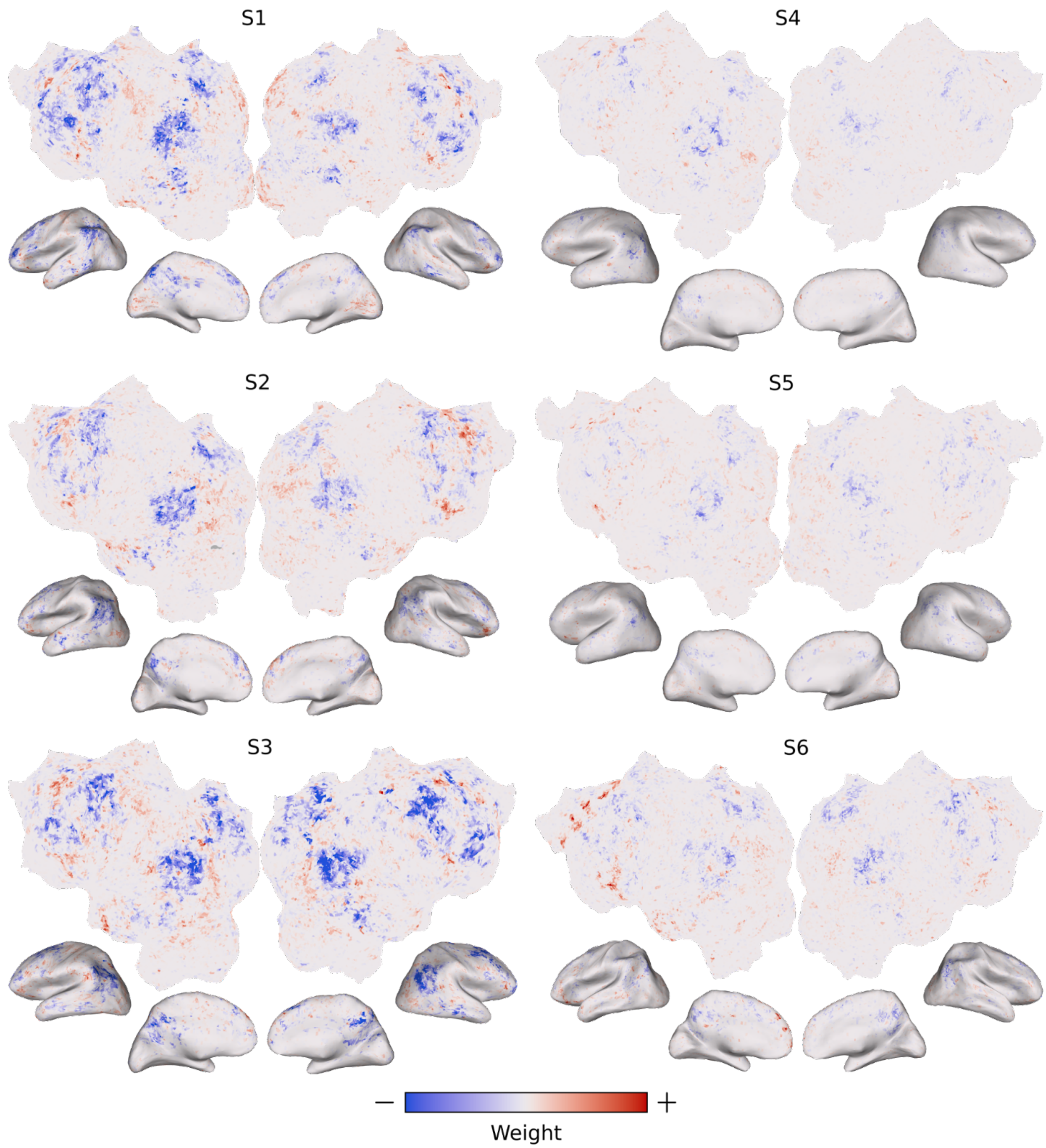


Figure 11. Estimated model weights for the character values feature across the cortical surface. Estimated model weights for the character values feature is shown on the flattened cortical surface of all six participants. The weight value is given by the color scale at the bottom. In all participants, voxels in left dmPFC and left IFG have positive estimated weights; and voxels in right dmPFC have negative estimated weights. In five out of six participants, a small cluster of voxels in left TPJ have positive estimated weights; and voxels in right SFG have negative estimated weights.

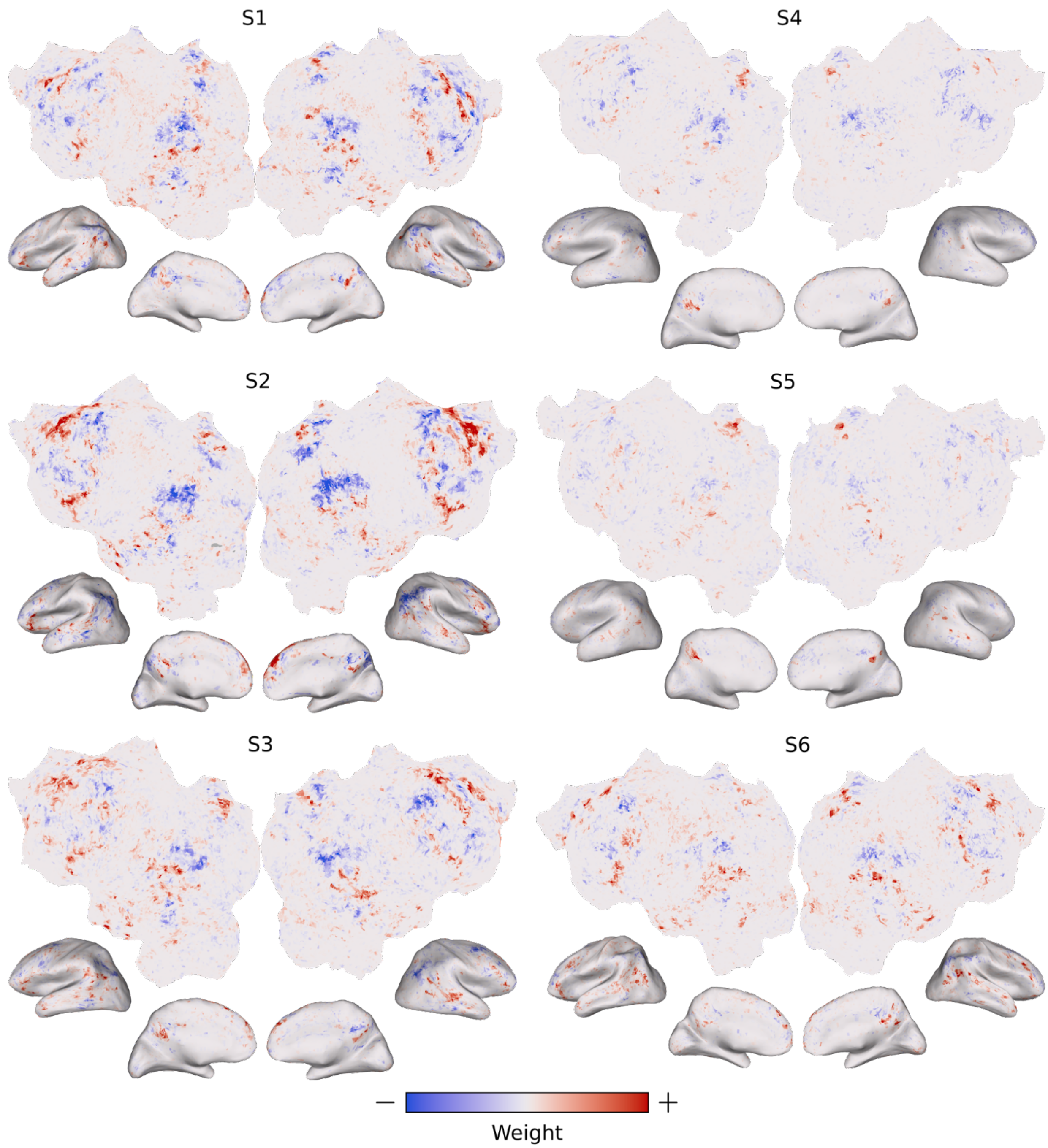


Figure 12. Estimated model weights for the relationship descriptions feature across the cortical surface. Estimated model weights for the relationship descriptions feature is shown on the flattened cortical surface of all six participants. The weight value is given by the color scale at the bottom. In all participants, voxels in left STS, left IFG, left SFS and SFG, left dmPFC, bilateral TPJ, and bilateral precuneus have positive estimated weights; and voxels in left SFS and SFG, right precuneus, bilateral IPL, and bilateral IFS have negative estimated weights. In five out of six participants, voxels in right STS and right SFS and SFG have positive estimated weights; and voxels in left ITS and ITG and right MFG have negative estimated weights.

To compare how strongly cortical voxels represent social information relative to non-social information, we compared the contributions of the five social feature spaces to the contributions of the nine non-social feature spaces. For every voxel in each participant, we first summed the contributions of the five social feature spaces and the nine non-social feature spaces separately. We then divided the two summed values by the joint model prediction accuracy to get the relative contributions of the social and non-social feature spaces, respectively. Finally, we subtracted the relative non-social feature space contribution from the relative social feature space contribution. The resulting relative contribution difference describes the relative strength of non-social and social representations in each voxel. A negative value indicates that the voxel represents non-social information more strongly than social information, a positive value indicates that the voxel represents social information more strongly than non-social information, and zero indicates that the voxel represents social and nonsocial information equally strongly. Figure 13 shows the relative contribution difference for all six participants. In all participants, voxels in bilateral visual, motor, and somatosensory cortices represent non-social information more strongly than social information. In contrast, voxels in a network of brain regions called the "social brain network" (Thornton et al., 2019) – bilateral lateral and medial prefrontal cortex, precuneus, STS, TPJ, and IPL – either represent social and non-social information equally strongly, or represent social information more strongly than non-social information have a zero or positive relative contribution difference. In addition, the precise pattern and proportion of voxels that have a positive relative contribution difference appears to be variable across participants. Together, these results show that voxels in visual, motor, and somatosensory cortices primarily represent non-social information; that many voxels in the social brain network represent social and non-social information equally strongly; and that many voxels in the social brain network represent primarily social information.

2.4 Discussion

The aim of this study was to characterize the cortical representations of five types of social information. We found that information about individual traits, character relationships, and subject judgments are strongly and consistently represented in the brain (Figure 4-6). In contrast, information about social networks is inconsistently represented in the brain across participants (Figure 7), and information about social groups is weakly represented in the brain (Figure 8). Furthermore, we found that most voxels only represent information about one of individual traits, character relationships, or subject judgments. Selectivity for these three types of social information is arranged in a complex pattern across the temporal, parietal, and prefrontal cortices, and this pattern is highly variable across participants (Figure 9). Finally, we found that many voxels that represent social information also represent non-social information (Figure 13).

Our results regarding which specific brain regions represent information about individual traits, character relationships, and subject judgments are generally consistent with results from prior neuroimaging studies. Prior studies found that individual traits are primarily represented in medial PFC and posterior medial parietal cortex (Heleven

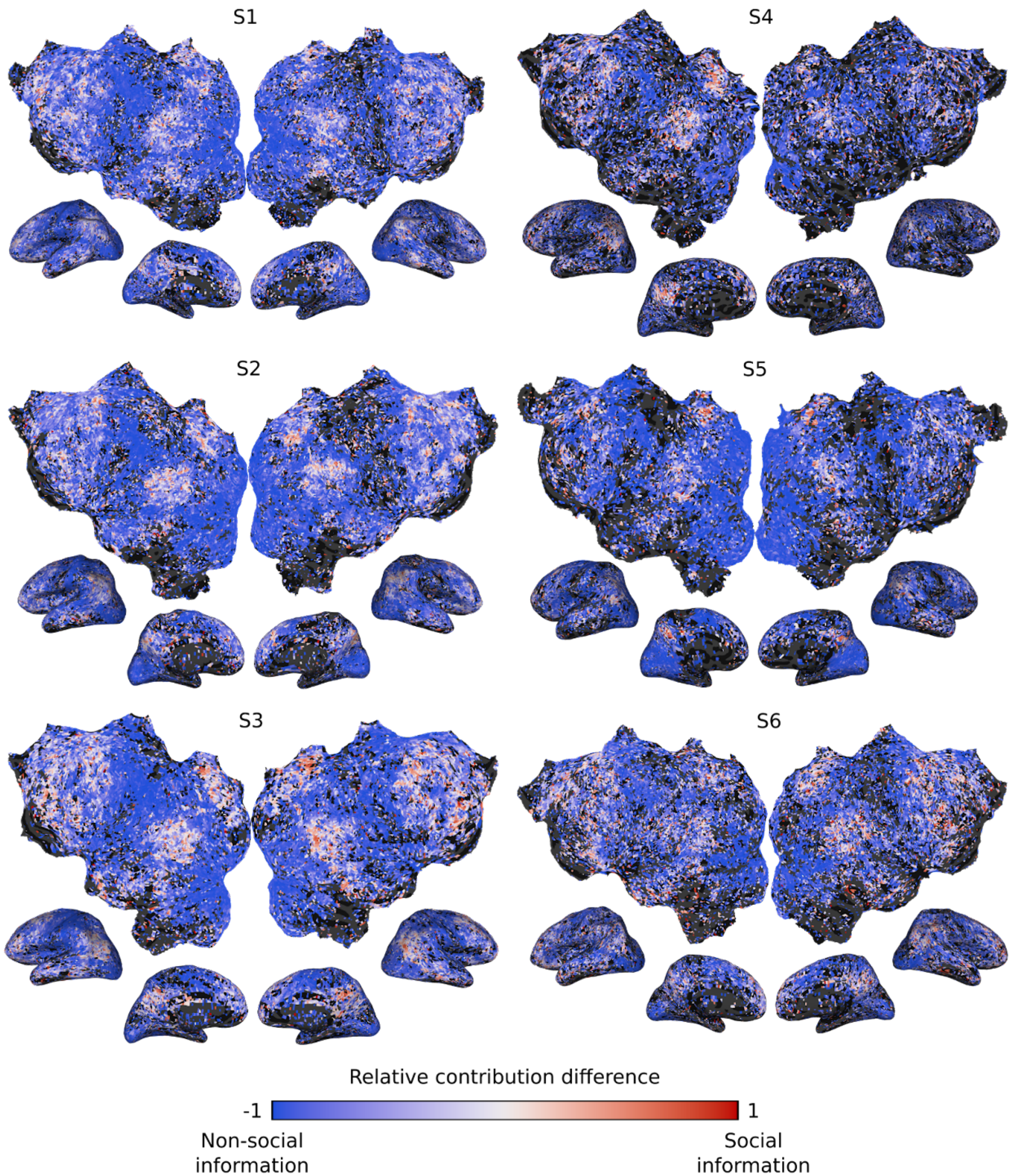


Figure 14. Relative contributions of social and non-social information to the joint model prediction accuracy across the cortical surface. For every voxel, the feature space contributions of the five social feature spaces were summed together, and the feature space contributions of the nine non-social feature spaces were summed together. The two sums were then divided by the joint model prediction accuracy to get the relative contributions of the social and non-social feature spaces, respectively. Finally, the relative contribution of the non-social feature spaces was subtracted from the relative contribution of the social feature

spaces. This relative contribution difference is plotted on the flattened cortical surface of all six participants. A negative value indicates that the voxel represents non-social information more strongly than social information, and a positive value indicates that the voxel represents social information more strongly than non-social information. A relative contribution difference value near 0 indicates that the voxel represents social and non-social information equally strongly. The relative contribution difference is given by the color scale at the bottom. Voxels that have a negative relative contribution difference appear blue, and voxels that have a positive relative contribution difference appear red. Voxels for which the joint model prediction accuracy is not significant ($p<0.05$, FDR-corrected) appear dark gray.

& Van Overwalle, 2016; Ma et al., 2014; Thornton et al., 2019; Thornton & Mitchell, 2017), character relationships are represented in left hippocampus and right precuneus (Tavares et al., 2015; Zhang et al., 2022), and self and other-knowledge (which are used during subject judgments) are represented in the medial PFC (Wagner et al., 2012). With the exception of the left hippocampus (the SNR is low in hippocampus), all of these results were replicated in five out of six participants in this study.

In our analysis, we also identified many additional brain regions that represent information about individual traits, character relationships, and subject judgments. Most of these additional regions are considered to be part of the “social brain” (Thornton et al., 2019), and they include left TPJ, left SFS and SFG, and right IPL for individual traits; left SFS and SFG, left precuneus, bilateral IPL, right IFS, and left orbital IFG for character relationships; and left SFS and SFG for subject judgments.

Prior studies most likely did not identify these brain regions because of three methodological differences. First, we did not smooth our data in this study. We analyzed data for each participant in their native brain space, and we did not spatially smooth the data across voxels. In contrast, almost all prior studies transformed their data into a standard brain space and spatially smoothed the data across voxels before analysis. These transformation and smoothing procedures can incorrectly assign signal to voxels and average away meaningful signal and individual variability. Thus, past studies may have failed to identify the additional brain regions we identified in this study because the signal in these regions was averaged out.

Second, we collected a relatively large amount of fMRI data per participant for six participants. In contrast, prior studies collected a small amount of fMRI data per participant from many (15-30) participants. Because fMRI data is noisy, these studies transformed their data into a common brain space (to average across participants) and/or spatially smoothed their data to observe the effects of interest. However, as discussed in the previous point, smoothing fMRI data can average out the effects of interest.

Finally, our experiment contained a large number of trials, and the trial questions covered a wide range of topics for each type of social information. In contrast, participants in most prior studies performed relatively few trials, so the experiments in those studies could only probe small parts of each type of social information. The additional brain regions we identified in this study could represent parts of each type of social information that were not probed by prior studies.

Our result that information about social groups is weakly represented in the brain is inconsistent with prior studies. Most prior studies of social group information have focused on the representation of stereotypes.These studies have primarily found that information about stereotypes is represented in the medial PFC and the anterior temporal lobes (Amodio, 2014; Delplanque et al., 2019; Spiers et al., 2017). In addition, one study found that stereotype information is represented in the orbitofrontal cortex (Kobayashi et al., 2022), and one study found that stereotype information is represented in anterior temporal lobe, TPJ, and posterior cingulate cortex (Van der Cruyssen et al., 2015). The inconsistencies between our study and prior studies is most likely due to two methodological differences. First, most prior studies collected very little data from many (15-30) participants and analyzed their data at the group level. As discussed earlier, transforming data from an individual brain space into a common brain space can incorrectly assign signals to voxels. Thus, group-level analyses may identify effects that are only true at the group level and not for any individual participant. Second, most prior studies used a contrast analysis or repetition suppression to identify brain regions that represent stereotype information. The success of these analyses depends on ensuring that the specific cognitive process of interest (stereotype representation) is isolated. However, there is no way to empirically verify that the cognitive process of interest is actually isolated in these study designs. Thus, the brain regions identified in prior studies could represent information unrelated to stereotypes.

Surprisingly, only one out of six participants in this study has a strong cortical representation of social network information. This result is in stark contrast to a recent high-profile study that mapped representations of individual social network metrics to different regions of the brain (Parkinson et al., 2017). In this one participant, social network information is represented in bilateral STS, bilateral IPL, bilateral IFS and IFG, bilateral SFS and SFG, bilateral precuneus, left angular gyrus, left MFG, and right dmPFC. With the exception of bilateral SFS and SFG, these regions are consistent with the brain regions identified in Parkinson et al. (2017). This suggests that the inconsistencies between our results and those in Parkinson et al. (2017) could be due to individual variability in the cortical representation of social network information. It is also possible that the experimental design in Parkinson et al. (2017) is more effective at evoking representations of social network information in the brain than the experimental design in this study. However, it is impossible to tell between these two possibilities, because Parkinson et al. (2017) did not report results in individual participants.

Other factors that could contribute to the inconsistencies included differences in experimental design and analytical methods between this study and Parkinson et al. (2017). There are three large differences between the experimental design in this study and the experimental design in Parkinson et al. (2017). First, Parkinson et al. (2017) recruited their participants from a cohort of 277 MBA students, and they based their experiment on the real-life social network of that cohort. In contrast, our experiment was based on the fictional Harry Potter social network. Second, in Parkinson et al.

(2017), participants watched short video clips of individuals in the MBA cohort. In contrast, participants performed a textual question answering task about Harry Potter characters and social groups in this study. Finally, in Parkinson et al. (2017), each participant only saw video clips of 12 individuals in the MBA cohort. In contrast, each participant answered 1120 questions about 21 characters and 13 social groups in this study. The results in Parkinson et al. (2017) could therefore be biased by their limited sampling of the MBA cohort.

There are also three large differences between the analysis methods used in this study and those used in Parkinson et al. (2017). First, Parkinson et al. (2017) used a combination of general linear models (GLMs) and representational similarity analysis (RSA) (Kriegeskorte et al., 2008) to analyze their data. In contrast, we used a voxelwise encoding model approach to analyze our data. Second, Parkinson et al. (2017) analyzed their data at the group level, and they smoothed their data with a 4-mm full-width at half-maximum Gaussian kernel. In contrast, we analyzed our data in individual participants and did not spatially smooth data across voxels. Finally, Parkinson et al. (2017), did not account for non-social cognitive processes that occurred during their experiment in their analysis. In contrast, we included feature spaces that captured linguistic information, participant behavior, and experimental parameters in our encoding model.

We hypothesize that this last methodological difference, accounting for non-social cognitive processes during the experiment, likely played a large role in the inconsistencies between our results and those in Parkinson et al. (2017) for two reasons. First, non-social cognitive processes in Parkinson et al. (2017) are likely correlated with social network metrics. For example, individuals with high eigenvector centrality may have particular facial features or movement patterns, and as a result these non-social visual features may be highly correlated with eigencentrality. Thus, BOLD activity that appears to represent eigenvector centrality may instead represent visual features. Second, in this study, we found that the nine non-social feature spaces have a large contribution to the joint model prediction accuracy in many brain regions (Figure 14). The experiment in Parkinson et al. (2017) contained some of the same types of non-social information as this study, such as the identity of the individual in each trial and participant button presses. In addition, studies have shown that low-level visual models and visual semantic models explain a comparable proportion of the variance in the BOLD response during movie watching (Huth et al., 2012; Nishimoto et al., 2011). Thus, it is likely that a large part of the variance in the BOLD responses collected in Parkinson et al. (2017) can be explained by non-social information.

One of our most striking results is that most cortical voxels only represent one type of social information, and that these voxels have a complex spatial organization across the cortical surface (Figure 9). To our knowledge, this result provides the first high-resolution map of social information representation in individual participants. These maps can help refine results from prior studies of the representation of social information. Many prior studies that investigated different types of social information independently identified the same brain regions. For example, (Kobayashi et al., 2022) found that medial PFC represents social groups, and (Thornton & Mitchell, 2017) found that the medial PFC represents self-related knowledge. However, because these studies only reported statistical significance, it was unclear if medial PFC represented both types of social information equally strongly, or if specific subregions of the medial PFC preferentially represented one of these types of social information. In this study, we see that separate subregions of the medial PFC represent individual traits and subject judgments. In addition, some voxels in the medial PFC represent information about character relationships. The specific locations of these subregions in the medial PFC are highly variable across the six participants in this study. This variability across participants is also present in the rest of the brain. This suggests that the cortical representation of social information is organized uniquely for each individual; however, further investigation is needed with more participants.

One limitation of our results is that the reported joint model prediction accuracy and feature space contribution values are not corrected by the noise ceiling. The noise ceiling of a voxel is the amount of variance in its BOLD response that could be explained by the perfect encoding model (i.e., the maximum possible prediction accuracy). The noise ceiling is affected by several sources of variability in the BOLD data, including magnetic inhomogeneity, proximity to blood vessels, voxel response variability, and subject attention. Thus, the joint model prediction accuracy and feature space contribution values reported here have a downward bias. Typically, the noise ceiling is approximated by taking the correlation between each pair of BOLD responses to repetitions of a fixed stimulus, and then taking the mean of the pairwise correlation between repeats (A. Hsu et al., 2004; Lage-Castellanos et al., 2019). However, it is impossible to repeat the stimulus in our experimental paradigm. This is because the presentation timing of each trial depends on the participant's response time in the previous trial. It is possible to reduce variability between repeated presentations of the stimulus by fixing the presentation timing of each trial. We performed this version of the experiment in a pilot version of this study. However, we found that fixing the presentation timing of each trial evoked a strong BOLD response that represented whether or not there was text on the screen. This "text" or "no text" response swamped out any other interesting information in the BOLD response.

Another limitation of these results is that the stimulus questions for each of the five types of social information were generated by the authors. Thus, the categorization of each stimulus question may reflect the personal biases of the authors. For example, some stimulus questions may be relevant for more than one type of social information. Other stimulus questions may be more relevant for types of social information outside of those explicitly studied in this experiment. Therefore, social feature spaces based on a different organization of the stimulus questions may predict voxel activity better than our five social feature spaces. The voxelwise modeling framework provides a straightforward method for evaluating alternative social feature spaces by comparing model prediction accuracy. Therefore, a valuable future direction would be to investigate social feature spaces based on alternative organizations of the stimulus questions.

A final limitation of this study concerns the experimental design. In this study, social information was modeled at the level of the five types of social information. Each type of social information contained multiple question subgroups, but there were too few trials per question subgroup to model the question subgroups individually. Therefore, a valuable future direction would be to conduct a longer, more extensive experiment that has many (>30) trials for each question subgroup. This would allow us to model each question subgroup individually and create a more detailed map of the cortical representation of social information.

2.5 Tables

Table 1. Organization of question templates

Social information type	Question subgroup	Question sub-subgroup	Question template
Individual Traits	Character Physical Traits	Age	How old is [character]?
		Gender	How masculine is [character]?
			How feminine is [character]?
		Lineage	Is [character] a Muggle?
			Is [character] a wizard or witch?
			Is [character] a non-human magical creature?
			Is [character] a Squib
		Mental Health	How is [character]'s physical health?
		Physical Health	How is [character]'s physical health?
	Character Social Traits	Respect	How much do characters respect [character]?
			How much prestige does [character] have?
		Power	How much power does [character] have?
		Economic Status	How wealthy is [character]?
		Education	How educated is [character]?
		Interests	How interested is [character] in Quidditch?
			How interested is [character] in academics?
			How interested is [character] in the Dark Arts?
	Character Values	Self-Direction	How much does [character] value independence?

			How much does [character] value curiosity?
			How much does [character] value creativity?
		Stimulation	How much does [character] value novelty?
			How much does [character] value adventure?
			How much does [character] value excitement?
		Hedonism	How much does [character] value enjoying life?
			How much does [character] value pleasure?
			How much does [character] value self-indulgence?
		Achievement	How much does [character] value being competent?
			How much does [character] value ambition?
			How much does [character] value outward achievements?
		Power	How much does [character] value authority?
			How much does [character] value wealth?
			How much does [character] value controlling others?
		Security	How much does [character] value cleanliness?
			How much does [character] value security?
			How much does [character] value social order?
		Conformity	How much does [character] value meeting obligations?
			How much does [character] value politeness?

			How much does [character] value self-discipline?
		Tradition	How much does [character] value tradition?
			How much does [character] value cultural customs?
			How much does [character] value humility?
		Benevolence	How much does [character] value being dependable?
			How much does [character] value loyalty to friends?
			How much does [character] value being helpful?
		Universalism	How much does [character] value social justice?
			How much does [character] value protecting the environment?
			How much does [character] value tolerance of others?
Character Relationships	Social Roles	Family Relationship	Is [character] [other character]'s parent?
			Is [character] [other character]'s aunt/uncle?
			Is [character] [other character]'s cousin?
			Is [character] [other character]'s sibling?
			Would [character] describe [other character] as their parent?
			Would [character] describe [other character] as their aunt/uncle?
			Would [character] describe [other character] as their cousin?
			Would [character] describe [other character] as their sibling?
		Non-Kin Personal Relationship	Is [character] [other character]'s friend?

			Is [character] [other character]'s enemy?
			Is [character] [other character]'s teacher?
			Is [character] [other character]'s acquaintance?
			Would [character] describe [other character] as their friend?
			Would [character] describe [other character] as their enemy?
			Would [character] describe [other character] as their teacher?
			Would [character] describe [other character] as their acquaintance?
		Work Relationship	Is [character] [other character]'s master?
			Is [character] [other character]'s colleague?
			Is [character] [other character]'s superior?
			Is [character] [other character]'s servant?
			Would [character] describe [other character] as their master?
			Would [character] describe [other character] as their colleague?
			Would [character] describe [other character] as their superior?
			Would [character] describe [other character] as their servant?
		Romantic Relationship	Is [character] [other character]'s crush?
			Is [character] [other character]'s date?
			Is [character] [other character]'s ex?
			Is [character] [other character]'s romantic partner?

			Would [character] describe [other character] as their crush?
			Would [character] describe [other character] as their date?
			Would [character] describe [other character] as their ex?
			Would [character] describe [other character] as their romantic partner?
		Geographic Relationship	Are [character] and [other character] from the same country?
			Are [character] and [other character] from the same neighborhood?
	Social Relationship Descriptions	Make Fun Of	Would [character] mock [other character]?
			Would [character] call [other character] names?
			Would [character] ridicule [other character]?
			Would [character] insult [other character]?
		Dominate	Would [character] argue with [other character]?
			Would [character] provoke [other character]?
			Would [character] criticize [other character]?
			Would [character] order [other character] around?
		Oppose/Fight	Would [character] oppose [other character]?
			Would [character] fight [other character]?
			Would [character] challenge [other character]?
			Would [character] question [other character]?

		Act	Would [character] persuade [other character] of something?
			Would [character] be honest with [other character]?
			Would [character] defend [other character]?
		Encourage/Support	Would [character] stand up for [other character]?
			Would [character] motivate [other character]?
			Would [character] encourage [other character]?
			Would [character] help [other character]?
		Protect/Comfort	Would [character] support [other character]?
			Would [character] reassure [other character]?
			Would [character] comfort [other character]?
			Would [character] protect [other character]?
		Agree/Comply	Would [character] go along with [other character]'s wishes?
			Would [character] put up with [other character]?
		Conform/Submit	Would [character] give in to [other character]?
			Would [character] yield to [other character]?
			Would [character] restrain themselves around [other character]?
		Fear/Awe	Would [character] look up to [other character]?
			Would [character] hold [other character] in awe?
		Betray	Would [character] betray [other character]?

			Would [character] cheat [other character]?
			Would [character] lie to [other character]?
			Would [character] hide things from [other character]?
		Fool/Exploit	Would [character] fool [other character]?
			Would [character] ignore [other character]?
			Would [character] slander [other character]?
			Would [character] exploit [other character]?
		Look Down On	Would [character] laugh at [other character]?
			Would [character] hurt [other character]?
			Would [character] disparage [other character]?
	Family And Partners	Character Family Interaction Frequency	How often does [character] interact with family?
		Character Family Closeness	Does [character] have a close relationship with their family?
		Character Have A Partner	Does [character] have a partner?
	Friends	Character Close Friend Interaction Frequency	How often does [character] interact with their closest friends?
		Character Ask For Help	Would [character] go to [other character] for help?
		Character Confidant Identity	Does [character] discuss important matters with [other character]?

		Character Ask For Help In Bad Spot	Would [character] go to [other character] first if [character] were sick?
			Would [character] go to [other character] first if [character] were depressed?
			Would [character] go to [other character] first if [character] were in a bad spot?
		Relationship Duration	Has [character] known [other character] for a long time?
Subject Judgment	Subject Related	Subject Character Friendship	Would you be friends with [character]?
		Subject Character Cultural Background	Do you and [character] have similar cultural backgrounds?
		Subject Character Socioeconomic Background	Do you and [character] have similar socioeconomic backgrounds?
		Subject Character Age	Are you similar in age to [character]?
		Subject Character Interests	Do you and [character] share similar interests?
		Subject Character Personality	Do you and [character] have similar personalities?
		Subject Character Life Events	Have you and [character] experienced similar life events?
		Subject Character Beliefs	Do you and [character] have similar beliefs?
		Subject Character Values	Do you and [character] have similar values?
		Subject Group Fit	Would you fit in with [group article] [group]?

			Would you join [group article] [group]?
Social Network	Degree Centrality	Well Known	How well-known is [character]?
		Count Regular Interactions	How many characters does [character] interact with regularly?
		Count Famousness	How many characters know of [character]?
		Popularity	How popular is [character]?
		Count Typical Day Interactions	How many characters does [character] interact with on a typical day?
		Count Direct Interactions	How many characters has [character] interacted with directly?
	Eigenvector Centrality	Well-Connected ness	How well-connected is [character]?
		Well-Connected Interaction	Does [character] regularly interact with many well-connected characters?
	Cross-Clique Centrality	Count Social Group Membership	How many different social groups is [character] part of?
		Count Social Group Knowledge	How many social groups does [character] know any members of?
	Brokerage	Social Group Interaction Frequency	Do [character]'s social groups interact regularly with each other?
		Specific Social Group Membership	Is [character] a member of [group article] [group]?
		Social Group Bridge	Does [character] act as a bridge for different social groups?
		Individual Interaction Frequency	Does [character] interact with many characters that don't interact with each other?
		Character Information Sources	Does [character] usually get information from a variety sources?

		Character Information Usefulness	How many characters get their information from [character]?
		Character Critical To Events	How critical is [character] to the events of the story?
	Clustering	Within Group Interaction Regularity	How often do those in [character]'s main social group interact?
		Character Other Character Interactions	Do those that [character] interacts with interact with each other?
		Character Friend Interactions	How many of [character]'s friends are also friends?
			Are [character]'s friends also friends with each other?
		Character Acquaintance Interactions	How many of [character]'s acquaintances know each other?
	Betweeness	Character Influence	How much influence does [character] have over other characters?
		Character Information Spread Usefulness	How useful is [character] for getting the word out about an event?
		Character Ease Of Shaping Impressions	How much does [character] shape others' impressions of events?
		Character Event Knowledge Speed	Does [character] often know about important events quickly?
		Character Contact Usefulness	Would somebody go through [character] to contact someone they didn't know?
		Character Power	How much power does [character] have over others?
	Closeness	Character Knowledge Likelihood	How likely is it that [character] would know a randomly picked character?

		Character Average Distance	How many degrees of separation lie between [character] and other characters?
	Homophily (Interactions)	Interaction Character And Character Similarity	How similar are most characters [character] interacts with to [character]?
		Character Interaction Share Beliefs	Does [character] mostly interact with characters who share their beliefs?
		Character Interaction Same Socioeconomic Class	Does [character] mostly interact with characters in the same socioeconomic class?
		Character Interaction Same House	Does [character] mostly interact with characters from the same House?
		Character Interaction Same Age	Are most characters [character] interacts with about the same age?
		Character Interaction Same Interests	Does [character] mostly interact with those that have similar interests?
			Does [character] mostly interact with those that do similar activities?
	Homophily (Friends)	Character Friend Similarity	How similar are [character]'s friends to [character]?
		Character Friends Share Beliefs	Do most of [character]'s friends share their beliefs?
		Character Friends Same Socioeconomic Class	Are most of [character]'s friends in the same social class?
		Character Friends Same House	Are most of [character]'s friends in the same House?

		Character Friends Same Age	Are most of [character]'s friends the same age?
		Character Friends Same Interests	How many of [character]'s friends have similar interests as [character]?
			How many of [character]'s friends do similar activities as [character]?
	Balancedness	Count Friends Are Not Friends	How many of [character]'s friends dislike each other?
		Mutual Enemies Of Character And Friends	Do [character] and their friends have mutual enemies?
		Character Work With Enemy Against Mutual Enemy Willingness	Would [character] work with an enemy to fight a mutual enemy?
		Character Different Social Groups Harmony	Do [character]'s different social groups get along?
Social Groups	Social Groups	Social Group Homophily	Are members of [group article] [group] similar to each other?
		Group Member Meet Frequency	How often do members of [group article] [group] meet?
		Count Group Membership	How many characters are members of [group article] [group]?
		Group Clear Power Structure	Does [group article] [group] have a clear power structure?
		Group Group Interactions	How involved with other groups is [group article] [group]?
			How isolated is [group article] [group]?
		Group Tight Knit	Is [group article] [group] a tight-knit group?

Table 2. List of characters and social groups

Characters	Social groups
Aunt Petunia	Dursley family
Dobby	Gryffindor
Draco	Gryffindor Quidditch team
Dudley	Hogwarts faculty
Dumbledore	Hogwarts staff
Filch	Hogwarts student body
Ginny	Hufflepuff
Hagrid	Malfoy family
Harry	Ravenclaw
Hermione	Slytherin
Lockhart	Slytherin Quidditch team
Lucius Malfoy	Voldemort's followers
McGonagall	Weasley family
Moaning Myrtle	
Neville	
Quirrell	
Ron	
Snape	
Uncle Vernon	
Voldemort	
[Participant's name]	

Table 3. Attributes used to compute homophily

Attribute category	Attribute	Scaling factor
Interests	Quidditch	1
	Chess	1
	Academics	1
	Animals	1
	Plants	1
	Potions	1
	Dark arts	1
Social group membership	Weasley Family	3
	Dursley Family	3
	Malfoy Family	3
	Other Family	3
	Voldemort's followers	3
	Hogwarts student body	3
	Hogwarts staff	3
	Hogwarts professors	3
	Hogwarts - other groups	3
	Gryffindor Quidditch team	3
	Slytherin Quidditch team	3
	Other Quidditch team	3
	Gryffindor House	3
	Slytherin House	3
	Hufflepuff House	3
	Ravenclaw House	3
Social traits	respect, prestige	2
	power, dominance	2
	economic status	2
	education	2
	occupation	2
Physical traits	age	4
	gender	2
	lineage	2

Values	Self-enhancement (power, pleasure, outward achievement)	4
	Conservation (tradition, security, conformity)	4
	Self-transcendence (caring about others/community)	4
	Openness to change (independence, excitement, challenges)	4
Personality (Big 5)	Openness	4
	Conscientiousness	4
	Extroversion	4
	Agreeableness	4
	Neuroticism	4

Table 4. Number of experiment questions from each question subgroup

Question subgroup	Number of question templates
Character Physical Traits	46
Character Social Traits	46
Character Values	120
Family And Partners	45
Friends	45
Balancedness	60
Betweeness	60
Brokerage	60
Closeness	40
Clustering	60
Cross-clique Centrality	40
Degree Centrality	60
Eigenvector Centrality	40
Groups	60
Homophily Friends	50
Homophily Interactions	50
Social Relationship Descriptions	118
Social Roles	60
Subject Related	60

Table 5. List of feature spaces

Feature space	Description	Number of features
Individual traits	Binary feature indicating the question subgroup of the presented question. Only Individual Traits question subgroups are included.	3
Character relationships	Binary feature indicating the question subgroup of the presented question. Only Character Relationships question subgroups are included.	4
Subject judgment	Binary feature indicating the question subgroup of the presented question. Only Subject Judgment question subgroups are included.	1
Social network	Binary feature indicating the question subgroup of the presented question. Only Social Network question subgroups are included.	10
Social groups	Binary feature indicating the question subgroup of the presented question. Only Social Groups question subgroups are included.	1
Language semantics	Word embedding representation of the words in the presented question. Word embeddings were created from word co-occurence statistics in a large text corpus (Huth et al., 2016).	985
Number of letters	Number of letters displayed.	1
Word length variation	Variance of the length of words displayed per TR.	1
Letter identity	Binary feature indicating the identity of displayed letters.	26
Number of words	Number of words displayed.	1
Character and social group identity	Binary feature indicating the character(s) or social group asked about in the presented question.	34
Question duration	Length of time to present the trial question.	1
Response time	Elapsed time between the end of the question presentation and the participant's response.	1
Button response	Binary feature indicating the participant's response.	5

Chapter 3

Mapping the representation of the self and different types of others in the brain

3.1 Introduction

The ability to distinguish the self from other people is fundamental to social cognition. Many prior neuroimaging studies have investigated whether the brain represents information about the self separately from information about others. Overall, results from these studies suggest that the ventromedial prefrontal cortex (vmPFC) represents self knowledge, while the dorsomedial prefrontal cortex (dmPFC) represents other knowledge (Wagner et al., 2012). However, there is significant overlap between brain regions that have been implicated in representing self knowledge and those that have been implicated in representing other knowledge (Denny et al., 2012; Wagner et al., 2012). Furthermore, relatively few studies have directly compared the brain representations of self knowledge and other knowledge directly. Studies that have directly compared the representations of self and other knowledge have identified several brain regions distributed across medial prefrontal, parietal, temporal, and cingulate cortices that have greater activations during self-referential cognition compared to other-referential cognition (or vice versa) (Benoit et al., 2010; D'Argembeau et al., 2007; Heatherton et al., 2006; Krienen et al., 2010; Powell et al., 2010; Schmitz et al., 2004; Vanderwal et al., 2008). However, there is little agreement in the brain regions identified across these studies. Thus, it is unclear to what extent the brain representation of self knowledge is separate from the brain representation of other knowledge, and it is unclear which brain areas are representing self knowledge and other knowledge.

Another crucial aspect of social cognition is the ability to distinguish between different types of other people. Most prior neuroimaging studies of self knowledge and other knowledge have only compared the self to one type of other (e.g., best friend). However, there are many different types of others, and the brain may represent information about each type of other separately. Results from prior studies that did compare the self to multiple types of others suggest that this is the case. For example, (Krienen et al., 2010) found large differences between activation patterns for friends and strangers. More recently, (Courtney & Meyer, 2020) found that brain responses for the self and three types of others cluster into three groups: the self, close others and acquaintances, and famous people. However, these studies only compared the representations of a few types of others, and they primarily organized others by closeness to the self (i.e., close others, familiar others, unfamiliar others). These closeness categories are broad, and each one contains multiple distinct types of others. For example, “best friend” and “mother” have both been used as examples of close others, but a best friend plays a very different role in one’s life than a mother. Given the limitations of these prior studies, it is still unclear how the brain represents or organizes information about different types of others.

To see whether the brain represents information about the self and different types of others separately, we mapped the cortical representations of the self and six different types of others in individual participants. During the experiment, participants answered personal questions about themselves and six types of others while blood oxygen level-dependent (BOLD) responses were recorded by functional magnetic resonance imaging (fMRI). The six types of others were: close friends, family, acquaintances, work colleagues, famous people, and fictional people (Figure 1). We then used a voxelwise encoding model approach (VM) to map the representation of the self and each type of other across the cortical surface.

3.2 Materials and Methods

Participants

Functional data were collected from one non-binary participant assigned female at birth and one male participant: S1 (non-binary, age 26), S2 (male, age 28). All participants were healthy and had normal hearing, and normal or corrected-to-normal vision.

MRI data collection

MRI data were collected on a 3T Siemens TIM Trio scanner with a 32-channel Siemens volume coil, located at the UC Berkeley Brain Imaging Center. Functional scans were collected using gradient echo EPI with repetition time (TR) = 2.0045s, echo time (TE) = 31ms, flip angle = 70 degrees, voxel size = 2.24 x 2.24 x 4.1 mm (slice thickness = 3.5 mm with 18% slice gap), matrix size = 100 x 100, and field of view = 224 x 224 mm. Thirty axial slices were prescribed to cover the entire cortex and were scanned in interleaved order. A custom-modified bipolar water excitation radiofrequency (RF) pulse was used to avoid signal from fat. Anatomical data were collected using a T1-weighted multi-echo MP-RAGE sequence on the same 3T scanner. On average, 81.4 min of fMRI data was collected for each participant.

fMRI data pre-processing

The FMRIB Linear Image Registration Tool (FLIRT) from FSL 5.0 (Jenkinson et al., 2002; Jenkinson & Smith, 2001) was used to motion-correct each functional run. A high-quality template volume was then created for each run by averaging all volumes in the run across time. FLIRT was used to automatically align the template volume for each run to an overall template, which was chosen to be the temporal average of the first functional run for each participant. These automatic alignments were manually checked

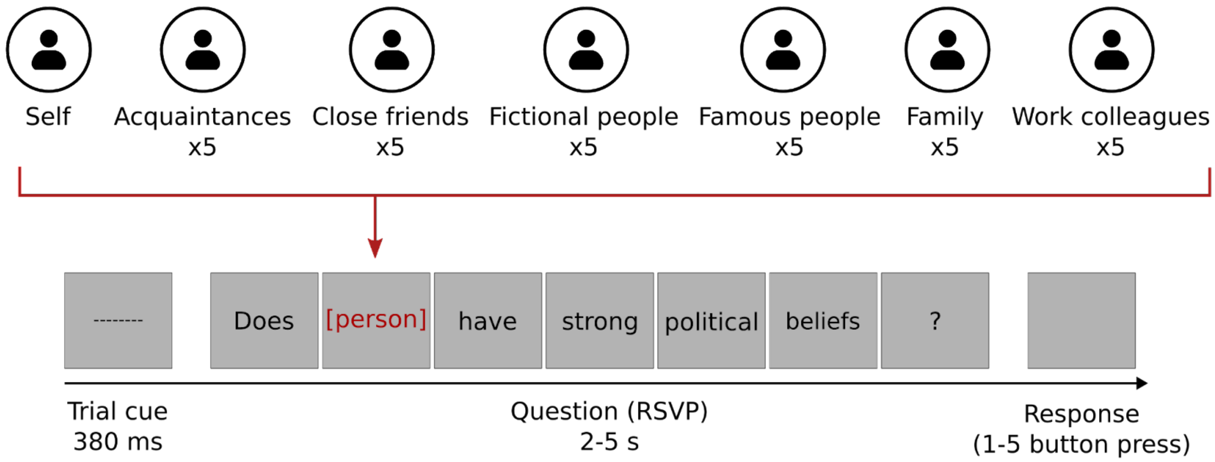


Figure 1. Experimental design. Participants provided a list of five acquaintances, five close friends, five fictional people, five famous people, five family members, and five work colleagues prior to the experiment. During the fMRI experiment, participants answered questions about different aspects of personal identity for themselves and for each of the provided people. In each trial, participants see a short pre-trial cue followed by a question presented in RSVP format. Participants then answer by pressing a button indicating their response from 1-5, where 1 = strongly disagree, few, etc. and 5 = strongly agree, many, etc.

and adjusted as necessary to improve accuracy. The cross-run transformation matrix was then concatenated to the motion-correction transformation matrices obtained using MCFLIRT, and the concatenated transformation was used to resample the original data directly into the overall template space.

White matter detrending (Behzadi et al., 2007) was used to identify low-frequency voxel response drift. This drift was subtracted from the signal before further processing. Responses for each run were z-scored separately before voxelwise modeling. In addition, 5 TRs were discarded from the beginning and the end (10 TRs total) of each run.

Cortical surface reconstruction and visualization

Freesurfer (Dale et al., 1999) was used to generate cortical surface meshes from the T1-weighted anatomical scans. Before surface reconstruction, Blender (https://www.blender.org/) and pycortex (http://pycortex.org; (Gao et al., 2015)) were used to carefully hand-check and correct anatomical surface segmentations. To aid in cortical flattening, Blender and pycortex were used to remove the surface crossing the corpus callosum and relaxation cuts were made into the surface of each hemisphere. The calcarine sulcus cut was made at the horizontal meridian in V1 as identified from retinotopic mapping data.

Pycortex (Gao et al., 2015) was used to align functional images to the cortical surface. The line-nearest scheme in pycortex was used to project functional data onto the surface for visualization and subsequent analysis. The line-nearest scheme samples the functional data at 64 evenly-spaced intervals between the inner (white matter) and outer (pial) surfaces of the cortex and averages the samples. Samples are taken using nearest-neighbor interpolation, in which each sample is given the value of its enclosing voxel.

Experimental design

Before the fMRI experiment, participants were asked to provide the names of five close friends, five acquaintances, five family members, five work colleagues, five famous people, and five fictional people. Participants were asked to choose famous people and fictional people with whom they were familiar. During the fMRI experiment, participants answered personal questions (see Stimulus questions) about themselves and the provided people. Questions were presented in individual trials. At the start of each trial, a trial marker "--------" was shown at the center of the screen for 380 ms. Then, the question was presented as text and shown one word at a time at the center of the screen using Rapid Serial Visual Presentation (RSVP) (Forster, 1970; Buchweitz et al., 2009). Words were presented for a baseline of 300 ms with an additional 10 ms for every character. For example, the word "apple" would be presented for 300 ms + 10 ms/character * (5 characters) = 350 ms. These parameters were determined after extensive pilot testing, and they provide a good balance between readability and keeping subject engagement. All questions ended with a question mark, which was presented for 200 ms. Participants responded to each question by pressing 1-5 on a five-button button box, where 1=low/disagree and 5=high/agree. All participants pressed buttons with their right hand. The next trial started immediately after the participant's response. If a participant didn't respond within an answering period of 3-5 seconds (jittered across trials), the next trial automatically started after the answering period. Missed trials were not repeated. Participant S1 completed all trials, and participant S2 completed 99.75% of the trials.

Both participants completed 8 scanning runs. There were 150 trials in each scanning run, and 140 of the 150 trials were unique. The remaining 10 trials in each run were repeated from the unique trials, and they were used as padding at the beginning (5 trials) and the end (5 trials) of each run. On average, participants took 10.2 minutes to complete each scanning run.

Stimulus questions

In this experiment, each participant answered 1120 unique questions about themselves and six types of others while fMRI was used to collect BOLD data. To generate these questions, we created a large number of question templates that probe many different aspects of personal identity. This was so that our results would not be biased towards a specific aspect of personal identity. The question templates were designed to be paired with different people across the seven types of people investigated in this study (the self and six types of others). For example, one question template is "Is [person] likely to do just enough work to get by?" Similar question templates were grouped together and organized hierarchically into a tree. Mixed-integer linear programming (MILP; (Slivkoff

& Gallant, 2021)) was used to find an optimal pairing of the question templates with people, and to find a balanced distribution of paired questions across scanning runs (see Question and experiment generation).

Question Organization. Question templates were organized hierarchically into a tree. This organization is given by Table 1. At the highest level of the tree, the question templates are organized into two question groups based on which of two types of personal identity information they probe: personality information or non-personality information. Each of these two question groups contains smaller subgroups of question templates that focus on different components of personality and non-personality information. The personality question group contains 5 question subgroups which correspond to the five factors of the Big5 personality model. The non-personality question group contains 30 question subgroups that cover various non-personality aspects of personal identity. Some examples of question subgroups are abilities, family background, life outlook, physical characteristics, politics, and emotions.

Each of these 35 question subgroups contain smaller question sub-subgroups of question templates that focus on different components of each question subgroup. For example the "Abilities" question subgroup contains five question sub-subgroups: academic ability, athletic ability, ability to play an instrument, ability to play a sport, and social ability. Most question sub-subgroups contain only one question template, and some question sub-subgroups contain multiple question templates. There are 296 question sub-subgroups and 316 question templates.

Question Sources. The question templates for the personality question group were taken from the IPIP-NEO-120 (J. A. Johnson, 2014). The question templates for the non-personality group were primarily based on questions from the General Social Survey (Davern et al., 2021) . The remaining question templates were taken from the Subject judgment questions (see previous chapter) or were generated by the authors.

Question and experiment generation. The 316 question templates and 31 people (5 people/type of other * 6 types of others + the participant) were paired together and distributed across scanning runs using mixed-integer linear programming (MILP) (Slivkoff & Gallant, 2021). MILP is an optimization tool that allows the incorporation of complex design constraints into an experiment. Here, we imposed several constraints on the experiment. First, we constrained the number of times that question templates from each of the 35 question subgroups would appear throughout the entire experiment. Second, we set a constraint that the 31 people had to appear approximately the same number of times across the experiment. Third, we set a constraint that approximately the same number of question templates from each question subgroup would be asked about each of the seven types of people. Fourth, we set a constraint that approximately the same number of people from each of the seven types of people would be paired with question templates from each of the question subgroups. Table 2 gives the number of question templates from each question subgroup that appeared in the experiment, and the full list of experiment questions is included in the Supplementary Materials.

Voxelwise encoding model fitting and validation

Model fitting. To identify voxels that represent different types of people, a linearized encoding model (Huth et al., 2012, 2016; Nishimoto et al., 2011) was fit to every cortical voxel in each participant's brain. The linearized encoding model consisted of 11 feature spaces. One feature space was designed to represent the seven types of people. This feature space consists of binary features that correspond to each type of person. Two feature spaces were designed to represent the two question groups, personality questions and non-personality questions. Each of these two feature spaces consists of binary features that correspond to the question subgroups for the personality and non-personality question groups, respectively. The remaining eight feature spaces were designed to capture non-social information, and these included a linguistic semantic feature space (Huth et al., 2016), four feature spaces that reflected low-level linguistic information, and three feature spaces that reflected participant behavior and experimental parameters. There were a total of 1064 features across the 11 feature spaces. A list of the 11 feature spaces and the number of features in each feature space is given in Table 3.

The features passed through three additional preprocessing steps before being fit to BOLD responses. First, to account for the hemodynamic response, a separate finite impulse response (FIR) filter with four delays was fit for each of the 1064 features, resulting in 4256 final features. This was accomplished by concatenating copies of the features delayed by 1, 2, 3, and 4 TRs (approximately 2, 4, 6, and 8 seconds). Taking the dot product of this concatenated feature space with a set of linear weights is functionally equivalent to convolving the undelayed features with a linear temporal kernel that has non-zero entries for 1-, 2-, 3-, and 4-time point delays. Second, 5 TRs were discarded from the beginning and the end (10 TRs total) of each run. Third, each feature was z-scored separately within each run. This was done so that the features would be on the same scale as the BOLD responses, which were also z-scored within each run.

A single joint model consisting of the 4256 features was fit to BOLD responses using banded ridge regression (Nunez-Elizalde et al., 2019) and the himalaya Python package (Dupré la Tour et al., 2022). A separate model was fit for every voxel in every participant and condition. For every model, a regularization parameter was estimated for each of the five feature spaces using a random search. In the random search, 1000 normalized hyperparameter candidates were sampled from a Dirichlet distribution and scaled by 30 log-spaced values ranging from 10^{-5} to 10^{20}. The best normalized hyperparameter candidate and scaling were selected for each feature space for each voxel. Finally, models were fit again on the BOLD responses with the selected hyperparameters.

Model validation. Models were validated using a leave-one-out cross validation (CV) scheme. For every participant, the joint model was trained on seven out of eight runs of BOLD data. The estimated model weights were then used to predict responses to the eighth run of BOLD data. This procedure was repeated for every split of seven "training" runs and one "test" run. Prediction accuracy for each cross validation fold was computed as the coefficient of determination (R^2) between the model-predicted BOLD responses and the recorded BOLD responses for the test run. Prediction accuracy values were averaged across the eight CV folds for every voxel in every participant. In this paper, the averaged prediction accuracy values are referred to simply as the "prediction accuracy".

Significance testing. Statistical significance of the joint model prediction accuracy was computed with permutation testing. For each CV fold, a null distribution was generated by first permuting the timepoints of the predicted BOLD response (y_hat) for the test run, and then computing the prediction accuracy for the permuted y_hat. The permutation was done in blocks of 10 TRs to account for temporal autocorrelations in the BOLD signal. There were 5000 permutations for each CV fold. The 5000 permutations were then averaged across the CV folds to create one null distribution for each voxel. A p-value was computed for each voxel by comparing the joint model prediction accuracy value with the null distribution. P-values were corrected for multiple comparisons within each participant using the false discovery rate (FDR) procedure (Benjamini & Hochberg, 1995).

Contribution of individual feature spaces. To estimate the contribution of each feature space to the joint model prediction accuracy, the joint model prediction accuracy was split using the "r2_score_split_svd" function in the himalaya Python package (Dupré la Tour et al., 2022). This function computes the relative weight (J. W. Johnson, 2000) of each feature space while also accounting for the magnitude of the predictions from each feature space with respect to the other feature spaces. In this paper, the contribution of each feature space to the joint model prediction accuracy is also referred to simply as the feature space's "contribution".

Model weight normalization and scaling. Model weights estimated for each individual voxel went through two preprocessing steps before visualization and principal components analysis (PCA). First, the estimated weights for each feature space were normalized by dividing the estimated weight for each feature by the L2-norm of the estimated weights for all features in the feature space. This was done because a separate regularization parameter was estimated for each feature space (see VM), so the estimated weights for features in different feature spaces could have different scales. Second, the normalized estimated model weights for each feature space were scaled by the square root of the contribution for that feature space. This was done so that estimated model weights for feature spaces with a small contribution would have a small value.

Software

All model fitting and analysis was performed using custom software written in Python, making heavy use of NumPy (Harris et al., 2020) and SciPy (Virtanen et al., 2020). Analysis and visualizations were developed using iPython (Perez & Granger, 2007), the interactive programming and visualization environment jupyter notebook (Kluyver et al., 2016), himalaya (Dupré la Tour et al., 2022), Pycortex (Gao et al., 2015), and Matplotlib (Hunter, 2007).

Code Accessibility

The himalaya package (Dupré la Tour et al., 2022) is publicly available on GitHub (https://github.com/gallantlab/himalaya). The pycortex package (Gao et al., 2015) is also publicly available on GitHub (https://github.com/gallantlab/pycortex).

3.3 Results

The goal of this study was to map the cortical representation of the self and six different types of others. Here, we show preliminary data from two participants who answered personal questions about themselves and six types of others while BOLD responses were recorded with fMRI.

To identify what information is represented in each voxel's BOLD response, we fit a linearized encoding model to every cortical voxel in each participant's brain (Huth et al., 2012, 2016; Nishimoto et al., 2011). The linearized encoding model consisted of 11 feature spaces, each of which captured a different kind of information in the experiment. One feature space was designed to represent the seven types of people in the experiment (the self and six types of others). This feature space includes seven binary features that each correspond to a person type, and this feature space is also referred to as the "person type feature space". Two feature spaces were designed to represent the two types of personal identity questions in the experiment (personality and non-personality). These two feature spaces also consist of binary features, and these features represent the question subgroups for each type of personal identity question. The remaining eight feature spaces were designed to represent non-social information in the experiment, and they capture linguistic information, the participant's behavior, and experimental parameters (see Table X for more details). The linearized encoding model was fit to the recorded BOLD responses for each participant using a leave-one-out cross-validation procedure. In each cross-validation fold, data from one scanning run was set aside as the test dataset, and data from the remaining runs comprised the training dataset. We used banded ridge regression (Nunez-Elizalde et al., 2019) to fit the 11 feature spaces as a single joint model to the recorded BOLD responses in the training dataset (see Figure 2 in Chapter 2). To validate that the model was not overfit to the training dataset, the model was then used to predict the recorded BOLD responses in the test dataset. Model goodness of fit was assessed on the test dataset, and it was computed as the amount of variance in the recorded BOLD responses explained by the model-predicted BOLD responses (i.e., the coefficient of determination R^2). Here, this value is also referred to as the model prediction accuracy. The model fitting and testing procedure was repeated for all possible splits of training and testing datasets, and all following results are an average across cross-validation splits (see Methods).

Figure 2 shows the joint model prediction accuracy for both participants. In both participants, the model prediction accuracy is high in voxels across bilateral visual cortex, superior temporal sulcus (STS), angular gyrus, temporal parietal junction (TPJ), precuneus, retrosplenial cortex (RSC), inferior frontal gyrus (IFG), superior frontal gyrus (SFG), superior frontal sulcus (SFS), dorsomedial prefrontal cortex (dmPFC),

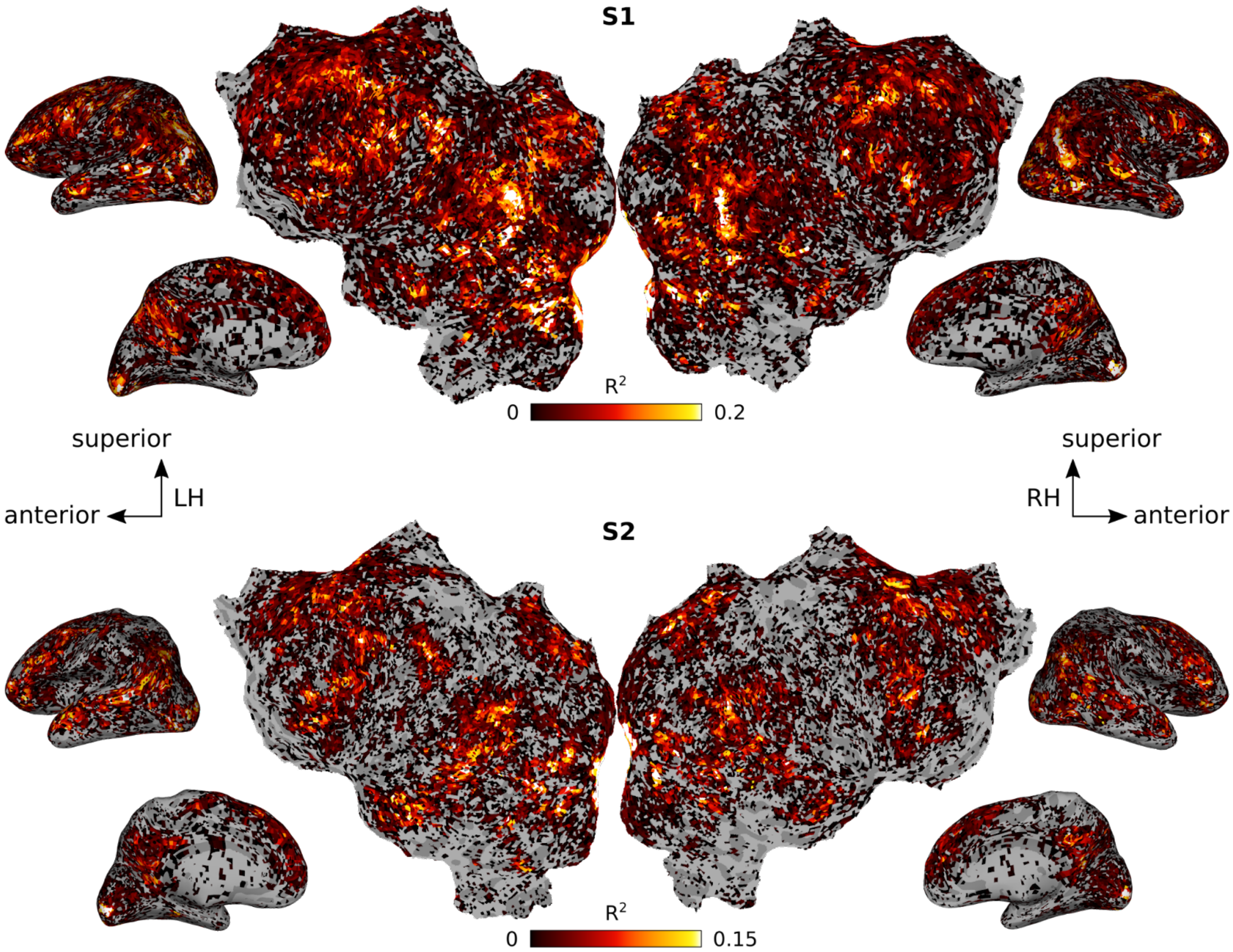


Figure 2. Joint model prediction accuracy across the cortical surface. Joint model prediction accuracy is shown on the flattened cortical surfaces of both participants. Voxelwise modeling was first used to jointly estimate model weights for all features. Joint model prediction accuracy was then computed as the coefficient of determination (R2) between each subject's recorded BOLD activity and the BOLD activity predicted by the joint model. In each panel, only voxels with significant joint model prediction accuracy ($p<0.05$, FDR-corrected) are shown. Prediction accuracy is given by the color scale at the bottom of each flattened cortical surface, and voxels that have a high prediction accuracy appear yellow. Voxels for which the joint model prediction accuracy is not statistically significant are shown with the curvature (gray). In all participants, many voxels located in bilateral early visual cortex, left superior temporal sulcus (STS), left angular gyrus, left inferior parietal lobule (IPL), left primary motor and somatosensory hand areas, bilateral inferior frontal gyrus (IFG), left superior frontal gyrus (SFG) and superior frontal sulcus (SFS), left dorsomedial prefrontal cortex (dmPFC), and bilateral precuneus are significantly predicted. This result shows that the joint model is able to capture voxel responses across the cortical surface.

ventromedial prefrontal cortex (vmPFC), and left primary motor and somatosensory hand areas. The joint model explained at least 1% of the variance in 27.1% of voxels in participant S1 and in 15% of the voxels in participant S2. This result shows that the joint model is able to explain variance in the BOLD responses of voxels across many regions of the brain.

To identify voxels that represent information about types of people, we estimated the contribution of the person type feature space to the joint model prediction accuracy for every voxel in each participant. The contribution of a feature space to the joint model prediction accuracy is the amount of the joint model prediction accuracy that can be attributed to that feature space. Here, a high contribution for the person type feature space indicates that a voxel represents information about types of people. Figure 3 shows the contribution of the person type feature space for both participants. In both participants, the person type feature space contributed to the joint model prediction accuracy in bilateral RSC, precuneus, anterior STS, SFG, dmPFC, vmPFC, and pars orbitalis. In addition, the person type feature space contributed to the joint model prediction accuracy in right Broca's area and in a region posterior to TPJ bilaterally in participant S1. These results suggest that person type information is represented in a distributed network across the brain.

Next, to identify voxels that represent each of the seven types of people, we visualized the estimated weights of individual features in the person type feature space. Figure 4 shows the estimated weights for each feature in the person type feature space for both participants. For each voxel, a positive estimated weight indicates that the BOLD response to the feature is above the average observed BOLD response in that voxel. In contrast, a negative weight indicates that the voxel's BOLD response to the feature is below the average observed BOLD response in that voxel. For the "Acquaintances" feature, no voxels in participant S1 have strong positive or negative estimated weights. In participant S2, voxels in bilateral precuneus and RSC have strong positive estimated weights. For the "Close friends" feature, voxels in left precuneus, bilateral SFS, and bilateral SFS have strong positive estimated weights in both participants. Voxels in bilateral pars orbitalis have strong negative weights in both participants. For the "Family" feature, voxels in bilateral precuneus, bilateral dmPFC, left SFS, and left SFG have strong positive estimated weights in both participants. No voxels have strong negative estimated weights in either participant. For the "Famous people" feature, voxels in right SFS, right SFG, and bilateral pars orbitalis have strong positive estimated weights in both participants. Voxels in bilateral SFS, bilateral SFG, left RSC, left precuneus, left dmPFC, and left vmPFC have strong negative estimated weights in both participants. For the "Fictional people" feature, voxels in bilateral RSC, bilateral pars orbitalis, bilateral SFS, bilateral SFG, and left anterior STS have strong positive estimated weights in both participants. Voxels in bilateral SFS, bilateral SFG, bilateral dmPFC, bilateral vmPFC, and left precuneus have strong negative estimated weights in both participants. For the "Work colleagues" feature, voxels in bilateral precuneus, bilateral SFS, bilateral SFG, left dmPFC, and left vmPFC have strong positive estimated weights in both participants. No voxels have strong negative estimated weights in either participant. Finally, for the "Self" feature, voxels in bilateral SFS, SFG, dmPFC, and vmPFC have strong positive weights in both participants. Voxels in bilateral precuneus, bilateral pars orbitalis, bilateral SFS, bilateral SFG, and left anterior STS have strong negative estimated weights in both participants. Together, these results provide a map of where the self and different types of others are represented across the cortex.

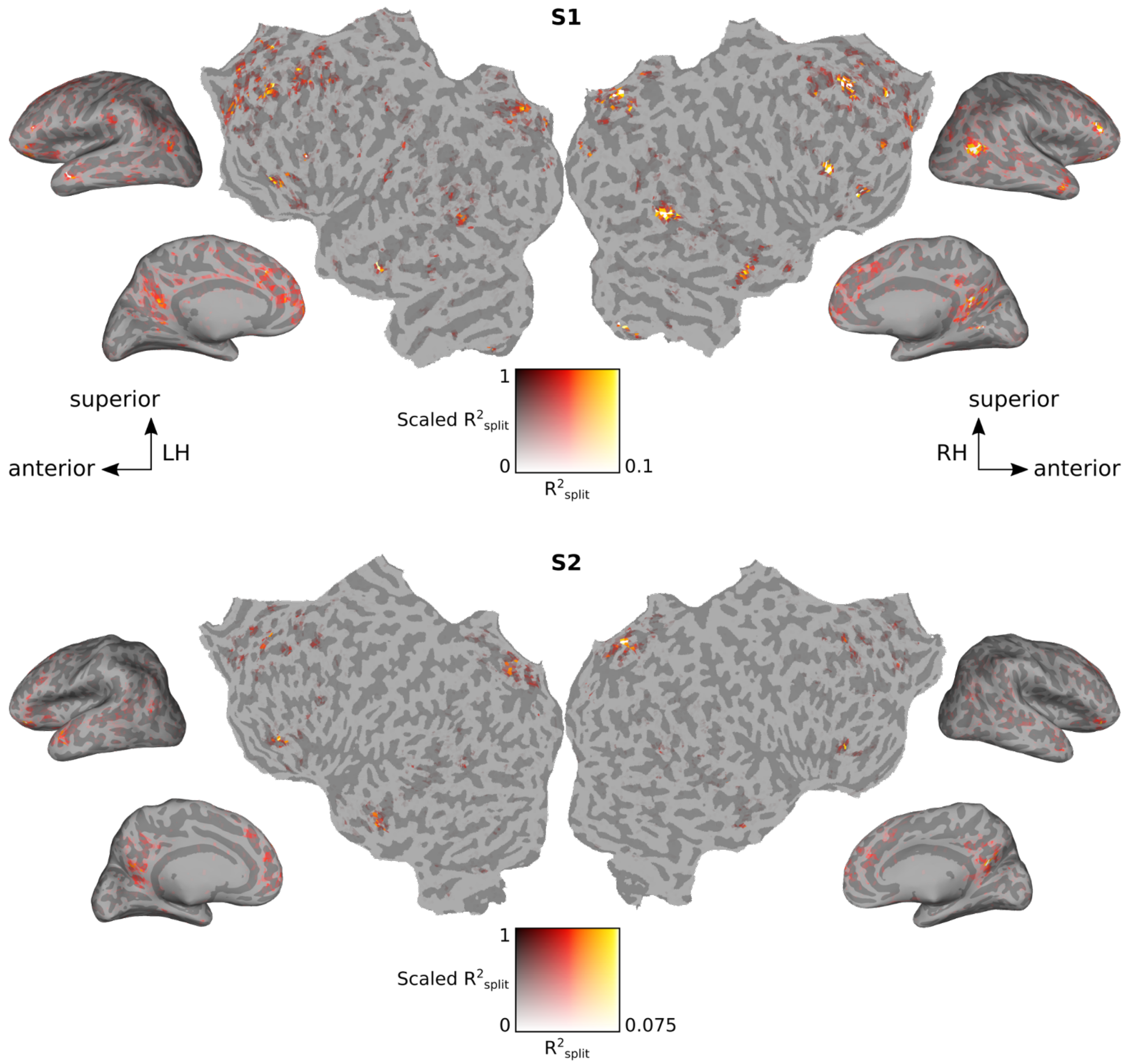
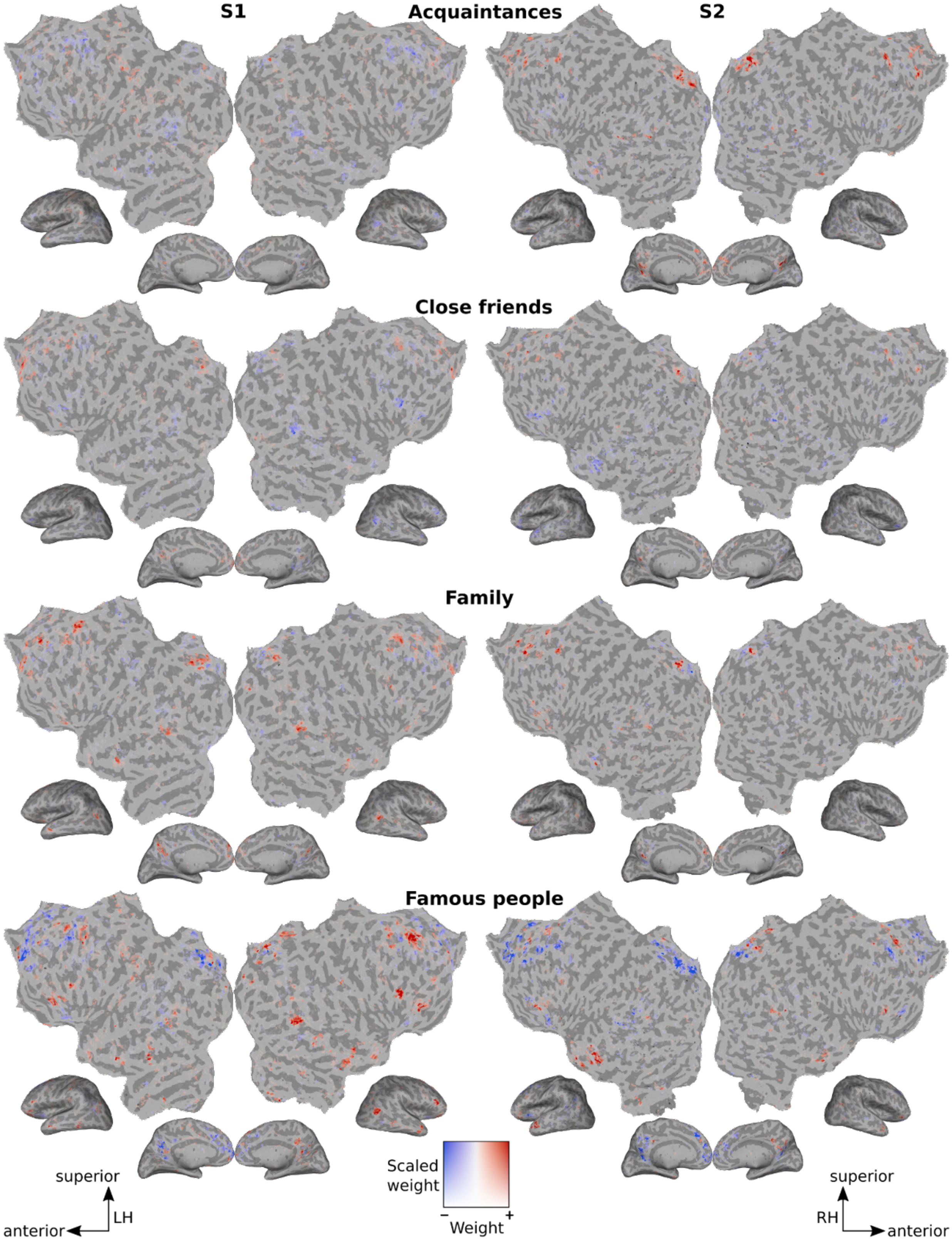


Figure 3. Contribution of the person type feature space to the joint model prediction accuracy across the cortical surface. The contribution of the person type feature space to the joint model prediction accuracy is shown on the flattened cortical surfaces of both participants. Person type feature space contribution is given by a 2D colormap. The 2D colormap was created by taking a 1D colormap (horizontal axis) and varying its opacity (vertical axis). Here, the horizontal axis corresponds to the person type feature space contribution, and the vertical axis corresponds to the person type feature space contribution scaled by 0.1 for participant S1 and by 0.075 for participant S2. Thus, voxels where the person type feature space has a high contribution appear yellow, and voxels where the person type feature space has low contribution appear gray. In each panel, only voxels with significant joint model prediction accuracy ($p<0.05$, FDR-corrected) are shown. In both participants, the person type feature space contributed to the joint model prediction accuracy in voxels in bilateral RSC, precuneus, anterior STS, SFG, dmPFC, vmPFC, and pars orbitalis. These results suggest that person type information is represented in a distributed network across the brain.


S1
Acquaintances
S2
Close friends
Family
Famous people
superior
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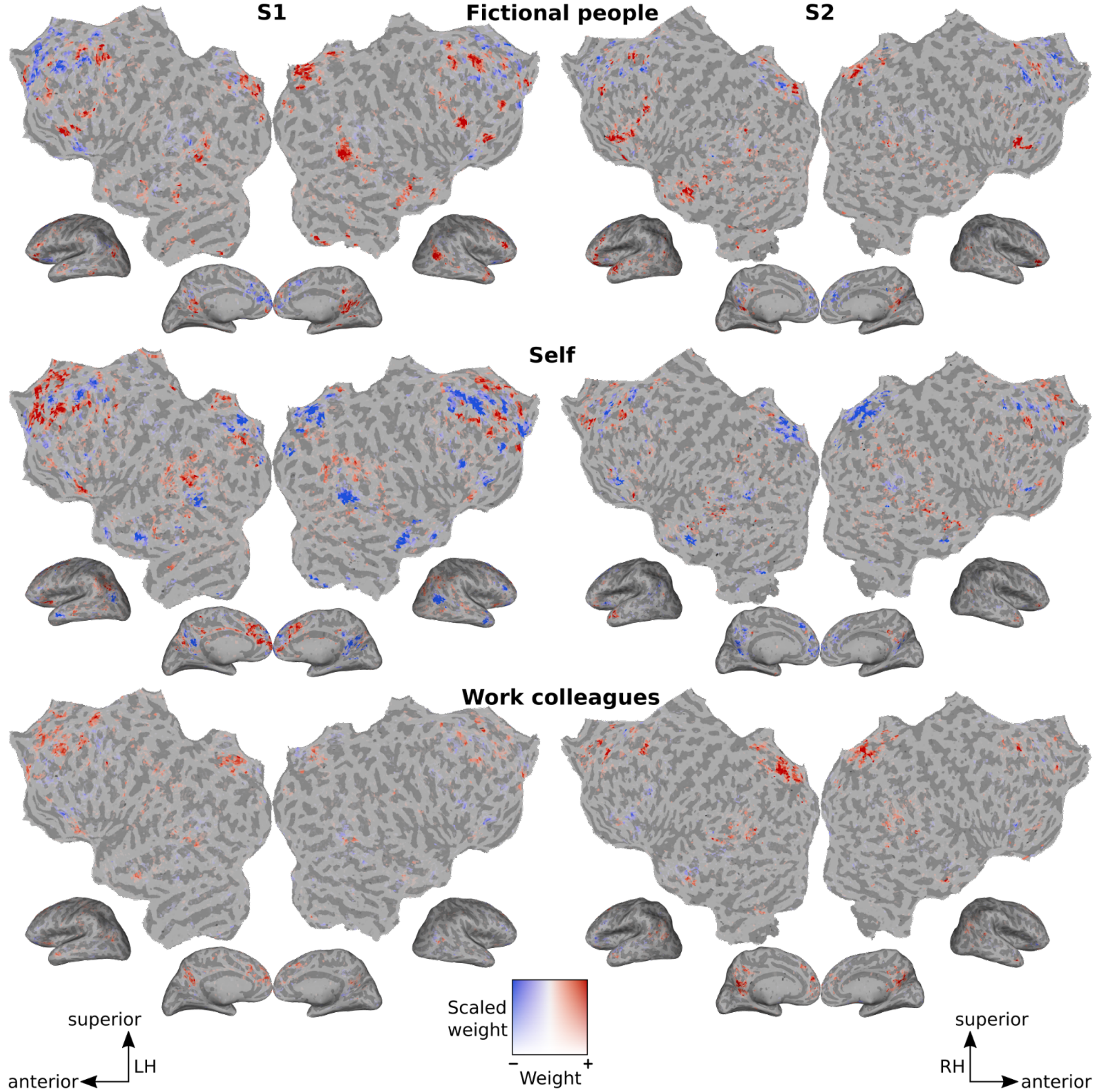

Figure 4. Estimated weights for each feature in the person type feature space. Estimated model weights for each feature in the person type feature space are shown on the flattened cortical surfaces of both participants. The weight value is given by a 2D colormap, and the format of the 2D colormap is the same as in Figure 3. Here, the horizontal axis corresponds to the estimated model weight value, and the vertical axis corresponds to the estimated model weight value scaled by 0.06 for participant S1 and 0.04 for participant S2. A detailed description of brain regions with strong positive and negative estimated weights for each feature is given in the text. These results provide a map of where the brain represents information about the self and six types of others.

To see whether the brain represents self knowledge separately from other knowledge, we contrasted the estimated weights for the "Self" feature with the estimated weights for six other features. To do this, we first constructed a template of person type feature space weights for a hypothetical voxel that represents self knowledge and not other knowledge. This template was a 7-dimensional vector that had a "1" for the "Self" feature and a "-1" for the six other features. We then computed the cosine similarity between the template and the estimated person type weights for every voxel in each participant. Figure 5 shows the cosine similarity for every voxel for the two participants. For each voxel, a positive cosine similarity value indicates that the voxel only represents self knowledge, while a negative cosine similarity value indicates that the voxel only represents other knowledge. In both participants, voxels in left vmPFC and bilateral anterior cingulate sulcus have positive cosine similarity values. Voxels in bilateral precuneus, left anterior STS, bilateral pars orbitalis, bilateral dmPFC, and bilateral SFS/SFG have negative cosine similarity values. These results suggest that the brain represents self knowledge separately from other knowledge.

To better understand the organization of person type representation in the brain, we performed principal components analysis (PCA) on the estimated person type weights for each participant. We first looked at the amount of variance in the estimated person type weights explained by each principal component (PC). Figure 6A shows a scree plot with the variance explained by each PC for each participant. In both participants, most of the variance in the estimated person type weights is captured by the first three PCs. The first three PCs explain 84.4% of the variance in participant S1 and 78.3% of the variance in participant S2. This suggests that the brain represents person type information along three main dimensions. Next, to see whether the PCs are similar across participants, we computed the correlation between each PC for the two participants. Figure 6B shows this correlation for each PC. Across the two participants, the first two PCs are very highly correlated, the third and the sixth PCs are highly correlated, and the remaining PCs are not correlated. This suggests that the first, second, third, and sixth PCs capture variance in the person type weights that is shared across participants, while the fourth, fifth, and seventh PCs capture variance that is unique to participants. Finally, to interpret the PCs, we plotted the direction of each PC in the person type feature space in Figure 6C. Here, we provide interpretations for the first three PCs (although the sixth PC is also interpretable, it explains very little variance in the estimated person type weights). The first PC differentiates between the self and others that one only knows from media (e.g., books, movies, TV). It has high weights for the "Self" feature and low weights for the "Fictional people" and "Famous people" features. The second PC differentiates between people that one interacts with and people that one knows more abstractly. It has high weights for the "Fictional people", "Famous people", and "Self" features; and it has low weights for the "Work colleague", "Family", "Close friends", and "Acquaintances" features. Finally, the third PC differentiates between famous people and fictional people. It has high weights for the "Fictional people" feature and low weights for the "Famous people" feature. Together, these results reveal three main dimensions along which the brain may organize person type information.

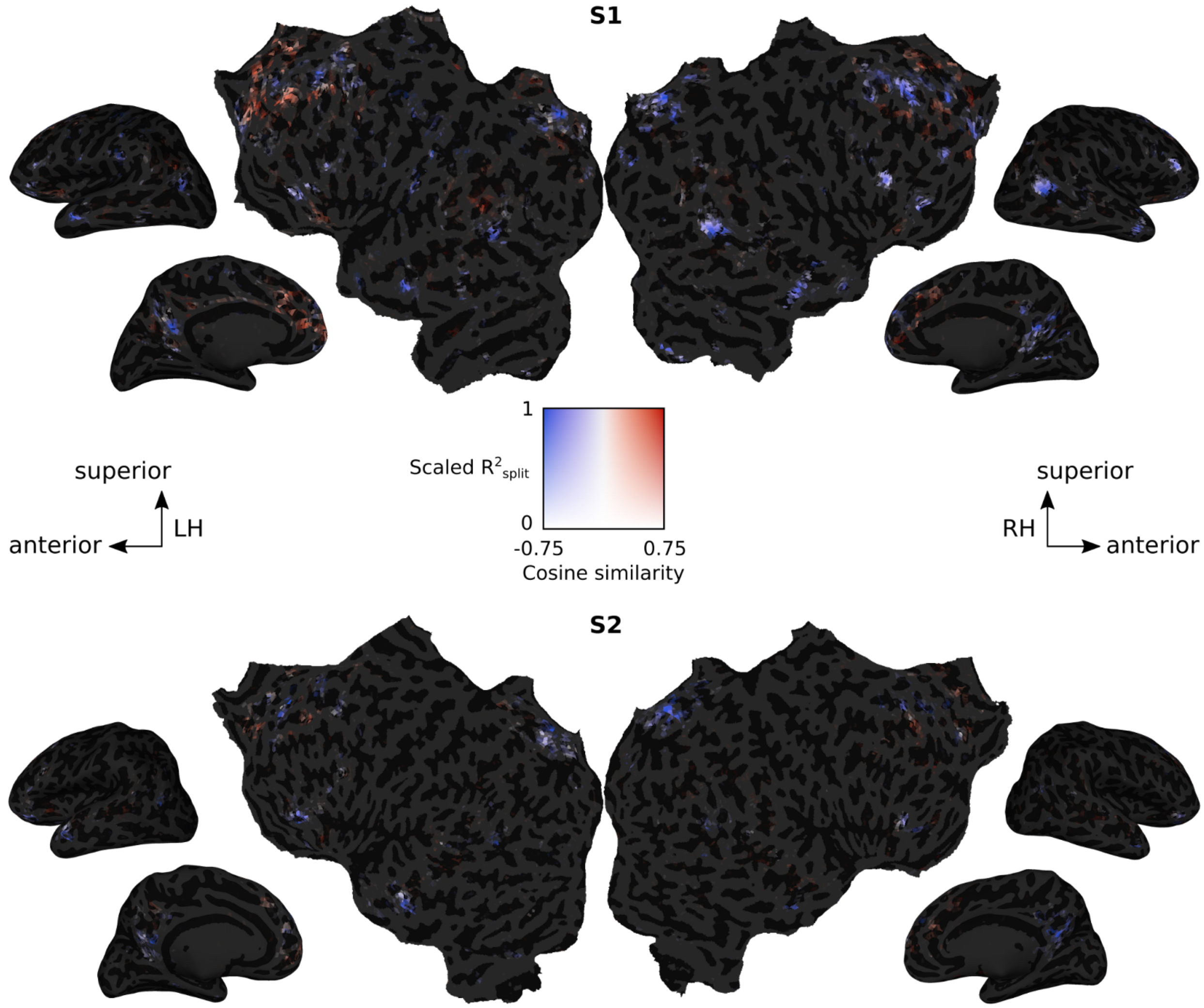

Figure 5. Representation of self knowledge and other knowledge across the cortical surface. To see whether separate brain regions represent self knowledge and other knowledge, we compared each voxel's person type selectivity to that of a hypothetical voxel that only represents self knowledge and not other knowledge. We first constructed a 7-dimensional template vector of estimated weights for the person type feature space. This template vector has a "1" for the "Self" feature and a "-1" for the six other features. We then computed the cosine similarity between the template and the estimated person type weights for every voxel in each participant. The cosine similarity is shown on the flattened cortical surfaces of both participants. Cosine similarity is given by a 2D colormap, and the format of the colormap is the same as in Figure 3. Here, the horizontal axis corresponds to the cosine similarity, and the vertical axis corresponds to the person type feature space contribution scaled by 0.1 for participant S1 and by 0.075 for participant S2. In both participants, voxels in left vmPFC and bilateral anterior cingulate sulcus have positive cosine similarity values. Voxels in bilateral precuneus, left anterior STS, bilateral pars orbitalis, bilateral dmPFC, and bilateral SFS/SFG have negative cosine similarity values. This suggests that the brain represents self knowledge separately from other knowledge.

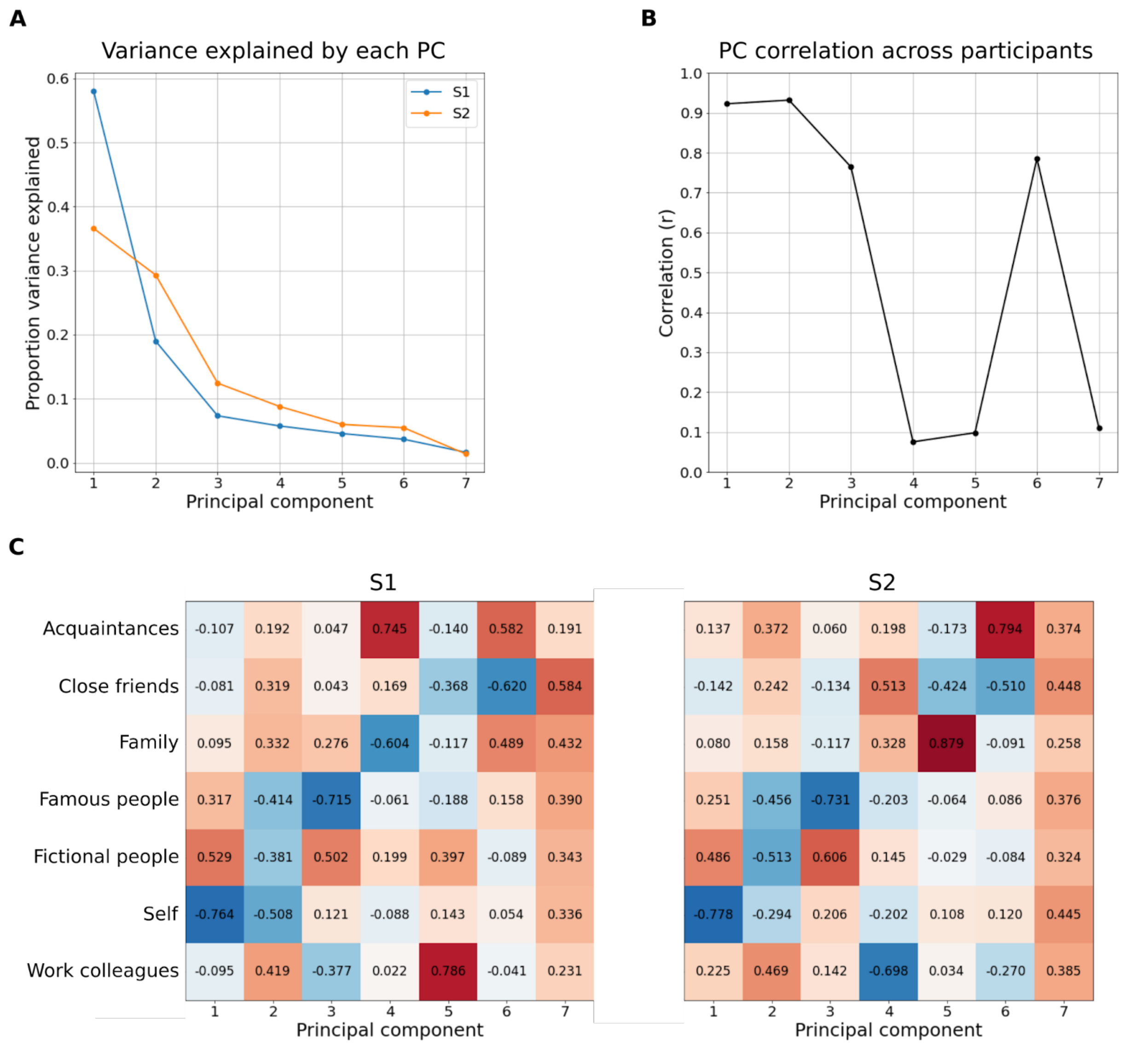

Figure 6. Principal components of the estimated weights for the person type feature space. To understand the organization of person type information in the brain, principal components analysis (PCA) was performed on the estimated weights for the person type feature space for each participant. **A.** The proportion of variance explained by each principal component (PC) is shown for each participant. In both participants, the first three PCs explain the majority of the variance. **B.** Pearson's correlation coefficient was computed for each PC between the two participants. The first two PCs are very highly correlated, the third and sixth PCs are highly correlated, and the remaining PCs are not correlated across participants. **C.** The directions of each PC in the person type feature space are shown for both participants. In both participants, only the first three PCs have clear interpretations. The first PC separates the self from others known through media (fictional people, famous people). The second PC separates people that one interacts with (acquaintances, friends, family, work colleagues) from people that one knows more abstractly (self, fictional people, famous people). Finally, the third PC separates fictional people from famous people. These three PCs reveal possible primary axes along which the brain organizes person type information.

To see how the brain organization of person type information is reflected spatially on the cortical surface, we projected each voxel's estimated person type weights onto the three PCs and visualized the projections with an RGB color scheme. For each voxel, the red value indicates the projection onto the first PC, the green value indicates the projection onto the second PC, and the blue value indicates the projection onto the third PC. Figure 7 shows the estimated person type weights projected onto the three PCs for both participants. In both participants, voxel selectivity for person types forms a complex pattern across the cortical surface. There are some similarities in the selectivity patterns across the two participants. For example, voxels in bilateral pars orbitalis are cyan and green, and voxels in left SFS, left vmPFC, and bilateral dmPFC are magenta. However, there are also many differences in the selectivity patterns between the two participants. For example, voxels in bilateral RSC are cyan and green in participant S1, but they are dark blue in participant S2. This result suggests that there is substantial individual variation in how person type information is spatially organized in the brain. However, further investigation is needed with more participants.

3.4 Discussion

The aim of this study was to map the representation of the self and six different types of others. In this chapter, we presented preliminary data from two participants. These data suggest that the brain represents information about the self and different types of others in distinct brain regions. Furthermore, these data reveal three possible axes along which the brain may organize information about the self and others.

Consistent with prior neuroimaging studies of the representation of self and other knowledge, we found that voxels in vmPFC represent self knowledge while voxels in dmPFC represent other knowledge. However, we found additional voxels in vmPFC that represent other knowledge and additional voxels in dmPFC that represent self knowledge in participant S1. Thus, there may be substantial individual variability in where self knowledge and other knowledge are represented in the mPFC. This variability could be one reason why prior studies that investigated either self knowledge or other knowledge identified the same regions in mPFC. Since most prior studies only analyzed their data at the group level, variability in individual participants could influence whether a prior study concluded that self knowledge is represented in the dmPFC and/or whether other knowledge is represented in the vmPFC.

To our knowledge, Courtney and Meyer 2020 is the only study that has explicitly looked at how the brain organizes information about the self and different types of others. This study had two main findings. First, Courtney and Meyer 2020 found that the brain differentiates between the self, others that are in one's social network, and others that are not in one's social network. Consistent with these results, the first PC of the estimated person type feature space weights separates the self from others that are not in one's social network (famous people and fictional people). The second PC of the estimated person type feature space weights further separates these two groups of people from others that are in one's social network (acquaintances, close friends, family, work colleagues). Thus, the first two PCs of the person type feature space separate

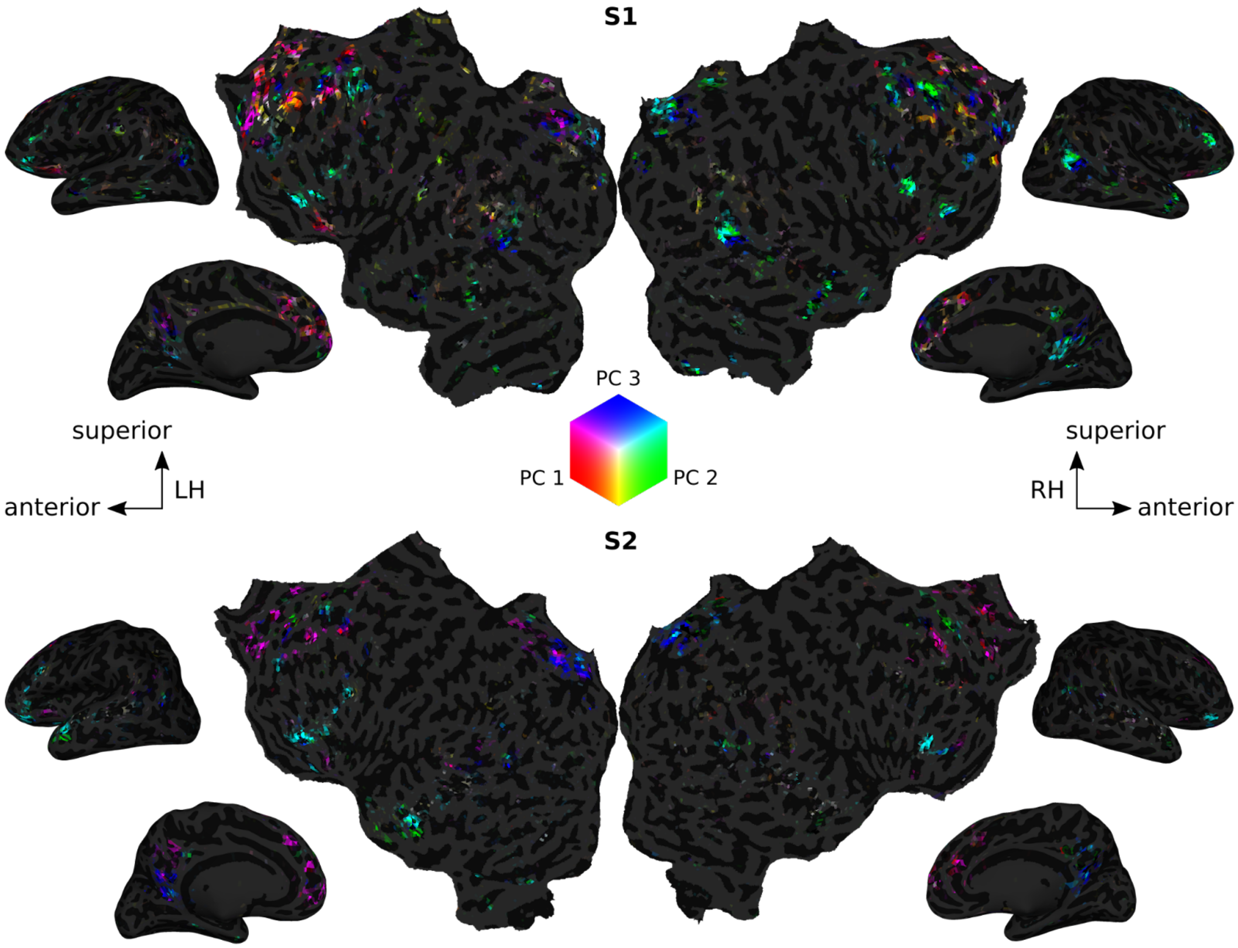

Figure 7. Spatial organization of person type information across the cortical surface. To see how the brain organization of person type information (see Figure 6) is reflected spatially on the cortical surface, we projected the estimated person type feature space weights of each voxel onto the first three PCs of the person type feature space weights. Each voxel is colored according to the projection of its estimated person type feature space weights onto the first (red), second (green), and third (blue) PCs. The opacity of the color is given by the contribution of the person type feature space to the joint model prediction accuracy scaled by 0.05 for participant S1 and 0.03 for participant S2. In both participants, voxels in bilateral pars orbitalis are cyan and green, and voxels in left SFS, left vmPFC, and bilateral dmPFC are magenta. However, there are many differences in the projection patterns between the two participants. This result suggests that there is substantial individual variation in the spatial organization of person type information in the brain.

people into the same three groups identified in Courtney and Meyer 2020. Second, Courtney and Meyer 2020 found that the brain organizes others by how close they are to the self. In the present study, it is unclear if the PCs of the estimated person type feature space weights organize different types of others based on how close they are to the self. None of the seven PCs in either participant appear to separate those usually considered close others (close friends, family) from familiar others (acquaintances, work colleagues, famous people, fictional people). However, we did not ask participants to provide a subjective closeness rating for the others that appeared in the experiment, so it is possible that participants would consider different sets of others as “close others” and “familiar others”. In addition, there was substantial individual variation between the seven PCs recovered for each participant. Thus, it is possible that some individuals organize others according to how close they are to the self.

Beyond the small number of participants, one limitation of our experiment is that there are not enough trials to investigate the brain representation of the self and others for different types of personal identity information. It is possible that the brain represents the self and others differently depending on which aspect of personal identity the participant is asked to attend to. Thus, a future direction is to conduct a more extensive experiment that has many trials for each person type and each aspect of personal identity.

Another limitation of this study is that the reported joint model prediction accuracy and feature space contribution values are not corrected by the noise ceiling. As described in Chapter 2, the noise ceiling of a voxel is the amount of variance in its BOLD response that can theoretically be explained by an encoding model (i.e., the highest possible prediction accuracy). The noise ceiling is usually computed by first recording BOLD responses to repetitions of a fixed stimulus, then taking the correlation between each pair of recorded BOLD responses, and finally taking the mean of the pairwise correlations (Hsu et al., 2004; Lage-Castellanos et al., 2019). In this experiment, it is impossible to repeat the stimulus because the presentation timing of each trial depends on the participant’s response time to the previous trial. Thus, we are not able to compute a noise ceiling for this experiment, and the joint model prediction accuracy and feature space contribution values reported here have a downward bias.

Finally, the person type feature space used in this study has two limitations. First, it assigns each person that appears in the experiment to one “person type.” Although these assignments are correct (they were provided by the participant), some people may be better described by multiple “person types.” For example, a person may be both a family member and a close friend. Thus, a feature space that allows for assigning people to multiple “person types” may explain more variance in the BOLD response. Second, the six types of others examined in this study were chosen by the author, and they may reflect the author’s personal biases. These potential biases could be mitigated by recovering the brain organization of others in a more data-driven way. Unfortunately, a data-driven analysis cannot be done with the current dataset, because there are not enough trials in the experiment to model the brain representation of each individual person. Thus, a valuable future direction is to conduct a longer experiment with a larger number of trials for each person, and to use dimensionality reduction methods to understand how individual people are organized in the brain.

3.5 Tables

Table 1. Organization of question templates

Personal identity information type	Question subgroup	Question sub-subgroup	Question template
Non-personality	Abilities	Athletics	How good is [person] at athletic activities?
		Academics	How good is [person] at academics?
		Socializing	How good is [person] at socializing with others?
		Play Sport	Does [person] play a sport?
		Play Instrument	Does [person] play an instrument?
	Sexuality	Same Gender	How attracted is [person] to people of the same gender?
		Different Gender	How attracted is [person] to people of a different gender?
		Sexual Attraction	How strongly does [person] experience sexual attraction?
		Romantic Attraction	How strongly does [person] experience romantic attraction?
	Gender	Masculine Identity	How masculine is [person]?
		Feminine Identity	How feminine is [person]?
		Feminine Presentation	How feminine is [person]'s gender presentation?
		Masculine Presentation	How masculine is [person]'s gender presentation?
	Health	Physical Health	How is [person]'s physical health?
		Mental Health	How is [person]'s mental health?
		Disability	Does [person] have a disability?
		Mental Illness	Has [person] experienced mental illness?
		Therapist	Has [person] seen a therapist?

	Interests	Politics	How interested is [person] in politics?
		Sports	How interested is [person] in sports?
		Science And Tech	How interested is [person] in science and tech?
		Arts	How interested is [person] in the arts?
		Humanities	How interested is [person] in the humanities?
		Business And Finance	How interested is [person] in business and finance?
	Close individuals	Number Close People	How many people does [person] feel close to?
		Close Interaction Frequency	How often does [person] spend quality time with those they are close to?
		Close Experience Share	Does [person] share important experiences with those they are close to?
		Develop Caring Relationship	How much does [person] prioritize developing caring relationships?
	Friends	Good Friend	Is [person] a good friend?
		Number Friends	How many friends does [person] have?
		Friend Share Belief	Do [person]'s friends share [person]'s beliefs?
		Friend Same Socioeconomic class	Are [person]'s friends in the same socioeconomic class as them?
		Friend Same Age	Are [person]'s friends the same age as them?
		Friend Same Activities	Do [person]'s friends do the same activities as them?
		Friendship Length	How long has [person] known their closest friends?
		Important Events Friends	Does [person] discuss important events with their friends?
	Partner(s)	Good Partner Importance	How much does [person] care about being a good romantic partner?

		Intimate Relationship Importance	How much does [person] care about having intimate relationships?
		Number Partners	How many partners does [person] have?
		Important Events Partners	Does [person] discuss important events with their partner(s)?
	Family relationship	Close Family Relationship	Does [person] have a close relationship with their family?
		Time With Family	How much time does [person] spend with their family?
		Frequency See Family	How often does [person] see their family?
		Important Matters Family	Does [person] discuss important matters with their family?
	Social capital	Popularity	How popular is [person]?
		Well Known	How well-known is [person]?
		Well Connected	How well-connected is [person]?
		Power Over Others	How much power does [person] have over others?
		Reputation	Does [person] have a good reputation?
		Attractiveness	How attractive is [person] to other people?
		Getting Word Out	How good is [person] at getting the word out about something?
		Important Events Know Speed	How quickly does [person] know about important events?
	Physical characteristics	Height	How tall is [person]?
		Weight	How much does [person] weigh?
		Age	How old is [person]?
		Skin Light	How light is [person]'s skin?
		Skin Dark	How dark is [person]'s skin?
		Hair Light	How light is [person]'s hair?

		Hair Dark	How dark is [person]'s hair?
		Eyes Light	How light are [person]'s eyes?
		Eyes Dark	How dark are [person]'s eyes?
	Impression on others	Be Yourself	Is [person] comfortable being themselves with other people?
		Seen As Self	Do others see [person] as they see themselves?
		Good Impression	Does [person] make a good impression on others?
		Treat With Respect	Do others generally treat [person] with respect?
		Acceptance	Do others generally accept [person]?
	Religion and spirituality	Spirituality Importance	How important is spirituality to [person]?
		Freq Prayer	How often does [person] pray?
		Freq Meditate	How often does [person] meditate?
		Strength And Comfort Religion	Does [person] find strength and comfort in religion?
		Freq Attend Religious Service	How frequently does [person] attend religious services?
		Freq Attend Religious Service Child	How often did [person] attend religious services growing up?
	Community	Belong City	Does [person] feel like they belong in their city?
		Belong Work	Does [person] feel like they belong at their workplace?
		Pride City	Is [person] proud to live in their city?
		Pride Work	Is [person] proud to be a member of their workplace?
		Num Social Groups	How many social groups is [person] part of?
		Social Groups Importance	Is [person] an important member of their social groups?
		Time Interest Group	How much time does [person] spend in clubs or interest groups?

	Politics	Strong Political Beliefs	Does [person] have strong political beliefs?
		Social Liberal	How socially liberal is [person]?
		Social Conservative	How socially conservative is [person]?
		Econ Liberal	How economically liberal is [person]?
		Econ Conservative	How economically conservative is [person]?
	Culture	American	How much does [person] identify with American culture?
		Non American	How much does [person] identify with non-American cultures?
		English Lg	How familiar is [person] with English?
		Non English Lg	How familiar is [person] with non-English languages?
		Belong Generation	Does [person] feel like they belong in their generation?
		Pride Generation	How proud is [person] of their generation?
	Money and possessions	Material Possessions	Does [person] have a lot of material possessions?
		Expensive Items Owned	How many expensive items does [person] own?
		Amount Money	How much money does [person] have?
		Amount Income	How much money does [person] make?
		Socioeconomic class	Which socioeconomic class is [person] in?
	Work	Length Current Job	How long has [person] been at their current job?
		Num Previous Jobs	How many previous jobs has [person] had?
		Time At Work	How much time does [person] spend on work?
		Time Relax	How much time does [person] have to relax?

		Work Satisfaction	How much satisfaction does [person] get from work?
		Work Pride	Is [person] proud of their work?
	Cultural activity	Freq Read Lit	How often does [person] read literature?
		Freq Live Theater	How often does [person] attend live theater shows?
		Freq Live Music	How often does [person] attend live music shows?
		Freq Art Exhibit	How often does [person] go to art exhibits?
		Freq Movie	How often does [person] go to movie theaters?
		Freq Public Lecture	How often does [person] go to public lectures?
	Self esteem	Self Satisfaction	Is [person] satisfied with themselves?
		Feel Like Failure	Is [person] inclined to feel like a failure?
		Self Esteem Level	How high is [person]'s self-esteem?
		Worth Compare Others	Does [person] believe that they are worth as much as others?
		Think Self No Good	How often does [person] think they are no good?
	Life outlook	Future Optimism	How optimistic is [person] about their future?
		Expect Things Go Smoothly	How often does [person] expect things to go their way?
		Expect Good Bad	Does [person] expect more good things to happen to them than bad things?
		Life Exciting	How exciting does [person] find life?
		Life Control	How much control does [person] feel like they have over their life?
	Altruism	Affected By Others Problems	How affected is [person] by others' problems?
		Give To Homeless	How often does [person] give to homeless people?

		Give To Charity	How much does [person] give to charities?
		Freq Volunteer	How often does [person] volunteer?
	Family background	Num Siblings	How many siblings does [person] have?
		Parent Edu	How educated are [person]'s parent(s)?
		Parent Wealth	How wealthy are [person]'s parent(s)?
		Parent Alive	Are [person]'s parent(s) alive?
		Money Growing Up	Was money a concern when [person] was growing up?
	Places lived	Num Places Lived	How many places has [person] lived at?
		Num Countries Lived	How many countries has [person] lived in?
		Length Place Lived Current	How long has [person] lived at their current place?
		Distance Moved To Current Living Place	How far is [person]'s current living place from their last place?
	Leisure time	Spend Evening Friend	How often does [person] spend the evening with friends?
		Spend Evening Family	How often does [person] spend the evening with family?
		Spend Evening Alone	How often does [person] spend the evening alone?
		Freq Drink	How often does [person] drink alcohol?
		Freq Smoke	How often does [person] smoke tobacco?
		Freq Drugs	How often does [person] do drugs?
	Recent stress	Recent Trauma	Has [person] recently experienced a traumatic event?
		Recent Stress	How stressed has [person] been in the past couple weeks?
		Big Changes	Has [person] recently experienced any big changes?
		Conflicts	Has [person] recently experienced any conflicts?

	Emotions	Freq Blues	How often does [person] feel like they can't shake the blues?
		Freq Calm	How often does [person] feel calm?
		Freq Outraged	How often does [person] feel outraged?
		Freq Ashamed	How often does [person] feel ashamed?
		Freq Excited	How often does [person] feel excited about something?
		Freq Anxious	How often does [person] feel anxious?
		Freq Restless	How often does [person] feel restless?
		Freq Proud	How often does [person] feel proud of something they did?
		Show Feelings	Does [person] show their feelings?
	Values	Self-direction	How much does [person] value independence?
			How much does [person] value curiosity?
			How much does [person] value creativity?
		Stimulation	How much does [person] value novelty?
			How much does [person] value adventure?
			How much does [person] value excitement?
		Hedonism	How much does [person] value enjoying life?
			How much does [person] value pleasure?
			How much does [person] value self-indulgence?
		Achievement	How much does [person] value being competent?
			How much does [person] value ambition?
			How much does [person] value outward achievements?

		Power	How much does [person] value authority?
			How much does [person] value wealth?
			How much does [person] value controlling others?
		Security	How much does [person] value cleanliness?
			How much does [person] value security?
			How much does [person] value social order?
		Conformity	How much does [person] value meeting obligations?
			How much does [person] value politeness?
		Tradition	How much does [person] value tradition?
			How much does [person] value cultural customs?
			How much does [person] value humility?
		Benevolence	How much does [person] value being dependable?
			How much does [person] value loyalty to friends?
			How much does [person] value being helpful?
		Universalism	How much does [person] value social justice?
			How much does [person] value protecting the environment?
			How much does [person] value tolerance of others?
	Subject Judgment	Subject Character Closeness	How close are you to [person]?
		Subject Character	Do you and [person] have similar cultural backgrounds?

		Cultural Background	
		Subject Character Socioeconomic Background	Do you and [person] have similar socioeconomic backgrounds?
		Subject Character Interests	Do you and [person] share similar interests?
		Subject Character Personality	Do you and [person] have similar personalities?
		Subject Character Life Events	Have you and [person] experienced similar life events?
		Subject Character Beliefs	Do you and [person] have similar beliefs?
		Subject Character Values	Do you and [person] have similar values?
	Problem Type	Problem Type Size Relationship	How big are [person]'s relationship problems?
		Problem Type Past Relationship	In the past has [person] suffered from major relationship problems?
		Problem Type Size Financial	How big are [person]'s financial problems?
		Problem Type Past Financial	In the past has [person] suffered from major financial problems?
		Problem Type Size Health	How big are [person]'s health problems?
		Problem Type Past Health	In the past has [person] suffered from major health problems?
		Problem Type Size Workplace	How big are [person]'s workplace problems?
		Problem Type Past Workplace	In the past has [person] suffered from major workplace problems?
Personality	Conscientiousness	Achievement Striving+ V1	Is [person] likely to work hard?

		Achievement Striving+ V2	Is [person] likely to do more than what's expected of them?
		Achievement Striving- V1	Is [person] likely to do just enough work to get by?
		Achievement Striving- V2	Is [person] likely to put little time and effort into their work?
		Competence+ V1	Is [person] likely to complete tasks successfully?
		Competence+ V2	Is [person] likely to excel in what they do?
		Competence+ V3	Is [person] likely to handle tasks smoothly?
		Competence+ V4	Is [person] likely to know how to get things done?
		Deliberation- V1	Is [person] likely to jump into things without thinking?
		Deliberation- V2	Is [person] likely to make rash decisions?
		Deliberation- V3	Is [person] likely to rush into things?
		Deliberation- V4	Is [person] likely to act without thinking?
		Dutifulness- V1	Is [person] likely to break rules?
		Dutifulness- V2	Is [person] likely to break their promises?
		Dutifulness+ V1	Is [person] likely to keep their promises?
		Dutifulness+ V2	Is [person] likely to tell the truth?
		Order- V1	Is [person] likely to often forget to put things back in their proper place?
		Order- V2	Is [person] likely to leave a mess in their room?
		Order- V3	Is [person] likely to leave their belongings around?
		Order+ V1	Is [person] likely to enjoy tidying up?
		Self Discipline- V1	Is [person] likely to waste their time?
		Self Discipline- V2	Is [person] likely to have difficulty starting tasks?

		Self Discipline+ V1	Is [person] likely to be prepared?
		Self Discipline+ V2	Is [person] likely to carry out their plans?
	Extraversion	Activity- V1	Is [person] likely to like to take it easy?
		Activity+ V1	Is [person] likely to be busy?
		Activity+ V2	Is [person] likely to be on the go?
		Activity+ V3	Is [person] likely to do a lot in their spare time?
		Assertiveness- V1	Is [person] likely to wait for others to lead the way?
		Assertiveness+ V1	Is [person] likely to take charge?
		Assertiveness+ V2	Is [person] likely to try to lead others?
		Assertiveness+ V3	Is [person] likely to take control of things?
		Excitement Seeking+ V1	Is [person] likely to love excitement?
		Excitement Seeking+ V2	Is [person] likely to act wild and crazy?
		Excitement Seeking+ V3	Is [person] likely to seek adventure?
		Excitement Seeking+ V4	Is [person] likely to enjoy being reckless?
		Gregariousness- V1	Is [person] likely to prefer to be alone?
		Gregariousness- V2	Is [person] likely to avoid crowds?
		Gregariousness + V1	Is [person] likely to love large parties?
		Gregariousness + V2	Is [person] likely to talk to a lot of different people at parties?
		Positive Emotions+ V1	Is [person] likely to radiate joy?
		Positive Emotions+ V2	Is [person] likely to have a lot of fun?

		Positive Emotions+ V3	Is [person] likely to love life?
		Positive Emotions+ V4	Is [person] likely to look at the bright side of life?
		Warmth- V1	Is [person] likely to avoid contact with others?
		Warmth- V2	Is [person] likely to keep others at a distance?
		Warmth+ V1	Is [person] likely to make friends easily?
		Warmth+ V2	Is [person] likely to feel comfortable around people?
	Agreeableness	Altruism- V1	Is [person] likely to be indifferent to feelings of others?
		Altruism+ V1	Is [person] likely to love helping others?
		Altruism+ V2	Is [person] likely to be concerned about others?
		Altruism+ V3	Is [person] likely to take time for others?
		Compliance- V1	Is [person] likely to love a good fight?
		Compliance- V2	Is [person] likely to yell at people?
		Compliance- V3	Is [person] likely to insult people?
		Compliance- V4	Is [person] likely to get back at others?
		Modesty- V1	Is [person] likely to believe that they are better than others?
		Modesty- V2	Is [person] likely to think highly of themselves?
		Modesty- V3	Is [person] likely to have a high opinion of themselves?
		Modesty- V4	Is [person] likely to boast about their virtues?
		Straightforwardness- V1	Is [person] likely to use others for their own ends?
		Straightforwardness- V2	Is [person] likely to cheat to get ahead?
		Straightforwardness- V3	Is [person] likely to take advantage of others?

		Straightforwardness- V4	Is [person] likely to obstruct others' plans?
		Tendermindedness- V1	Is [person] likely to be uncaring about other people's problems?
		Tendermindedness- V2	Is [person] likely to avoid thinking about the needy?
		Tendermindedness+ V1	Is [person] likely to sympathize with the homeless?
		Tendermindedness+ V2	Is [person] likely to feel sympathy for those who are worse off than themselves?
		Trust- V1	Is [person] likely to distrust people?
		Trust+ V1	Is [person] likely to trust others?
		Trust+ V2	Is [person] likely to believe that others have good intentions?
		Trust+ V3	Is [person] likely to trust what people say?
	Neuroticism	Anxiety+ V1	Is [person] likely to worry about things?
		Anxiety+ V2	Is [person] likely to fear for the worst?
		Anxiety+ V3	Is [person] likely to be afraid of many things?
		Anxiety+ V4	Is [person] likely to get stressed out easily?
		Depression- V1	Is [person] likely to feel comfortable with themselves?
		Depression+ V1	Is [person] likely to feel blue?
		Depression+ V2	Is [person] likely to dislike themselves?
		Depression+ V3	Is [person] likely to be down in the dumps?
		Hostility+ V1	Is [person] likely to get angry easily?
		Hostility+ V2	Is [person] likely to get irritated easily?
		Hostility+ V3	Is [person] likely to get irritated easily?
		Hostility+ V4	Is [person] likely to be easily annoyed?

		Impulsiveness- V1	Is [person] likely to resist overindulging?
		Impulsiveness- V2	Is [person] likely to easily resist temptations?
		Impulsiveness- V3	Is [person] likely to be able to control their cravings?
		Impulsiveness+ V1	Is [person] likely to go on binges?
		Selfconsciousness- V1	Is [person] likely to be comfortable in difficult social situations?
		Selfconsciousness+ V1	Is [person] likely to find it difficult to approach others?
		Selfconsciousness+ V2	Is [person] likely to be afraid to draw attention to themselves?
		Selfconsciousness+ V3	Is [person] likely to only feel comfortable with friends?
		Vulnerability- V1	Is [person] likely to remain calm under pressure?
		Vulnerability+ V1	Is [person] likely to panic easily?
		Vulnerability+ V2	Is [person] likely to become overwhelmed by events?
		Vulnerability+ V3	Is [person] likely to feel that they are unable to deal with things?
	Openness	Actions- V1	Is [person] likely to prefer to stick with things that they know?
		Actions- V2	Is [person] likely to dislike changes?
		Actions- V3	Is [person] likely to be attached to conventional ways?
		Actions+ V1	Is [person] likely to prefer variety to routine?
		Aesthetics- V1	Is [person] likely to dislike poetry?
		Aesthetics- V2	Is [person] likely to dislike going to art museums?
		Aesthetics+ V1	Is [person] likely to believe in the importance of art?
		Aesthetics+ V2	Is [person] likely to see beauty in things that others might not notice?

		Fantasy+ V1	Is [person] likely to have a vivid imagination?
		Fantasy+ V2	Is [person] likely to enjoy wild flights of fantasy?
		Fantasy+ V3	Is [person] likely to daydream?
		Fantasy+ V4	Is [person] likely to get lost in thought?
		Feelings- V1	Is [person] likely to ignore their emotional reactions?
		Feelings- V2	Is [person] likely to misunderstand people who get emotional?
		Feelings+ V1	Is [person] likely to experience their emotions intensely?
		Feelings+ V2	Is [person] likely to feel others' emotions?
		Ideas- V1	Is [person] likely to avoid philosophical discussions?
		Ideas- V2	Is [person] likely to have difficulty understanding abstract ideas?
		Ideas- V3	Is [person] likely to be bored by theoretical discussions?
		Ideas+ V1	Is [person] likely to love to read challenging material?
		Values- V1	Is [person] likely to vote for conservative political candidates?
		Values- V2	Is [person] likely to believe that we should be tough on crime?
		Values+ V1	Is [person] likely to vote for liberal political candidates?
		Values+ V2	Is [person] likely to believe that there is no absolute right and wrong?

Table 2. Number of experiment questions from each question subgroup

Question subgroup	Number of question templates
Abilities	28
Altruism	28
Close Individuals	35
Community	49
Cultural Activity	28
Culture	28
Emotions	56
Family Background	28
Family Relationship	35
Friends	35
Gender	35
Health	28
Impression On Others	28
Interests	28
Leisure Time	28
Life Outlook	28
Money And Possessions	28
Partner(s)	35
Physical Characteristics	35
Places Lived	28
Politics	28
Problem Type	35
Recent Stress	28
Religion And Spirituality	35
Self Esteem	28
Sexuality	35
Social Capital	49
Subject Judgment	48
Values	49
Work	28

Conscientiousness	21
Extraversion	22
Agreeableness	21
Neuroticism	21
Openness	21

Table 3. List of feature spaces

Feature space	**Description**	**Number of features**
Non-personality personal identity information	Binary feature indicating the question subgroup of the presented question. Only non-personality question subgroups are included. An additional intercept feature consisting of only 1's was included.	31
Personality information	Binary feature indicating the question subgroup of the presented question. Only personality question subgroups are included. An additional intercept feature consisting of only 1's was included.	6
Person type	Binary feature indicating the type of person asked about in the presented question. An additional intercept feature consisting of only 1's was included.	8
Language semantics	Word embedding representation of the words in the presented question. Word embeddings were created from word co-occurrence statistics in a large text corpus (Huth et al., 2016).	985
Number of letters	Number of letters displayed.	1
Word length variation	Variance of the length of words displayed per TR.	1
Letter identity	Binary feature indicating the identity of displayed letters.	26
Number of words	Number of words displayed.	1
Question duration	Length of time to present the trial	1

	question.	
Response time	Elapsed time between the end of the question presentation and the participant's response.	1
Button response	Binary feature indicating the participant's response.	5

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Chapter 4

Appendix to mapping the representation of social information in the brain

4.1 List of experiment questions

Act
- Would Dobby persuade Uncle Vernon of something?
- Would Draco be honest with Voldemort?
- Would Dudley defend Hagrid?
- Would Dumbledore defend Lockhart?
- Would Harry persuade McGonagall of something?
- Would Hermione defend Aunt Petunia?
- Would Neville persuade Filch of something?
- Would Quirrell be honest with Christine?
- Would Ron be honest with Lucius Malfoy?
- Would Snape persuade Ginny of something?

Age
- How old is Christine?
- How old is Dudley?
- How old is Filch?
- How old is Ginny?
- How old is Hermione?
- How old is McGonagall?
- How old is Neville?
- How old is Uncle Vernon?
- How old is Voldemort?

Agree/comply
- Would Dobby go along with Christine's wishes?
- Would Draco put up with Quirrell?
- Would Dudley put up with Filch?
- Would Dumbledore go along with Aunt Petunia's wishes?
- Would Ginny put up with McGonagall?
- Would Hermione go along with Moaning Myrtle's wishes?
- Would Lockhart go along with Hagrid's wishes?
- Would Ron put up with Neville?
- Would Snape put up with Harry?
- Would Voldemort go along with Lucius Malfoy's wishes?

Betray
- Would Aunt Petunia lie to Dumbledore?

Would Christine cheat Uncle Vernon?
Would Draco lie to Dudley?
Would Ginny hide things from Moaning Myrtle?
Would Hagrid cheat Dobby?
Would Harry hide things from Neville?
Would McGonagall betray Filch?
Would Ron cheat Lucius Malfoy?
Would Snape betray Quirrell?
Would Voldemort hide things from Hermione?

Character Acquaintance Interactions

How many of Dobby's acquaintances know each other?
How many of Draco's acquaintances know each other?
How many of Dudley's acquaintances know each other?
How many of Dumbledore's acquaintances know each other?
How many of Filch's acquaintances know each other?
How many of Ginny's acquaintances know each other?
How many of Lockhart's acquaintances know each other?
How many of Lucius Malfoy's acquaintances know each other?
How many of McGonagall's acquaintances know each other?
How many of Moaning Myrtle's acquaintances know each other?
How many of Neville's acquaintances know each other?
How many of Quirrell's acquaintances know each other?
How many of Ron's acquaintances know each other?
How many of Snape's acquaintances know each other?
How many of Voldemort's acquaintances know each other?

Character Ask for Help

Would Aunt Petunia go to Dumbledore for help?
Would Christine go to Dudley for help?
Would Dobby go to McGonagall for help?
Would Draco go to Lucius Malfoy for help?
Would Filch go to Voldemort for help?
Would Hermione go to Quirrell for help?
Would Moaning Myrtle go to Lockhart for help?
Would Ron go to Neville for help?
Would Uncle Vernon go to Ginny for help?

Character Ask for Help in Bad Spot

Would Dumbledore go to Quirrell first if Dumbledore were sick?
Would Filch go to Neville first if Filch were sick?
Would Ginny go to Dobby first if Ginny were depressed?
Would Hermione go to Hagrid first if Hermione were depressed?
Would Lockhart go to Draco first if Lockhart were sick?
Would Moaning Myrtle go to McGonagall first if Moaning Myrtle were in a bad spot?
Would Snape go to Christine first if Snape were in a bad spot?
Would Uncle Vernon go to Ron first if Uncle Vernon were in a bad spot?
Would Voldemort go to Lucius Malfoy first if Voldemort were depressed?

Character Average Distance

How many degrees of separation lie between Aunt Petunia and other characters?

How many degrees of separation lie between Christine and other characters?
How many degrees of separation lie between Dobby and other characters?
How many degrees of separation lie between Draco and other characters?
How many degrees of separation lie between Dudley and other characters?
How many degrees of separation lie between Dumbledore and other characters?
How many degrees of separation lie between Filch and other characters?
How many degrees of separation lie between Ginny and other characters?
How many degrees of separation lie between Hagrid and other characters?
How many degrees of separation lie between Harry and other characters?
How many degrees of separation lie between Hermione and other characters?
How many degrees of separation lie between Lockhart and other characters?
How many degrees of separation lie between Lucius Malfoy and other characters?
How many degrees of separation lie between McGonagall and other characters?
How many degrees of separation lie between Moaning Myrtle and other characters?
How many degrees of separation lie between Quirrell and other characters?
How many degrees of separation lie between Ron and other characters?
How many degrees of separation lie between Snape and other characters?
How many degrees of separation lie between Uncle Vernon and other characters?
How many degrees of separation lie between Voldemort and other characters?

Character Close Friend Interaction Frequency

How often does Aunt Petunia interact with their closest friends?
How often does Draco interact with their closest friends?
How often does Dumbledore interact with their closest friends?
How often does Ginny interact with their closest friends?
How often does Harry interact with their closest friends?
How often does Lockhart interact with their closest friends?
How often does McGonagall interact with their closest friends?
How often does Uncle Vernon interact with their closest friends?
How often does Voldemort interact with their closest friends?

Character Confidant Identity

Does Aunt Petunia discuss important matters with Hagrid?
Does Draco discuss important matters with Dobby?
Does Dumbledore discuss important matters with Lucius Malfoy?
Does Filch discuss important matters with Uncle Vernon?
Does Ginny discuss important matters with Lockhart?
Does Harry discuss important matters with Neville?
Does Hermione discuss important matters with Quirrell?
Does McGonagall discuss important matters with Ron?
Does Moaning Myrtle discuss important matters with Dudley?

Character Contact Usefulness

Would somebody go through Christine to contact someone they didn't know?
Would somebody go through Dobby to contact someone they didn't know?
Would somebody go through Draco to contact someone they didn't know?
Would somebody go through Filch to contact someone they didn't know?
Would somebody go through Ginny to contact someone they didn't know?
Would somebody go through Hermione to contact someone they didn't know?
Would somebody go through Lockhart to contact someone they didn't know?

Would somebody go through Neville to contact someone they didn't know?
Would somebody go through Quirrell to contact someone they didn't know?
Would somebody go through Snape to contact someone they didn't know?

Character Critical to Events
How critical is Aunt Petunia to the events of the story?
How critical is Dudley to the events of the story?
How critical is Dumbledore to the events of the story?
How critical is Hagrid to the events of the story?
How critical is McGonagall to the events of the story?
How critical is Moaning Myrtle to the events of the story?
How critical is Quirrell to the events of the story?
How critical is Uncle Vernon to the events of the story?
How critical is Voldemort to the events of the story?

Character Different Social Groups Harmony
Do Aunt Petunia's different social groups get along?
Do Christine's different social groups get along?
Do Draco's different social groups get along?
Do Dumbledore's different social groups get along?
Do Filch's different social groups get along?
Do Hagrid's different social groups get along?
Do Harry's different social groups get along?
Do Hermione's different social groups get along?
Do Lockhart's different social groups get along?
Do McGonagall's different social groups get along?
Do Neville's different social groups get along?
Do Quirrell's different social groups get along?
Do Snape's different social groups get along?
Do Uncle Vernon's different social groups get along?
Do Voldemort's different social groups get along?

Character Ease of Shaping Impressions
How much does Aunt Petunia shape others' impressions of events?
How much does Christine shape others' impressions of events?
How much does Dumbledore shape others' impressions of events?
How much does Filch shape others' impressions of events?
How much does Harry shape others' impressions of events?
How much does Hermione shape others' impressions of events?
How much does Lucius Malfoy shape others' impressions of events?
How much does Moaning Myrtle shape others' impressions of events?
How much does Snape shape others' impressions of events?
How much does Voldemort shape others' impressions of events?

Character Event Knowledge Speed
Does Dobby often know about important events quickly?
Does Draco often know about important events quickly?
Does Dumbledore often know about important events quickly?
Does Filch often know about important events quickly?
Does Ginny often know about important events quickly?
Does Hagrid often know about important events quickly?

Does Hermione often know about important events quickly?
Does Quirrell often know about important events quickly?
Does Uncle Vernon often know about important events quickly?
Does Voldemort often know about important events quickly?

Character Family Closeness

Does Aunt Petunia have a close relationship with their family?
Does Christine have a close relationship with their family?
Does Dobby have a close relationship with their family?
Does Draco have a close relationship with their family?
Does Dudley have a close relationship with their family?
Does Ginny have a close relationship with their family?
Does Hagrid have a close relationship with their family?
Does Harry have a close relationship with their family?
Does Hermione have a close relationship with their family?
Does Lockhart have a close relationship with their family?
Does McGonagall have a close relationship with their family?
Does Quirrell have a close relationship with their family?
Does Ron have a close relationship with their family?
Does Uncle Vernon have a close relationship with their family?
Does Voldemort have a close relationship with their family?

Character Family Interaction Frequency

How often does Christine interact with family?
How often does Dobby interact with family?
How often does Draco interact with family?
How often does Dudley interact with family?
How often does Ginny interact with family?
How often does Hagrid interact with family?
How often does Harry interact with family?
How often does Hermione interact with family?
How often does Lucius Malfoy interact with family?
How often does McGonagall interact with family?
How often does Quirrell interact with family?
How often does Ron interact with family?
How often does Snape interact with family?
How often does Uncle Vernon interact with family?
How often does Voldemort interact with family?

Character Friend Interactions

Are Draco's friends also friends with each other?
Are Dudley's friends also friends with each other?
Are Filch's friends also friends with each other?
Are Hermione's friends also friends with each other?
Are Lucius Malfoy's friends also friends with each other?
Are Moaning Myrtle's friends also friends with each other?
Are Uncle Vernon's friends also friends with each other?
Are Voldemort's friends also friends with each other?
How many of Aunt Petunia's friends are also friends?
How many of Dobby's friends are also friends?

How many of Harry's friends are also friends?
How many of Lockhart's friends are also friends?
How many of McGonagall's friends are also friends?
How many of Quirrell's friends are also friends?
How many of Snape's friends are also friends?

Character Friend Similarity

How similar are Draco's friends to Draco?
How similar are Dudley's friends to Dudley?
How similar are Filch's friends to Filch?
How similar are Harry's friends to Harry?
How similar are Lucius Malfoy's friends to Lucius Malfoy?
How similar are Ron's friends to Ron?
How similar are Uncle Vernon's friends to Uncle Vernon?
How similar are Voldemort's friends to Voldemort?

Character Friends Same Age

Are most of Aunt Petunia's friends the same age?
Are most of Filch's friends the same age?
Are most of Hagrid's friends the same age?
Are most of Harry's friends the same age?
Are most of Moaning Myrtle's friends the same age?
Are most of Neville's friends the same age?
Are most of Ron's friends the same age?
Are most of Snape's friends the same age?

Character Friends Same House

Are most of Christine's friends in the same House?
Are most of Filch's friends in the same House?
Are most of Hagrid's friends in the same House?
Are most of Hermione's friends in the same House?
Are most of Lucius Malfoy's friends in the same House?
Are most of McGonagall's friends in the same House?
Are most of Moaning Myrtle's friends in the same House?
Are most of Ron's friends in the same House?
Are most of Snape's friends in the same House?

Character Friends Same Interests

How many of Aunt Petunia's friends do similar activities as Aunt Petunia?
How many of Dobby's friends have similar interests as Dobby?
How many of Dudley's friends have similar interests as Dudley?
How many of Filch's friends do similar activities as Filch?
How many of Lockhart's friends have similar interests as Lockhart?
How many of Quirrell's friends do similar activities as Quirrell?
How many of Ron's friends do similar activities as Ron?
How many of Uncle Vernon's friends have similar interests as Uncle Vernon?

Character Friends Same Socioeconomic Class

Are most of Aunt Petunia's friends in the same social class?
Are most of Christine's friends in the same social class?
Are most of Hagrid's friends in the same social class?
Are most of Harry's friends in the same social class?

Are most of Hermione's friends in the same social class?
Are most of Lockhart's friends in the same social class?
Are most of McGonagall's friends in the same social class?
Are most of Neville's friends in the same social class?
Are most of Voldemort's friends in the same social class?

Character Friends Share Beliefs

Do most of Christine's friends share their beliefs?
Do most of Draco's friends share their beliefs?
Do most of Dudley's friends share their beliefs?
Do most of Dumbledore's friends share their beliefs?
Do most of Filch's friends share their beliefs?
Do most of Ginny's friends share their beliefs?
Do most of Uncle Vernon's friends share their beliefs?
Do most of Voldemort's friends share their beliefs?

Character Have A Partner

Does Aunt Petunia have a partner?
Does Christine have a partner?
Does Dobby have a partner?
Does Dudley have a partner?
Does Dumbledore have a partner?
Does Ginny have a partner?
Does Harry have a partner?
Does Hermione have a partner?
Does Lucius Malfoy have a partner?
Does McGonagall have a partner?
Does Neville have a partner?
Does Quirrell have a partner?
Does Ron have a partner?
Does Snape have a partner?
Does Uncle Vernon have a partner?

Character Influence

How much influence does Dobby have over other characters?
How much influence does Filch have over other characters?
How much influence does Ginny have over other characters?
How much influence does Hagrid have over other characters?
How much influence does Harry have over other characters?
How much influence does Hermione have over other characters?
How much influence does Lockhart have over other characters?
How much influence does Moaning Myrtle have over other characters?
How much influence does Quirrell have over other characters?
How much influence does Uncle Vernon have over other characters?

Character Information Sources

Does Aunt Petunia usually get information from a variety sources?
Does Ginny usually get information from a variety sources?
Does Hagrid usually get information from a variety sources?
Does Hermione usually get information from a variety sources?
Does Moaning Myrtle usually get information from a variety sources?

Does Quirrell usually get information from a variety sources?
Does Ron usually get information from a variety sources?
Does Voldemort usually get information from a variety sources?

Character Information Spread Usefulness

How useful is Dobby for getting the word out about an event?
How useful is Draco for getting the word out about an event?
How useful is Filch for getting the word out about an event?
How useful is Hermione for getting the word out about an event?
How useful is Lockhart for getting the word out about an event?
How useful is Lucius Malfoy for getting the word out about an event?
How useful is McGonagall for getting the word out about an event?
How useful is Moaning Myrtle for getting the word out about an event?
How useful is Uncle Vernon for getting the word out about an event?
How useful is Voldemort for getting the word out about an event?

Character Information Usefulness

How many characters get their information from Dobby?
How many characters get their information from Dudley?
How many characters get their information from Dumbledore?
How many characters get their information from Ginny?
How many characters get their information from Hagrid?
How many characters get their information from Harry?
How many characters get their information from Lucius Malfoy?
How many characters get their information from Quirrell?
How many characters get their information from Ron?

Character Interaction Same Age

Are most characters Christine interacts with about the same age?
Are most characters Dobby interacts with about the same age?
Are most characters Dudley interacts with about the same age?
Are most characters Harry interacts with about the same age?
Are most characters Lockhart interacts with about the same age?
Are most characters Lucius Malfoy interacts with about the same age?
Are most characters Neville interacts with about the same age?
Are most characters Quirrell interacts with about the same age?

Character Interaction Same House

Does Christine mostly interact with characters from the same House?
Does Dobby mostly interact with characters from the same House?
Does Dumbledore mostly interact with characters from the same House?
Does Filch mostly interact with characters from the same House?
Does Neville mostly interact with characters from the same House?
Does Quirrell mostly interact with characters from the same House?
Does Ron mostly interact with characters from the same House?
Does Uncle Vernon mostly interact with characters from the same House?

Character Interaction Same Interests

Does Draco mostly interact with those that have similar interests?
Does Dumbledore mostly interact with those that have similar interests?
Does Filch mostly interact with those that do similar activities?
Does Ginny mostly interact with those that have similar interests?

Does Lucius Malfoy mostly interact with those that do similar activities?
Does Moaning Myrtle mostly interact with those that have similar interests?
Does Quirrell mostly interact with those that have similar interests?
Does Ron mostly interact with those that do similar activities?
Does Uncle Vernon mostly interact with those that do similar activities?

Character Interaction Same Socioeconomic Class

Does Christine mostly interact with characters in the same socioeconomic class?
Does Dobby mostly interact with characters in the same socioeconomic class?
Does Dumbledore mostly interact with characters in the same socioeconomic class?
Does Harry mostly interact with characters in the same socioeconomic class?
Does Lockhart mostly interact with characters in the same socioeconomic class?
Does Moaning Myrtle mostly interact with characters in the same socioeconomic class?
Does Ron mostly interact with characters in the same socioeconomic class?
Does Voldemort mostly interact with characters in the same socioeconomic class?

Character Interaction Share Beliefs

Does Christine mostly interact with characters who share their beliefs?
Does Draco mostly interact with characters who share their beliefs?
Does Dudley mostly interact with characters who share their beliefs?
Does Harry mostly interact with characters who share their beliefs?
Does Lucius Malfoy mostly interact with characters who share their beliefs?
Does Quirrell mostly interact with characters who share their beliefs?
Does Ron mostly interact with characters who share their beliefs?
Does Snape mostly interact with characters who share their beliefs?
Does Voldemort mostly interact with characters who share their beliefs?

Character Knowledge Likelihood

How likely is it that Aunt Petunia would know a randomly picked character?
How likely is it that Christine would know a randomly picked character?
How likely is it that Dobby would know a randomly picked character?
How likely is it that Draco would know a randomly picked character?
How likely is it that Dudley would know a randomly picked character?
How likely is it that Dumbledore would know a randomly picked character?
How likely is it that Filch would know a randomly picked character?
How likely is it that Ginny would know a randomly picked character?
How likely is it that Hagrid would know a randomly picked character?
How likely is it that Harry would know a randomly picked character?
How likely is it that Hermione would know a randomly picked character?
How likely is it that Lockhart would know a randomly picked character?
How likely is it that Lucius Malfoy would know a randomly picked character?
How likely is it that Moaning Myrtle would know a randomly picked character?
How likely is it that Neville would know a randomly picked character?
How likely is it that Quirrell would know a randomly picked character?
How likely is it that Ron would know a randomly picked character?
How likely is it that Snape would know a randomly picked character?
How likely is it that Uncle Vernon would know a randomly picked character?
How likely is it that Voldemort would know a randomly picked character?

Character Other Character Interactions

Do those that Draco interacts with interact with each other?
Do those that Dumbledore interacts with interact with each other?
Do those that Filch interacts with interact with each other?
Do those that Ginny interacts with interact with each other?
Do those that Hagrid interacts with interact with each other?
Do those that Harry interacts with interact with each other?
Do those that Hermione interacts with interact with each other?
Do those that Lockhart interacts with interact with each other?
Do those that Lucius Malfoy interacts with interact with each other?
Do those that McGonagall interacts with interact with each other?
Do those that Moaning Myrtle interacts with interact with each other?
Do those that Neville interacts with interact with each other?
Do those that Snape interacts with interact with each other?
Do those that Uncle Vernon interacts with interact with each other?
Do those that Voldemort interacts with interact with each other?

Character Power

How much power does Christine have over others?
How much power does Draco have over others?
How much power does Dudley have over others?
How much power does Filch have over others?
How much power does Ginny have over others?
How much power does Lockhart have over others?
How much power does McGonagall have over others?
How much power does Moaning Myrtle have over others?
How much power does Ron have over others?
How much power does Snape have over others?

Character Work with Enemy against Mutual Enemy Willingness

Would Aunt Petunia work with an enemy to fight a mutual enemy?
Would Draco work with an enemy to fight a mutual enemy?
Would Dudley work with an enemy to fight a mutual enemy?
Would Dumbledore work with an enemy to fight a mutual enemy?
Would Filch work with an enemy to fight a mutual enemy?
Would Hagrid work with an enemy to fight a mutual enemy?
Would Harry work with an enemy to fight a mutual enemy?
Would Hermione work with an enemy to fight a mutual enemy?
Would Lockhart work with an enemy to fight a mutual enemy?
Would Lucius Malfoy work with an enemy to fight a mutual enemy?
Would McGonagall work with an enemy to fight a mutual enemy?
Would Moaning Myrtle work with an enemy to fight a mutual enemy?
Would Quirrell work with an enemy to fight a mutual enemy?
Would Uncle Vernon work with an enemy to fight a mutual enemy?
Would Voldemort work with an enemy to fight a mutual enemy?

Conform/submit

Would Aunt Petunia restrain themselves around Neville?
Would Christine give in to Draco?
Would Dobby give in to Uncle Vernon?
Would Filch yield to Dudley?

Would Ginny yield to Hermione?
Would Lucius Malfoy restrain themselves around Moaning Myrtle?
Would McGonagall give in to Snape?
Would Quirrell give in to Harry?
Would Ron restrain themselves around Dumbledore?
Would Voldemort yield to Lockhart?

Count Direct Interactions

How many characters has Christine interacted with directly?
How many characters has Dobby interacted with directly?
How many characters has Ginny interacted with directly?
How many characters has Hermione interacted with directly?
How many characters has Lucius Malfoy interacted with directly?
How many characters has McGonagall interacted with directly?
How many characters has Moaning Myrtle interacted with directly?
How many characters has Neville interacted with directly?
How many characters has Ron interacted with directly?
How many characters has Snape interacted with directly?

Count Famousness

How many characters know of Aunt Petunia?
How many characters know of Draco?
How many characters know of Dudley?
How many characters know of Dumbledore?
How many characters know of Hermione?
How many characters know of Lockhart?
How many characters know of Moaning Myrtle?
How many characters know of Quirrell?
How many characters know of Uncle Vernon?
How many characters know of Voldemort?

Count Friends Are Not Friends

How many of Aunt Petunia's friends dislike each other?
How many of Christine's friends dislike each other?
How many of Dobby's friends dislike each other?
How many of Draco's friends dislike each other?
How many of Dudley's friends dislike each other?
How many of Filch's friends dislike each other?
How many of Ginny's friends dislike each other?
How many of Hagrid's friends dislike each other?
How many of Lockhart's friends dislike each other?
How many of Lucius Malfoy's friends dislike each other?
How many of Moaning Myrtle's friends dislike each other?
How many of Neville's friends dislike each other?
How many of Ron's friends dislike each other?
How many of Snape's friends dislike each other?
How many of Uncle Vernon's friends dislike each other?

Count Group Membership

How many characters are members of Gryffindor?
How many characters are members of Hufflepuff?

How many characters are members of Slytherin?
How many characters are members of Voldemort's followers?
How many characters are members of the Dursley family?
How many characters are members of the Hogwarts faculty?
How many characters are members of the Hogwarts staff?
How many characters are members of the Malfoy family?
How many characters are members of the Slytherin Quidditch team?
How many characters are members of the Weasley family?

Count Regular Interactions

How many characters does Aunt Petunia interact with regularly?
How many characters does Dumbledore interact with regularly?
How many characters does Hagrid interact with regularly?
How many characters does Harry interact with regularly?
How many characters does Hermione interact with regularly?
How many characters does Lockhart interact with regularly?
How many characters does Lucius Malfoy interact with regularly?
How many characters does Neville interact with regularly?
How many characters does Quirrell interact with regularly?
How many characters does Ron interact with regularly?

Count Social Group Knowledge

How many social groups does Aunt Petunia know any members of?
How many social groups does Christine know any members of?
How many social groups does Dobby know any members of?
How many social groups does Draco know any members of?
How many social groups does Dudley know any members of?
How many social groups does Dumbledore know any members of?
How many social groups does Ginny know any members of?
How many social groups does Hagrid know any members of?
How many social groups does Harry know any members of?
How many social groups does Hermione know any members of?
How many social groups does Lockhart know any members of?
How many social groups does Lucius Malfoy know any members of?
How many social groups does McGonagall know any members of?
How many social groups does Moaning Myrtle know any members of?
How many social groups does Neville know any members of?
How many social groups does Quirrell know any members of?
How many social groups does Ron know any members of?
How many social groups does Snape know any members of?
How many social groups does Uncle Vernon know any members of?
How many social groups does Voldemort know any members of?

Count Social Group Membership

How many different social groups is Aunt Petunia part of?
How many different social groups is Christine part of?
How many different social groups is Dobby part of?
How many different social groups is Draco part of?
How many different social groups is Dudley part of?
How many different social groups is Dumbledore part of?

- How many different social groups is Ginny part of?
- How many different social groups is Hagrid part of?
- How many different social groups is Harry part of?
- How many different social groups is Hermione part of?
- How many different social groups is Lockhart part of?
- How many different social groups is Lucius Malfoy part of?
- How many different social groups is McGonagall part of?
- How many different social groups is Moaning Myrtle part of?
- How many different social groups is Neville part of?
- How many different social groups is Quirrell part of?
- How many different social groups is Ron part of?
- How many different social groups is Snape part of?
- How many different social groups is Uncle Vernon part of?
- How many different social groups is Voldemort part of?

Count Typical Day Interactions

- How many characters does Christine interact with on a typical day?
- How many characters does Dobby interact with on a typical day?
- How many characters does Draco interact with on a typical day?
- How many characters does Dudley interact with on a typical day?
- How many characters does Dumbledore interact with on a typical day?
- How many characters does Filch interact with on a typical day?
- How many characters does Hermione interact with on a typical day?
- How many characters does Moaning Myrtle interact with on a typical day?
- How many characters does Ron interact with on a typical day?
- How many characters does Snape interact with on a typical day?

Dominate

- Would Aunt Petunia criticize Dobby?
- Would Christine order Snape around?
- Would Draco provoke Lucius Malfoy?
- Would Dudley argue with Lockhart?
- Would Filch order Hermione around?
- Would Ginny provoke Moaning Myrtle?
- Would Hagrid argue with Quirrell?
- Would Neville provoke Harry?
- Would Ron criticize Dumbledore?
- Would Voldemort order McGonagall around?

Economic status

- How wealthy is Aunt Petunia?
- How wealthy is Draco?
- How wealthy is Dudley?
- How wealthy is Ginny?
- How wealthy is Hagrid?
- How wealthy is Harry?
- How wealthy is Hermione?
- How wealthy is Moaning Myrtle?
- How wealthy is Snape?

Education

How educated is Aunt Petunia?
How educated is Dobby?
How educated is Draco?
How educated is Dumbledore?
How educated is Hagrid?
How educated is Moaning Myrtle?
How educated is Quirrell?
How educated is Uncle Vernon?
How educated is Voldemort?
Encourage/support 2-1-
Would Dudley motivate Hermione?
Would Dumbledore motivate Ginny?
Would Hagrid encourage Ron?
Would Harry encourage Draco?
Would Lucius Malfoy encourage Uncle Vernon?
Would McGonagall help Filch?
Would Neville stand up for Dobby?
Would Quirrell stand up for Moaning Myrtle?
Would Snape stand up for Aunt Petunia?
Would Voldemort help Lockhart?
Family Relationship
Is Dudley Dobby's cousin?
Is Filch Christine's aunt/uncle?
Is Ginny Dudley's cousin?
Is Hagrid Dumbledore's parent?
Is Hermione Ron's sibling?
Is Lucius Malfoy Draco's aunt/uncle?
Is Quirrell Lockhart's sibling?
Would Aunt Petunia describe Filch as their sibling?
Would Harry describe Snape as their parent?
Would Lockhart describe Uncle Vernon as their cousin?
Would McGonagall describe Neville as their aunt/uncle?
Would Moaning Myrtle describe Voldemort as their cousin?
Fear/awe
Would Dobby look up to Lockhart?
Would Draco hold Quirrell in awe?
Would Filch hold Aunt Petunia in awe?
Would Ginny hold Dudley in awe?
Would Hagrid look up to Moaning Myrtle?
Would Harry look up to Uncle Vernon?
Would McGonagall look up to Hermione?
Would Neville hold Ron in awe?
Would Snape hold Christine in awe?
Fool/Exploit
Would Aunt Petunia fool Quirrell?
Would Christine slander Hagrid?
Would Dumbledore fool Dobby?

Would Ginny slander Hermione?
Would Harry exploit Draco?
Would Lucius Malfoy fool Moaning Myrtle?
Would Neville exploit Ron?
Would Snape slander McGonagall?
Would Uncle Vernon ignore Lockhart?
Would Voldemort ignore Dudley?

Gender

How feminine is Dumbledore?
How feminine is Ginny?
How feminine is Harry?
How feminine is Lucius Malfoy?
How feminine is Neville?
How masculine is Lockhart?
How masculine is Ron?
How masculine is Snape?
How masculine is Voldemort?

Geographic Relationship

Are Aunt Petunia and Lockhart from the same neighborhood?
Are Christine and Uncle Vernon from the same neighborhood?
Are Dobby and Neville from the same country?
Are Draco and Ron from the same country?
Are Dudley and Moaning Myrtle from the same country?
Are Dumbledore and Harry from the same neighborhood?
Are Filch and Aunt Petunia from the same neighborhood?
Are Ginny and Snape from the same country?
Are Hagrid and Quirrell from the same country?
Are Hermione and Voldemort from the same neighborhood?
Are McGonagall and Dudley from the same neighborhood?
Are Neville and Lucius Malfoy from the same country?

Group Clear Power Structure

Does Hufflepuff have a clear power structure?
Does Slytherin have a clear power structure?
Does Voldemort's followers have a clear power structure?
Does the Dursley family have a clear power structure?
Does the Hogwarts faculty have a clear power structure?
Does the Hogwarts staff have a clear power structure?
Does the Hogwarts student body have a clear power structure?
Does the Malfoy family have a clear power structure?
Does the Slytherin Quidditch team have a clear power structure?
Does the Weasley family have a clear power structure?

Group Group Interactions

How involved with other groups is Gryffindor?
How involved with other groups is the Dursley family?
How involved with other groups is the Gryffindor Quidditch team?
How involved with other groups is the Hogwarts faculty?
How involved with other groups is the Hogwarts staff?

How isolated is Ravenclaw?
How isolated is Voldemort's followers?
How isolated is the Hogwarts student body?
How isolated is the Malfoy family?
How isolated is the Slytherin Quidditch team?

Group Member Meet Frequency

How often do members of Hufflepuff meet?
How often do members of Ravenclaw meet?
How often do members of Slytherin meet?
How often do members of Voldemort's followers meet?
How often do members of the Gryffindor Quidditch team meet?
How often do members of the Hogwarts staff meet?
How often do members of the Hogwarts student body meet?
How often do members of the Malfoy family meet?
How often do members of the Slytherin Quidditch team meet?
How often do members of the Weasley family meet?

Group Tight Knit

Is Gryffindor a tight-knit group?
Is Hufflepuff a tight-knit group?
Is Ravenclaw a tight-knit group?
Is Slytherin a tight-knit group?
Is Voldemort's followers a tight-knit group?
Is the Gryffindor Quidditch team a tight-knit group?
Is the Hogwarts faculty a tight-knit group?
Is the Hogwarts student body a tight-knit group?
Is the Slytherin Quidditch team a tight-knit group?
Is the Weasley family a tight-knit group?

Individual Interaction Frequency

Does Christine interact with many characters that don't interact with each other?
Does Filch interact with many characters that don't interact with each other?
Does Ginny interact with many characters that don't interact with each other?
Does Hagrid interact with many characters that don't interact with each other?
Does Hermione interact with many characters that don't interact with each other?
Does Moaning Myrtle interact with many characters that don't interact with each other?
Does Quirrell interact with many characters that don't interact with each other?
Does Snape interact with many characters that don't interact with each other?
Does Voldemort interact with many characters that don't interact with each other?

Interaction Character And Character Similarity

How similar are most characters Christine interacts with to Christine?
How similar are most characters Dumbledore interacts with to Dumbledore?
How similar are most characters Filch interacts with to Filch?
How similar are most characters Lockhart interacts with to Lockhart?
How similar are most characters McGonagall interacts with to McGonagall?
How similar are most characters Neville interacts with to Neville?
How similar are most characters Quirrell interacts with to Quirrell?
How similar are most characters Snape interacts with to Snape?

Interests
- How interested is Aunt Petunia in academics?
- How interested is Dumbledore in Quidditch?
- How interested is Hagrid in academics?
- How interested is Harry in the Dark Arts?
- How interested is McGonagall in the Dark Arts?
- How interested is Moaning Myrtle in Quidditch?
- How interested is Neville in the Dark Arts?
- How interested is Snape in academics?
- How interested is Voldemort in Quidditch?

Lineage
- Is Aunt Petunia a wizard or witch?
- Is Christine a Muggle?
- Is Dobby a Squib?
- Is Draco a Muggle?
- Is Dudley a Muggle?
- Is Filch a non-human magical creature?
- Is Hagrid a Squib?
- Is Ron a non-human magical creature?
- Is Uncle Vernon a wizard or witch?

Look down on
- Would Aunt Petunia laugh at Lockhart?
- Would Dobby hurt Christine?
- Would Filch disparage Draco?
- Would Ginny disparage Voldemort?
- Would Harry hurt Snape?
- Would Hermione laugh at Dudley?
- Would McGonagall hurt Dumbledore?
- Would Neville disparage Quirrell?
- Would Ron disparage Moaning Myrtle?
- Would Uncle Vernon laugh at Lucius Malfoy?

Make fun of
- Would Aunt Petunia ridicule Hagrid?
- Would Christine insult Snape?
- Would Dobby call McGonagall names?
- Would Filch mock Uncle Vernon?
- Would Ginny ridicule Dumbledore?
- Would Hermione mock Lockhart?
- Would Lucius Malfoy call Moaning Myrtle names?
- Would Neville call Voldemort names?
- Would Quirrell insult Harry?
- Would Ron insult Draco?

Mental Health
- How is Draco's mental health?
- How is Dudley's mental health?
- How is Filch's mental health?
- How is Hagrid's mental health?

How is Harry's mental health?
How is Hermione's mental health?
How is Moaning Myrtle's mental health?
How is Quirrell's mental health?
How is Ron's mental health?

Mutual Enemies of Character and Friends
Do Christine and their friends have mutual enemies?
Do Dobby and their friends have mutual enemies?
Do Dudley and their friends have mutual enemies?
Do Dumbledore and their friends have mutual enemies?
Do Filch and their friends have mutual enemies?
Do Ginny and their friends have mutual enemies?
Do Hagrid and their friends have mutual enemies?
Do Harry and their friends have mutual enemies?
Do Hermione and their friends have mutual enemies?
Do Lockhart and their friends have mutual enemies?
Do McGonagall and their friends have mutual enemies?
Do Neville and their friends have mutual enemies?
Do Quirrell and their friends have mutual enemies?
Do Ron and their friends have mutual enemies?
Do Snape and their friends have mutual enemies?

Non-kin Personal Relationship
Is Christine Uncle Vernon's friend?
Is Dumbledore Voldemort's enemy?
Is Lockhart Ginny's friend?
Is McGonagall Dobby's acquaintance?
Is Quirrell Hermione's teacher?
Is Ron Draco's teacher?
Would Dobby describe Moaning Myrtle as their teacher?
Would Dudley describe Lockhart as their friend?
Would Filch describe Hagrid as their enemy?
Would Harry describe Neville as their enemy?
Would Hermione describe Lucius Malfoy as their acquaintance?
Would Snape describe Aunt Petunia as their friend?

Oppose/fight
Would Aunt Petunia question Ron?
Would Dobby fight Filch?
Would Draco fight Christine?
Would Dudley challenge Hermione?
Would Dumbledore oppose Uncle Vernon?
Would Harry challenge Hagrid?
Would Lockhart oppose Neville?
Would Moaning Myrtle oppose McGonagall?
Would Voldemort question Ginny?

Physical Health
How is Christine's physical health?
How is Dudley's physical health?

How is Filch's physical health?
How is Ginny's physical health?
How is Lockhart's physical health?
How is McGonagall's physical health?
How is Neville's physical health?
How is Quirrell's physical health?
How is Ron's physical health?
How is Voldemort's physical health?

Popularity

How popular is Aunt Petunia?
How popular is Draco?
How popular is Dudley?
How popular is Lockhart?
How popular is Lucius Malfoy?
How popular is Neville?
How popular is Quirrell?
How popular is Ron?
How popular is Uncle Vernon?
How popular is Voldemort?

Power

How much power does Aunt Petunia have?
How much power does Filch have?
How much power does Ginny have?
How much power does McGonagall have?
How much power does Moaning Myrtle have?
How much power does Neville have?
How much power does Quirrell have?
How much power does Snape have?
How much power does Voldemort have?

Protect/comfort

Would Aunt Petunia protect Lockhart?
Would Christine reassure Dumbledore?
Would Draco support Hermione?
Would Filch reassure Ron?
Would Hagrid reassure Quirrell?
Would Lucius Malfoy comfort Moaning Myrtle?
Would McGonagall comfort Dobby?
Would Neville support Harry?
Would Snape comfort Ginny?
Would Voldemort protect Uncle Vernon?

Relationship Duration

Has Draco known Ginny for a long time?
Has Dudley known Dumbledore for a long time?
Has Filch known Dobby for a long time?
Has Hagrid known Moaning Myrtle for a long time?
Has Hermione known Neville for a long time?
Has Lockhart known Lucius Malfoy for a long time?

Has Quirrell known McGonagall for a long time?
Has Snape known Christine for a long time?
Has Uncle Vernon known Ron for a long time?

Respect

How much do characters respect Dudley?
How much do characters respect Dumbledore?
How much do characters respect Lockhart?
How much do characters respect Lucius Malfoy?
How much do characters respect Uncle Vernon?
How much prestige does Aunt Petunia have?
How much prestige does Christine have?
How much prestige does Ginny have?
How much prestige does Hagrid have?
How much prestige does Neville have?

Romantic Relationship

Is Hermione Harry's romantic partner?
Is Lucius Malfoy Voldemort's date?
Is Moaning Myrtle Ginny's ex?
Is Ron Neville's crush?
Is Uncle Vernon Quirrell's date?
Would Christine describe McGonagall as their date?
Would Dobby describe Snape as their crush?
Would Dudley describe Moaning Myrtle as their romantic partner?
Would Dumbledore describe Draco as their date?
Would Hagrid describe Aunt Petunia as their ex?
Would Lockhart describe Uncle Vernon as their romantic partner?
Would Snape describe Filch as their crush?

Social Group Bridge

Does Dobby act as a bridge for different social groups?
Does Ginny act as a bridge for different social groups?
Does Harry act as a bridge for different social groups?
Does Lockhart act as a bridge for different social groups?
Does Lucius Malfoy act as a bridge for different social groups?
Does McGonagall act as a bridge for different social groups?
Does Quirrell act as a bridge for different social groups?
Does Ron act as a bridge for different social groups?

Social Group Homophily

Are members of Gryffindor similar to each other?
Are members of Hufflepuff similar to each other?
Are members of Ravenclaw similar to each other?
Are members of Slytherin similar to each other?
Are members of Voldemort's followers similar to each other?
Are members of the Dursley family similar to each other?
Are members of the Gryffindor Quidditch team similar to each other?
Are members of the Hogwarts faculty similar to each other?
Are members of the Hogwarts student body similar to each other?
Are members of the Weasley family similar to each other?

Social Group Interaction Frequency
Do Christine's social groups interact regularly with each other?
Do Dobby's social groups interact regularly with each other?
Do Ginny's social groups interact regularly with each other?
Do Hagrid's social groups interact regularly with each other?
Do Harry's social groups interact regularly with each other?
Do Lockhart's social groups interact regularly with each other?
Do Lucius Malfoy's social groups interact regularly with each other?
Do McGonagall's social groups interact regularly with each other?
Specific Social Group Membership
Is Aunt Petunia a member of Slytherin?
Is Dobby a member of the Hogwarts faculty?
Is Draco a member of the Malfoy family?
Is Hagrid a member of the Hogwarts student body?
Is Harry a member of Hufflepuff?
Is Lockhart a member of Ravenclaw?
Is Moaning Myrtle a member of the Gryffindor Quidditch team?
Is Neville a member of the Hogwarts staff?
Is Uncle Vernon a member of Gryffindor?
Subject Character age
Are you similar in age to Aunt Petunia?
Are you similar in age to Christine?
Are you similar in age to Dobby?
Are you similar in age to Draco?
Are you similar in age to Dudley?
Are you similar in age to Hagrid?
Subject Character beliefs
Do you and Aunt Petunia have similar beliefs?
Do you and Christine have similar beliefs?
Do you and Filch have similar beliefs?
Do you and Hermione have similar beliefs?
Do you and Lucius Malfoy have similar beliefs?
Do you and Moaning Myrtle have similar beliefs?
Subject Character cultural background
Do you and Aunt Petunia have similar cultural backgrounds?
Do you and Dudley have similar cultural backgrounds?
Do you and Ginny have similar cultural backgrounds?
Do you and Hermione have similar cultural backgrounds?
Do you and Lockhart have similar cultural backgrounds?
Do you and Snape have similar cultural backgrounds?
Subject Character friendship
Would you be friends with Aunt Petunia?
Would you be friends with Ginny?
Would you be friends with Harry?
Would you be friends with Lucius Malfoy?
Would you be friends with Moaning Myrtle?
Would you be friends with Snape?

Subject Character interests
  Do you and Christine share similar interests?
  Do you and Dumbledore share similar interests?
  Do you and Filch share similar interests?
  Do you and Hermione share similar interests?
  Do you and Lockhart share similar interests?
  Do you and Moaning Myrtle share similar interests?
Subject Character life events
  Have you and Aunt Petunia experienced similar life events?
  Have you and Christine experienced similar life events?
  Have you and Dobby experienced similar life events?
  Have you and Dumbledore experienced similar life events?
  Have you and Snape experienced similar life events?
  Have you and Uncle Vernon experienced similar life events?
Subject Character personality
  Do you and Hagrid have similar personalities?
  Do you and Lucius Malfoy have similar personalities?
  Do you and McGonagall have similar personalities?
  Do you and Ron have similar personalities?
  Do you and Snape have similar personalities?
  Do you and Voldemort have similar personalities?
Subject Character socioeconomic background
  Do you and Aunt Petunia have similar socioeconomic backgrounds?
  Do you and Christine have similar socioeconomic backgrounds?
  Do you and Dudley have similar socioeconomic backgrounds?
  Do you and Harry have similar socioeconomic backgrounds?
  Do you and Uncle Vernon have similar socioeconomic backgrounds?
  Do you and Voldemort have similar socioeconomic backgrounds?
Subject Character values
  Do you and Aunt Petunia have similar values?
  Do you and Dobby have similar values?
  Do you and Filch have similar values?
  Do you and Lucius Malfoy have similar values?
  Do you and Neville have similar values?
  Do you and Voldemort have similar values?
Subject Group fit
  Would you fit in with the Gryffindor Quidditch team?
  Would you fit in with the Malfoy family?
  Would you fit in with the Weasley family?
  Would you join Ravenclaw?
  Would you join the Dursley family?
  Would you join the Hogwarts staff?
Well Known
  How well-known is Christine?
  How well-known is Dumbledore?
  How well-known is Hagrid?
  How well-known is Harry?

How well-known is Hermione?
How well-known is Lucius Malfoy?
How well-known is McGonagall?
How well-known is Moaning Myrtle?
How well-known is Snape?
How well-known is Uncle Vernon?

Well-connected Interaction

Does Aunt Petunia regularly interact with many well-connected characters?
Does Christine regularly interact with many well-connected characters?
Does Dobby regularly interact with many well-connected characters?
Does Draco regularly interact with many well-connected characters?
Does Dudley regularly interact with many well-connected characters?
Does Dumbledore regularly interact with many well-connected characters?
Does Filch regularly interact with many well-connected characters?
Does Ginny regularly interact with many well-connected characters?
Does Hagrid regularly interact with many well-connected characters?
Does Harry regularly interact with many well-connected characters?
Does Hermione regularly interact with many well-connected characters?
Does Lockhart regularly interact with many well-connected characters?
Does Lucius Malfoy regularly interact with many well-connected characters?
Does McGonagall regularly interact with many well-connected characters?
Does Moaning Myrtle regularly interact with many well-connected characters?
Does Neville regularly interact with many well-connected characters?
Does Ron regularly interact with many well-connected characters?
Does Snape regularly interact with many well-connected characters?
Does Uncle Vernon regularly interact with many well-connected characters?
Does Voldemort regularly interact with many well-connected characters?

Well-connectedness

How well-connected is Christine?
How well-connected is Dobby?
How well-connected is Draco?
How well-connected is Dudley?
How well-connected is Dumbledore?
How well-connected is Filch?
How well-connected is Ginny?
How well-connected is Hagrid?
How well-connected is Harry?
How well-connected is Hermione?
How well-connected is Lockhart?
How well-connected is Lucius Malfoy?
How well-connected is McGonagall?
How well-connected is Moaning Myrtle?
How well-connected is Neville?
How well-connected is Quirrell?
How well-connected is Ron?
How well-connected is Snape?
How well-connected is Uncle Vernon?

How well-connected is Voldemort?

Within Group Interaction Regularity

How often do those in Aunt Petunia's main social group interact?
How often do those in Dobby's main social group interact?
How often do those in Dudley's main social group interact?
How often do those in Dumbledore's main social group interact?
How often do those in Ginny's main social group interact?
How often do those in Hagrid's main social group interact?
How often do those in Harry's main social group interact?
How often do those in Lucius Malfoy's main social group interact?
How often do those in McGonagall's main social group interact?
How often do those in Neville's main social group interact?
How often do those in Quirrell's main social group interact?
How often do those in Ron's main social group interact?
How often do those in Snape's main social group interact?
How often do those in Uncle Vernon's main social group interact?
How often do those in Voldemort's main social group interact?

Work Relationship

Is Dumbledore Harry's colleague?
Is Filch Hermione's servant?
Is Hermione Lucius Malfoy's master?
Is McGonagall Draco's superior?
Is Moaning Myrtle Dudley's master?
Is Quirrell Hagrid's superior?
Is Ron Voldemort's servant?
Would Aunt Petunia describe Neville as their colleague?
Would Ginny describe Snape as their superior?
Would Hagrid describe Dobby as their master?
Would Neville describe Christine as their superior?
Would Uncle Vernon describe Lockhart as their servant?

achievement

How much does Aunt Petunia value being competent?
How much does Christine value being competent?
How much does Dudley value ambition?
How much does Dumbledore value being competent?
How much does Ginny value outward achievements?
How much does Hagrid value outward achievements?
How much does Lucius Malfoy value outward achievements?
How much does McGonagall value ambition?
How much does Moaning Myrtle value ambition?
How much does Neville value being competent?
How much does Ron value ambition?
How much does Uncle Vernon value outward achievements?

benevolence

How much does Aunt Petunia value loyalty to friends?
How much does Christine value being helpful?
How much does Dobby value loyalty to friends?

How much does Dudley value being dependable?
How much does Harry value being helpful?
How much does Lucius Malfoy value being dependable?
How much does McGonagall value being dependable?
How much does Neville value loyalty to friends?
How much does Quirrell value being helpful?
How much does Ron value being dependable?
How much does Snape value loyalty to friends?
How much does Uncle Vernon value being helpful?

conformity

How much does Aunt Petunia value politeness?
How much does Dobby value self-discipline?
How much does Draco value politeness?
How much does Dudley value self-discipline?
How much does Dumbledore value meeting obligations?
How much does Filch value meeting obligations?
How much does Ginny value politeness?
How much does Hagrid value self-discipline?
How much does McGonagall value meeting obligations?
How much does Quirrell value meeting obligations?
How much does Ron value self-discipline?
How much does Snape value politeness?

hedonism

How much does Dobby value self-indulgence?
How much does Draco value pleasure?
How much does Dudley value pleasure?
How much does Dumbledore value pleasure?
How much does Harry value self-indulgence?
How much does Hermione value enjoying life?
How much does Lucius Malfoy value enjoying life?
How much does McGonagall value enjoying life?
How much does Moaning Myrtle value pleasure?
How much does Neville value self-indulgence?
How much does Quirrell value self-indulgence?
How much does Uncle Vernon value enjoying life?

power

How much does Draco value wealth?
How much does Dumbledore value controlling others?
How much does Filch value authority?
How much does Ginny value authority?
How much does Hagrid value wealth?
How much does Harry value authority?
How much does Lockhart value wealth?
How much does Lucius Malfoy value controlling others?
How much does McGonagall value authority?
How much does Moaning Myrtle value wealth?
How much does Neville value controlling others?

How much does Uncle Vernon value controlling others?
security
How much does Christine value security?
How much does Dobby value cleanliness?
How much does Draco value security?
How much does Dumbledore value cleanliness?
How much does Harry value cleanliness?
How much does Hermione value social order?
How much does Lockhart value social order?
How much does Lucius Malfoy value social order?
How much does Quirrell value cleanliness?
How much does Ron value security?
How much does Snape value social order?
How much does Voldemort value security?
self-direction
How much does Dobby value creativity?
How much does Draco value creativity?
How much does Dumbledore value independence?
How much does Hagrid value curiosity?
How much does Harry value curiosity?
How much does Lockhart value curiosity?
How much does McGonagall value independence?
How much does Moaning Myrtle value independence?
How much does Neville value creativity?
How much does Snape value creativity?
How much does Uncle Vernon value curiosity?
How much does Voldemort value independence?
stimulation
How much does Dudley value novelty?
How much does Filch value novelty?
How much does Ginny value adventure?
How much does Hagrid value excitement?
How much does Harry value adventure?
How much does McGonagall value adventure?
How much does Moaning Myrtle value excitement?
How much does Neville value novelty?
How much does Quirrell value excitement?
How much does Ron value novelty?
How much does Snape value excitement?
How much does Voldemort value adventure?
tradition
How much does Aunt Petunia value humility?
How much does Draco value cultural customs?
How much does Dumbledore value tradition?
How much does Filch value humility?
How much does Hermione value humility?
How much does Lucius Malfoy value cultural customs?

How much does McGonagall value cultural customs?
How much does Neville value tradition?
How much does Quirrell value tradition?
How much does Ron value cultural customs?
How much does Snape value tradition?
How much does Voldemort value humility?

universalism

How much does Christine value tolerance of others?
How much does Draco value social justice?
How much does Dudley value tolerance of others?
How much does Dumbledore value tolerance of others?
How much does Ginny value social justice?
How much does Hagrid value social justice?
How much does Harry value protecting the environment?
How much does Lucius Malfoy value protecting the environment?
How much does Neville value social justice?
How much does Snape value protecting the environment?
How much does Uncle Vernon value protecting the environment?
How much does Voldemort value tolerance of others?

Chapter 5

Appendix to mapping the representation of the self and different types of others in the brain

5.1 List of experiment questions

Problem Type Past Financial
- In the past has [acquaintance_5] suffered from major financial problems?
- In the past has [family_4] suffered from major financial problems?
- In the past has [famous_person_4] suffered from major financial problems?
- In the past has [fictional_person_2] suffered from major financial problems?
- In the past has [work_colleague_5] suffered from major financial problems?

Problem Type Past Health
- In the past has [acquaintance_5] suffered from major health problems?
- In the past has [close_friend_3] suffered from major health problems?
- In the past has [family_4] suffered from major health problems?
- In the past have [self] suffered from major health problems?

Problem Type Past Relationship
- In the past has [acquaintance_2] suffered from major relationship problems?
- In the past has [family_5] suffered from major relationship problems?
- In the past has [famous_person_5] suffered from major relationship problems?
- In the past have [self] suffered from major relationship problems?
- In the past has [work_colleague_5] suffered from major relationship problems?

Problem Type Past Workplace
- In the past has [acquaintance_3] suffered from major workplace problems?
- In the past has [fictional_person_5] suffered from major workplace problems?
- In the past have [self] suffered from major workplace problems?

Problem Type Size Financial
- How big are [acquaintance_1]'s financial problems?
- How big are [close_friend_2]'s financial problems?
- How big are [family_4]'s financial problems?
- How big are [fictional_person_1]'s financial problems?
- How big are [self] financial problems?
- How big are [work_colleague_5]'s financial problems?

Problem Type Size Health
- How big are [acquaintance_4]'s health problems?
- How big are [close_friend_3]'s health problems?
- How big are [family_5]'s health problems?
- How big are [fictional_person_4]'s health problems?

How big are [work_colleague_5]'s health problems?
Problem Type Size Relationship
How big are [acquaintance_3]'s relationship problems?
How big are [famous_person_5]'s relationship problems?
How big are [fictional_person_3]'s relationship problems?
How big are [self] relationship problems?
How big are [work_colleague_5]'s relationship problems?
Problem Type Size Workplace
How big are [famous_person_5]'s workplace problems?
How big are [fictional_person_4]'s workplace problems?
Subject Character Age
Are [self] similar in age to [acquaintance_4]?
Are [self] similar in age to [close_friend_3]?
Are [self] similar in age to [family_2]?
Are [self] similar in age to [famous_person_4]?
Are [self] similar in age to [fictional_person_1]?
Are [self] similar in age to [work_colleague_5]?
Subject Character Beliefs
Do [self] and [acquaintance_1] have similar beliefs?
Do [self] and [close_friend_2] have similar beliefs?
Do [self] and [family_4] have similar beliefs?
Do [self] and [famous_person_4] have similar beliefs?
Do [self] and [fictional_person_1] have similar beliefs?
Do [self] and [work_colleague_5] have similar beliefs?
Subject Character Closeness
How close are [self] to [close_friend_5]?
How close are [self] to [famous_person_5]?
How close are [self] to [work_colleague_5]?
Subject Character Cultural Background
Do [self] and [acquaintance_4] have similar cultural backgrounds?
Do [self] and [close_friend_4] have similar cultural backgrounds?
Do [self] and [family_1] have similar cultural backgrounds?
Do [self] and [famous_person_4] have similar cultural backgrounds?
Do [self] and [fictional_person_1] have similar cultural backgrounds?
Do [self] and [work_colleague_5] have similar cultural backgrounds?
Subject Character Interests
Do [self] and [acquaintance_3] share similar interests?
Do [self] and [close_friend_2] share similar interests?
Do [self] and [family_3] share similar interests?
Do [self] and [famous_person_4] share similar interests?
Do [self] and [fictional_person_4] share similar interests?
Do [self] and [work_colleague_5] share similar interests?
Subject Character Life Events
Have [self] and [acquaintance_5] experienced similar life events?
Have [self] and [close_friend_2] experienced similar life events?
Have [self] and [family_1] experienced similar life events?
Have [self] and [famous_person_4] experienced similar life events?

Have [self] and [fictional_person_5] experienced similar life events?
Have [self] and [work_colleague_5] experienced similar life events?

Subject Character Personality
Do [self] and [acquaintance_2] have similar personalities?
Do [self] and [close_friend_2] have similar personalities?
Do [self] and [family_4] have similar personalities?
Do [self] and [work_colleague_5] have similar personalities?

Subject Character Socioeconomic Background
Do [self] and [acquaintance_1] have similar socioeconomic backgrounds?
Do [self] and [close_friend_2] have similar socioeconomic backgrounds?
Do [self] and [famous_person_4] have similar socioeconomic backgrounds?
Do [self] and [fictional_person_1] have similar socioeconomic backgrounds?
Do [self] and [work_colleague_3] have similar socioeconomic backgrounds?

Subject Character Values
Do [self] and [acquaintance_3] have similar values?
Do [self] and [close_friend_2] have similar values?
Do [self] and [family_2] have similar values?
Do [self] and [famous_person_4] have similar values?
Do [self] and [fictional_person_5] have similar values?
Do [self] and [work_colleague_3] have similar values?

Academics
How good is [acquaintance_4] at academics?
How good is [close_friend_4] at academics?
How good is [family_5] at academics?
How good is [famous_person_4] at academics?
How good is [fictional_person_5] at academics?
How good are [self] at academics?
How good is [work_colleague_3] at academics?

Acceptance
Do others generally accept [acquaintance_2]?
Do others generally accept [close_friend_5]?
Do others generally accept [family_4]?
Do others generally accept [famous_person_3]?
Do others generally accept [fictional_person_4]?
Do others generally accept [self]?
Do others generally accept [work_colleague_3]?

Achievement
How much does [acquaintance_2] value ambition?
How much does [close_friend_2] value outward achievements?
How much does [family_4] value outward achievements?
How much does [famous_person_3] value outward achievements?
How much does [fictional_person_2] value being competent?
How much do [self] value ambition?

Achievement Striving+ V1
Are [self] likely to work hard?

Achievement Striving+ V2
Is [family_5] likely to do more than what's expected of them?

Is [famous_person_3] likely to do more than what's expected of them?
Achievement Striving- V1
Is [fictional_person_1] likely to do just enough work to get by?
Are [self] likely to do just enough work to get by?
Achievement Striving- V2
Is [work_colleague_2] likely to put little time and effort into their work?
Actions+ V1
Is [acquaintance_2] likely to prefer variety to routine?
Is [fictional_person_3] likely to prefer variety to routine?
Activity+ V1
Is [fictional_person_3] likely to be busy?
Activity+ V2
Is [fictional_person_2] likely to be on the go?
Activity+ V3
Are [self] likely to do a lot in [self]r spare time?
Aesthetics+ V1
Is [self] likely to believe in the importance of art?
Is [work_colleague_3] likely to believe in the importance of art?
Aesthetics+ V2
Is [acquaintance_5] likely to see beauty in things that others might not notice?
Is [close_friend_2] likely to see beauty in things that others might not notice?
Is [family_5] likely to see beauty in things that others might not notice?
Is [famous_person_3] likely to see beauty in things that others might not notice?
Affected By Others Problems
How affected is [acquaintance_4] by others' problems?
How affected is [close_friend_2] by others' problems?
How affected is [family_2] by others' problems?
How affected is [famous_person_3] by others' problems?
How affected is [fictional_person_3] by others' problems?
How affected is [self] by others' problems?
How affected is [work_colleague_3] by others' problems?
Age
How old is [acquaintance_2]?
How old is [family_3]?
How old is [famous_person_3]?
How old is [fictional_person_1]?
How old is [work_colleague_3]?
Altruism+ V1
Is [close_friend_4] likely to love helping others?
Altruism+ V3
Is [fictional_person_2] likely to take time for others?
Is [work_colleague_3] likely to take time for others?
American
How much does [famous_person_3] identify with American culture?
How much does [fictional_person_1] identify with American culture?
How much does [work_colleague_3] identify with American culture?
Amount Income

How much money does [acquaintance_2] make?
How much money does [close_friend_5] make?
How much money does [family_5] make?
How much money does [famous_person_3] make?
How much money does [fictional_person_2] make?
How much money does [self] make?
How much money does [work_colleague_3] make?

Amount Money

How much money does [acquaintance_2] have?
How much money does [close_friend_4] have?
How much money does [family_2] have?
How much money does [famous_person_2] have?
How much money does [fictional_person_1] have?
How much money does [work_colleague_2] have?

Anxiety+ V1

Is [acquaintance_2] likely to worry about things?
Is [fictional_person_5] likely to worry about things?

Arts

How interested is [famous_person_3] in the arts?
How interested is [fictional_person_5] in the arts?
How interested is [work_colleague_2] in the arts?

Assertiveness+ V1

Is [famous_person_2] likely to take charge?

Assertiveness+ V2

Is [close_friend_2] likely to try to lead others?

Assertiveness+ V3

Is [famous_person_5] likely to take control of things?

Assertiveness- V1

Is [famous_person_5] likely to wait for others to lead the way?

Athletics

How good is [acquaintance_1] at athletic activities?
How good is [close_friend_4] at athletic activities?
How good is [family_2] at athletic activities?
How good is [famous_person_2] at athletic activities?
How good is [fictional_person_4] at athletic activities?
How good is [work_colleague_2] at athletic activities?

Attractiveness

How attractive is [acquaintance_4] to other people?
How attractive is [close_friend_2] to other people?
How attractive is [family_3] to other people?
How attractive is [famous_person_2] to other people?
How attractive is [fictional_person_1] to other people?
How attractive is [self] to other people?
How attractive is [work_colleague_2] to other people?

Be Yourself

Is [acquaintance_1] comfortable being themselves with other people?
Is [close_friend_4] comfortable being themselves with other people?

Is [family_2] comfortable being themselves with other people?
Is [famous_person_3] comfortable being themselves with other people?
Is [fictional_person_2] comfortable being themselves with other people?
Is [work_colleague_2] comfortable being themselves with other people?
Belong City
Does [acquaintance_3] feel like they belong in their city?
Does [close_friend_5] feel like they belong in their city?
Does [family_5] feel like they belong in their city?
Does [famous_person_2] feel like they belong in their city?
Does [fictional_person_3] feel like they belong in their city?
Does [self] feel like they belong in their city?
Does [work_colleague_2] feel like they belong in their city?
Belong Generation
Does [acquaintance_1] feel like they belong in their generation?
Does [close_friend_3] feel like they belong in their generation?
Does [family_3] feel like they belong in their generation?
Does [fictional_person_4] feel like they belong in their generation?
Do [self] feel like [self] belong in [self]r generation?
Does [work_colleague_2] feel like they belong in their generation?
Belong Work
Does [acquaintance_2] feel like they belong at their workplace?
Does [close_friend_1] feel like they belong at their workplace?
Does [family_5] feel like they belong at their workplace?
Does [famous_person_2] feel like they belong at their workplace?
Does [fictional_person_4] feel like they belong at their workplace?
Do [self] feel like [self] belong at [self]r workplace?
Does [work_colleague_4] feel like they belong at their workplace?
Benevolence
How much does [acquaintance_4] value loyalty to friends?
How much does [close_friend_5] value being dependable?
How much does [family_5] value loyalty to friends?
How much does [famous_person_2] value loyalty to friends?
How much do [self] value being dependable?
Big Changes
Has [acquaintance_2] recently experienced any big changes?
Has [close_friend_3] recently experienced any big changes?
Has [family_4] recently experienced any big changes?
Has [famous_person_4] recently experienced any big changes?
Has [fictional_person_2] recently experienced any big changes?
Have [self] recently experienced any big changes?
Has [work_colleague_5] recently experienced any big changes?
Business And Finance
How interested is [acquaintance_1] in business and finance?
How interested is [close_friend_4] in business and finance?
How interested is [family_3] in business and finance?
How interested is [fictional_person_5] in business and finance?
How interested are [self] in business and finance?

How interested is [work_colleague_5] in business and finance?
Close Experience Share
Does [acquaintance_4] share important experiences with those they are close to?
Does [close_friend_4] share important experiences with those they are close to?
Does [close_friend_2] share important experiences with those they are close to?
Does [family_5] share important experiences with those they are close to?
Does [family_4] share important experiences with those they are close to?
Does [famous_person_5] share important experiences with those they are close to?
Does [famous_person_1] share important experiences with those they are close to?
Does [fictional_person_1] share important experiences with those they are close to?
Does [fictional_person_2] share important experiences with those they are close to?
Do [self] share important experiences with those [self] are close to?
Does [work_colleague_3] share important experiences with those they are close to?
Close Family Relationship
Does [acquaintance_3] have a close relationship with their family?
Does [close_friend_2] have a close relationship with their family?
Does [close_friend_3] have a close relationship with their family?
Does [family_2] have a close relationship with their family?
Does [family_4] have a close relationship with their family?
Does [famous_person_3] have a close relationship with their family?
Does [famous_person_4] have a close relationship with their family?
Does [fictional_person_1] have a close relationship with their family?
Does [fictional_person_2] have a close relationship with their family?
Do [self] have a close relationship with [self]r family?
Does [work_colleague_4] have a close relationship with their family?
Close Interaction Freq
How often does [acquaintance_4] spend quality time with those they are close to?
How often does [close_friend_1] spend quality time with those they are close to?
How often does [family_3] spend quality time with those they are close to?
How often does [famous_person_2] spend quality time with those they are close to?
How often does [fictional_person_3] spend quality time with those they are close to?
How often does [self] spend quality time with those they are close to?
How often does [work_colleague_5] spend quality time with those they are close to?
Competence+ V1
Is [acquaintance_4] likely to complete tasks successfully?
Competence+ V2
Is [acquaintance_3] likely to excel in what they do?
Is [close_friend_4] likely to excel in what they do?
Competence+ V3
Is [family_4] likely to handle tasks smoothly?
Are [self] likely to handle tasks smoothly?
Compliance- V3
Is [close_friend_4] likely to insult people?
Conflicts
Has [acquaintance_4] recently experienced any conflicts?
Has [close_friend_2] recently experienced any conflicts?
Has [family_2] recently experienced any conflicts?

Has [famous_person_2] recently experienced any conflicts?
Has [fictional_person_4] recently experienced any conflicts?
Have [self] recently experienced any conflicts?
Has [work_colleague_5] recently experienced any conflicts?

Conformity
How much does [acquaintance_2] value politeness?
How much does [close_friend_5] value meeting obligations?
How much does [famous_person_5] value politeness?
How much does [fictional_person_1] value meeting obligations?
How much does [work_colleague_4] value self-discipline?

Deliberation- V2
Is [famous_person_2] likely to make rash decisions?

Depression+ V1
Are [self] likely to feel blue?
Is [work_colleague_1] likely to feel blue?

Depression+ V2
Is [acquaintance_3] likely to dislike themselves?
Is [close_friend_1] likely to dislike themselves?
Is [family_2] likely to dislike themselves?
Is [famous_person_2] likely to dislike themselves?

Develop Caring Relationship
How much does [acquaintance_1] prioritize developing caring relationships?
How much does [close_friend_5] prioritize developing caring relationships?
How much does [family_5] prioritize developing caring relationships?
How much does [famous_person_2] prioritize developing caring relationships?
How much does [fictional_person_2] prioritize developing caring relationships?
How much do [self] prioritize developing caring relationships?
How much does [work_colleague_2] prioritize developing caring relationships?

Different Gender
How attracted is [acquaintance_2] to people of a different gender?
How attracted is [close_friend_4] to people of a different gender?
How attracted is [close_friend_5] to people of a different gender?
How attracted is [family_2] to people of a different gender?
How attracted is [family_4] to people of a different gender?
How attracted is [famous_person_5] to people of a different gender?
How attracted is [famous_person_4] to people of a different gender?
How attracted is [fictional_person_4] to people of a different gender?
How attracted is [fictional_person_2] to people of a different gender?
How attracted are [self] to people of a different gender?
How attracted is [work_colleague_1] to people of a different gender?

Disability
Does [acquaintance_3] have a disability?
Does [close_friend_3] have a disability?
Does [family_5] have a disability?
Does [famous_person_2] have a disability?
Does [fictional_person_5] have a disability?
Do [self] have a disability?

Does [work_colleague_2] have a disability?
Distance Moved To Current Living Place
How far is [acquaintance_4]'s current living place from their last place?
How far is [close_friend_2]'s current living place from their last place?
How far is [family_1]'s current living place from their last place?
How far is [famous_person_3]'s current living place from their last place?
How far is [fictional_person_3]'s current living place from their last place?
How far is [self] current living place from [self] last place?
How far is [work_colleague_2]'s current living place from their last place?
Dutifulness+ V1
Is [fictional_person_2] likely to keep their promises?
Are [self] likely to keep [self]r promises?
Dutifulness- V2
Is [famous_person_5] likely to break their promises?
Econ Conservative
How economically conservative is [acquaintance_1]?
How economically conservative is [close_friend_2]?
How economically conservative is [family_2]?
How economically conservative is [famous_person_2]?
How economically conservative is [fictional_person_5]?
How economically conservative are [self]?
How economically conservative is [work_colleague_5]?
Econ Liberal
How economically liberal is [acquaintance_1]?
How economically liberal is [close_friend_1]?
How economically liberal is [family_4]?
How economically liberal is [famous_person_2]?
How economically liberal is [fictional_person_2]?
How economically liberal is [work_colleague_5]?
English Lg
How familiar is [acquaintance_3] with English?
How familiar is [close_friend_5] with English?
How familiar is [work_colleague_4] with English?
Excitement Seeking+ V1
Is [acquaintance_1] likely to love excitement?
Are [self] likely to love excitement?
Expect Good Bad
Does [acquaintance_5] expect more good things to happen to them than bad things?
Does [close_friend_5] expect more good things to happen to them than bad things?
Does [family_4] expect more good things to happen to them than bad things?
Does [famous_person_2] expect more good things to happen to them than bad things?
Does [fictional_person_5] expect more good things to happen to them than bad things?
Do [self] expect more good things to happen to [self] than bad things?
Does [work_colleague_5] expect more good things to happen to them than bad things?

Expect Things Go Smoothly
How often does [acquaintance_4] expect things to go their way?
How often does [close_friend_2] expect things to go their way?
How often does [family_2] expect things to go their way?
How often does [famous_person_2] expect things to go their way?
How often does [fictional_person_1] expect things to go their way?
How often does [work_colleague_4] expect things to go their way?
Expensive Items Owned
How many expensive items does [acquaintance_1] own?
How many expensive items does [close_friend_1] own?
How many expensive items does [family_3] own?
How many expensive items does [famous_person_5] own?
How many expensive items does [fictional_person_5] own?
How many expensive items does [work_colleague_5] own?
Eyes Dark
How dark are [acquaintance_5]'s eyes?
How dark are [close_friend_3]'s eyes?
How dark are [family_3]'s eyes?
Eyes Light
How light are [acquaintance_4]'s eyes?
How light are [family_5]'s eyes?
How light are [famous_person_2]'s eyes?
How light are [fictional_person_4]'s eyes?
Fantasy+ V1
Is [acquaintance_2] likely to have a vivid imagination?
Fantasy+ V4
Is [fictional_person_3] likely to get lost in thought?
Feel Like Failure
Is [acquaintance_2] inclined to feel like a failure?
Is [close_friend_2] inclined to feel like a failure?
Is [family_3] inclined to feel like a failure?
Is [famous_person_2] inclined to feel like a failure?
Is [fictional_person_4] inclined to feel like a failure?
Are [self] inclined to feel like a failure?
Is [work_colleague_5] inclined to feel like a failure?
Feelings- V2
Is [close_friend_1] likely to misunderstand people who get emotional?
Is [famous_person_2] likely to misunderstand people who get emotional?
Is [work_colleague_3] likely to misunderstand people who get emotional?
Feminine Identity
How feminine is [acquaintance_1]?
How feminine is [close_friend_2]?
How feminine is [close_friend_3]?
How feminine is [family_5]?
How feminine is [family_2]?
How feminine is [famous_person_1]?
How feminine is [famous_person_4]?

How feminine is [fictional_person_4]?
How feminine is [fictional_person_2]?
How feminine are [self]?
How feminine is [work_colleague_1]?

Feminine Presentation

How feminine is [acquaintance_2]'s gender presentation?
How feminine is [close_friend_5]'s gender presentation?
How feminine is [family_2]'s gender presentation?
How feminine is [famous_person_2]'s gender presentation?
How feminine is [fictional_person_4]'s gender presentation?
How feminine is [self] gender presentation?
How feminine is [work_colleague_2]'s gender presentation?

Freq Anxious

How often does [acquaintance_3] feel anxious?
How often does [close_friend_2] feel anxious?
How often does [family_2] feel anxious?
How often does [famous_person_2] feel anxious?
How often does [fictional_person_4] feel anxious?
How often do [self] feel anxious?
How often does [work_colleague_1] feel anxious?

Freq Art Exhibit

How often does [famous_person_5] go to art exhibits?
How often does [fictional_person_3] go to art exhibits?
How often does [work_colleague_1] go to art exhibits?

Freq Ashamed

How often does [acquaintance_2] feel ashamed?
How often does [close_friend_3] feel ashamed?
How often does [family_4] feel ashamed?
How often does [famous_person_4] feel ashamed?
How often does [fictional_person_3] feel ashamed?
How often does [self] feel ashamed?
How often does [work_colleague_4] feel ashamed?

Freq Attend Religious Service

How frequently does [acquaintance_1] attend religious services?
How frequently does [close_friend_4] attend religious services?
How frequently does [family_3] attend religious services?
How frequently does [famous_person_4] attend religious services?
How frequently does [fictional_person_5] attend religious services?
How frequently do [self] attend religious services?
How frequently does [work_colleague_1] attend religious services?

Freq Attend Religious Service Child

How often did [acquaintance_5] attend religious services growing up?
How often did [close_friend_3] attend religious services growing up?
How often did [family_3] attend religious services growing up?
How often did [famous_person_3] attend religious services growing up?
How often did [self] attend religious services growing up?
How often did [work_colleague_4] attend religious services growing up?

Freq Blues
  How often does [acquaintance_3] feel like they can't shake the blues?
  How often does [close_friend_3] feel like they can't shake the blues?
  How often does [famous_person_2] feel like they can't shake the blues?
  How often does [fictional_person_2] feel like they can't shake the blues?
  How often do [self] feel like [self] can't shake the blues?
  How often does [work_colleague_1] feel like they can't shake the blues?
Freq Calm
  How often does [acquaintance_1] feel calm?
  How often does [close_friend_1] feel calm?
  How often does [family_2] feel calm?
  How often does [famous_person_2] feel calm?
  How often does [fictional_person_1] feel calm?
  How often do [self] feel calm?
  How often does [work_colleague_1] feel calm?
Freq Drink
  How often does [famous_person_2] drink alcohol?
  How often does [fictional_person_4] drink alcohol?
  How often does [work_colleague_4] drink alcohol?
Freq Drugs
  How often does [acquaintance_2] do drugs?
  How often does [close_friend_5] do drugs?
  How often does [family_4] do drugs?
  How often does [fictional_person_1] do drugs?
  How often do [self] do drugs?
  How often does [work_colleague_1] do drugs?
Freq Excited
  How often does [acquaintance_3] feel excited about something?
  How often does [close_friend_3] feel excited about something?
  How often does [family_5] feel excited about something?
  How often does [fictional_person_5] feel excited about something?
Freq Live Music
  How often does [acquaintance_1] attend live music shows?
  How often does [close_friend_1] attend live music shows?
  How often does [family_1] attend live music shows?
  How often does [fictional_person_5] attend live music shows?
  How often do [self] attend live music shows?
  How often does [work_colleague_4] attend live music shows?
Freq Live Theater
  How often does [acquaintance_5] attend live theater shows?
  How often does [close_friend_2] attend live theater shows?
  How often does [work_colleague_3] attend live theater shows?
Freq Meditate
  How often does [acquaintance_1] meditate?
  How often does [close_friend_3] meditate?
  How often does [family_1] meditate?
  How often does [famous_person_3] meditate?

How often does [fictional_person_2] meditate?
How often do [self] meditate?
How often does [work_colleague_2] meditate?

Freq Movie
How often does [close_friend_5] go to movie theaters?
How often does [famous_person_3] go to movie theaters?
How often does [fictional_person_3] go to movie theaters?
How often do [self] go to movie theaters?
How often does [work_colleague_4] go to movie theaters?

Freq Outraged
How often does [acquaintance_3] feel outraged?
How often does [close_friend_4] feel outraged?
How often does [family_2] feel outraged?
How often does [famous_person_1] feel outraged?
How often does [fictional_person_1] feel outraged?
How often do [self] feel outraged?
How often does [work_colleague_3] feel outraged?

Freq Prayer
How often does [acquaintance_2] pray?
How often does [close_friend_5] pray?
How often does [fictional_person_5] pray?
How often do [self] pray?
How often does [work_colleague_4] pray?

Freq Proud
How often does [acquaintance_1] feel proud of something they did?
How often does [close_friend_1] feel proud of something they did?
How often does [famous_person_5] feel proud of something they did?
How often does [fictional_person_4] feel proud of something they did?
How often do [self] feel proud of something [self] did?
How often does [work_colleague_1] feel proud of something they did?

Freq Public Lecture
How often does [acquaintance_3] go to public lectures?
How often does [close_friend_1] go to public lectures?
How often does [fictional_person_2] go to public lectures?
How often do [self] go to public lectures?
How often does [work_colleague_1] go to public lectures?

Freq Read Lit
How often does [acquaintance_1] read literature?
How often does [family_2] read literature?
How often does [famous_person_4] read literature?
How often does [fictional_person_4] read literature?
How often do [self] read literature?
How often does [work_colleague_4] read literature?

Freq Restless
How often does [acquaintance_1] feel restless?
How often does [close_friend_3] feel restless?
How often does [family_3] feel restless?

How often does [famous_person_4] feel restless?
How often does [fictional_person_3] feel restless?
How often do [self] feel restless?
How often does [work_colleague_1] feel restless?

Freq See Family
How often does [acquaintance_5] see their family?
How often does [close_friend_3] see their family?
How often does [family_4] see their family?
How often does [famous_person_1] see their family?
How often does [fictional_person_5] see their family?
How often does [self] see their family?
How often does [work_colleague_4] see their family?

Freq Smoke
How often does [acquaintance_3] smoke tobacco?
How often does [close_friend_4] smoke tobacco?
How often does [work_colleague_1] smoke tobacco?

Freq Volunteer
How often does [acquaintance_1] volunteer?
How often does [close_friend_1] volunteer?
How often does [family_3] volunteer?
How often does [famous_person_2] volunteer?
How often does [fictional_person_4] volunteer?
How often do [self] volunteer?
How often does [work_colleague_5] volunteer?

Friend Same Activities
Do [acquaintance_2]'s friends do the same activities as them?
Do [family_2]'s friends do the same activities as them?
Do [famous_person_4]'s friends do the same activities as them?
Do [fictional_person_4]'s friends do the same activities as them?
Do [work_colleague_5]'s friends do the same activities as them?

Friend Same Age
Are [acquaintance_3]'s friends the same age as them?
Are [close_friend_1]'s friends the same age as them?
Are [family_1]'s friends the same age as them?
Are [self]'s friends the same age as them?

Friend Same Socioecon
Are [acquaintance_5]'s friends in the same socioeconomic class as them?
Are [family_1]'s friends in the same socioeconomic class as them?
Are [famous_person_3]'s friends in the same socioeconomic class as them?
Are [self]'s friends in the same socioeconomic class as them?
Are [work_colleague_1]'s friends in the same socioeconomic class as them?

Friend Share Belief
Do [acquaintance_1]'s friends share [acquaintance_1]'s beliefs?
Do [fictional_person_4]'s friends share [fictional_person_4]'s beliefs?
Do [self] friends share [self] beliefs?

Friendship Length
How long has [acquaintance_2] known their closest friends?

How long has [close_friend_1] known their closest friends?
How long has [family_2] known their closest friends?
How long has [fictional_person_2] known their closest friends?
How long has [self] known their closest friends?
How long has [work_colleague_4] known their closest friends?

Future Optimism
How optimistic is [acquaintance_3] about their future?
How optimistic is [close_friend_3] about their future?
How optimistic is [family_4] about their future?
How optimistic is [famous_person_4] about their future?
How optimistic is [fictional_person_2] about their future?
How optimistic is [work_colleague_4] about their future?

Getting Word Out
How good is [acquaintance_3] at getting the word out about something?
How good is [close_friend_3] at getting the word out about something?
How good is [family_5] at getting the word out about something?
How good is [famous_person_3] at getting the word out about something?
How good is [fictional_person_1] at getting the word out about something?
How good is [self] at getting the word out about something?
How good is [work_colleague_1] at getting the word out about something?

Give To Charity
How much does [acquaintance_3] give to charities?
How much does [close_friend_3] give to charities?
How much does [family_4] give to charities?
How much does [famous_person_2] give to charities?
How much does [fictional_person_3] give to charities?
How much do [self] give to charities?
How much does [work_colleague_2] give to charities?

Give To Homeless
How often does [acquaintance_2] give to homeless people?
How often does [close_friend_5] give to homeless people?
How often does [family_3] give to homeless people?
How often does [famous_person_4] give to homeless people?
How often does [fictional_person_3] give to homeless people?
How often does [self] give to homeless people?
How often does [work_colleague_2] give to homeless people?

Good Friend
Is [acquaintance_5] a good friend?
Is [close_friend_1] a good friend?
Is [family_3] a good friend?
Is [fictional_person_5] a good friend?
Is [work_colleague_1] a good friend?

Good Impression
Does [acquaintance_4] make a good impression on others?
Does [close_friend_2] make a good impression on others?
Does [family_3] make a good impression on others?
Does [famous_person_1] make a good impression on others?

Does [fictional_person_1] make a good impression on others?
Does [work_colleague_4] make a good impression on others?
Good Partner Importance
How much does [acquaintance_5] care about being a good romantic partner?
How much does [close_friend_4] care about being a good romantic partner?
How much does [close_friend_3] care about being a good romantic partner?
How much does [family_2] care about being a good romantic partner?
How much does [family_4] care about being a good romantic partner?
How much does [famous_person_3] care about being a good romantic partner?
How much does [famous_person_1] care about being a good romantic partner?
How much does [fictional_person_1] care about being a good romantic partner?
How much does [fictional_person_2] care about being a good romantic partner?
How much does [self] care about being a good romantic partner?
How much does [work_colleague_4] care about being a good romantic partner?
Gregariousness+ V1
Is [close_friend_5] likely to love large parties?
Is [work_colleague_4] likely to love large parties?
Gregariousness+ V2
Is [fictional_person_1] likely to talk to a lot of different people at parties?
Gregariousness- V1
Is [family_3] likely to prefer to be alone?
Gregariousness- V2
Is [work_colleague_1] likely to avoid crowds?
Hair Dark
How dark is [acquaintance_3]'s hair?
How dark is [close_friend_2]'s hair?
How dark is [self]'s hair?
Hair Light
How light is [acquaintance_1]'s hair?
How light is [close_friend_4]'s hair?
How light is [fictional_person_4]'s hair?
Hedonism
How much does [acquaintance_1] value pleasure?
How much does [close_friend_3] value enjoying life?
How much does [famous_person_1] value pleasure?
How much does [self] value pleasure?
How much does [work_colleague_4] value self-indulgence?
Height
How tall is [close_friend_2]?
How tall is [family_4]?
How tall is [famous_person_1]?
How tall is [fictional_person_1]?
Hostility+ V1
Is [acquaintance_1] likely to get angry easily?
Hostility+ V4
Is [fictional_person_1] likely to be easily annoyed?
Humanities

How interested is [acquaintance_1] in the humanities?
How interested is [close_friend_4] in the humanities?
How interested is [work_colleague_4] in the humanities?
Ideas+ V1
Is [acquaintance_2] likely to love to read challenging material?
Ideas- V1
Is [family_1] likely to avoid philosophical discussions?
Ideas- V2
Is [self] likely to have difficulty understanding abstract ideas?
Important Events Friends
Does [acquaintance_3] discuss important events with their friends?
Does [famous_person_5] discuss important events with their friends?
Does [fictional_person_5] discuss important events with their friends?
Does [self] discuss important events with their friends?
Does [work_colleague_1] discuss important events with their friends?
Important Events Know Speed
How quickly does [acquaintance_1] know about important events?
How quickly does [close_friend_5] know about important events?
How quickly does [family_1] know about important events?
How quickly does [famous_person_3] know about important events?
How quickly does [fictional_person_5] know about important events?
How quickly does [self] know about important events?
How quickly does [work_colleague_2] know about important events?
Important Events Partners
Does [acquaintance_3] discuss important events with their partner(s)?
Does [close_friend_3] discuss important events with their partner(s)?
Does [family_5] discuss important events with their partner(s)?
Does [famous_person_4] discuss important events with their partner(s)?
Does [fictional_person_1] discuss important events with their partner(s)?
Does [self] discuss important events with their partner(s)?
Does [work_colleague_4] discuss important events with their partner(s)?
Important Matters Family
Does [acquaintance_1] discuss important matters with their family?
Does [close_friend_4] discuss important matters with their family?
Does [family_5] discuss important matters with their family?
Does [famous_person_5] discuss important matters with their family?
Does [fictional_person_2] discuss important matters with their family?
Does [self] discuss important matters with their family?
Does [work_colleague_5] discuss important matters with their family?
Impulsiveness- V3
Is [close_friend_3] likely to be able to control their cravings?
Is [famous_person_3] likely to be able to control their cravings?
Is [work_colleague_2] likely to be able to control their cravings?
Intimate Relationship Importance
How much does [acquaintance_2] care about having intimate relationships?
How much does [close_friend_3] care about having intimate relationships?
How much does [family_1] care about having intimate relationships?

How much does [famous_person_4] care about having intimate relationships?
How much does [fictional_person_1] care about having intimate relationships?
How much does [self] care about having intimate relationships?
How much does [work_colleague_4] care about having intimate relationships?
Length Current Job
How long has [famous_person_5] been at their current job?
How long has [fictional_person_1] been at their current job?
How long has [work_colleague_1] been at their current job?
Length Place Lived Current
How long has [acquaintance_2] lived at their current place?
How long has [close_friend_1] lived at their current place?
How long has [family_3] lived at their current place?
How long has [famous_person_1] lived at their current place?
How long has [fictional_person_2] lived at their current place?
How long has [self] lived at their current place?
How long has [work_colleague_2] lived at their current place?
Life Control
How much control does [acquaintance_5] feel like they have over their life?
How much control does [close_friend_3] feel like they have over their life?
How much control does [family_2] feel like they have over their life?
How much control does [fictional_person_1] feel like they have over their life?
How much control does [self] feel like they have over their life?
Life Exciting
How exciting does [acquaintance_5] find life?
How exciting does [famous_person_5] find life?
How exciting does [fictional_person_5] find life?
How exciting does [work_colleague_2] find life?
Masculine Identity
How masculine is [acquaintance_1]?
How masculine is [close_friend_5]?
How masculine is [family_1]?
How masculine is [famous_person_1]?
How masculine is [fictional_person_5]?
How masculine is [self]?
How masculine is [work_colleague_5]?
Masculine Presentation
How masculine is [acquaintance_4]'s gender presentation?
How masculine is [acquaintance_5]'s gender presentation?
How masculine is [close_friend_4]'s gender presentation?
How masculine is [close_friend_2]'s gender presentation?
How masculine is [family_5]'s gender presentation?
How masculine is [family_4]'s gender presentation?
How masculine is [famous_person_5]'s gender presentation?
How masculine is [fictional_person_2]'s gender presentation?
How masculine is [self]'s gender presentation?
How masculine is [work_colleague_1]'s gender presentation?
Material Possessions

Does [acquaintance_4] have a lot of material possessions?
Does [close_friend_1] have a lot of material possessions?
Does [family_2] have a lot of material possessions?
Does [fictional_person_4] have a lot of material possessions?
Do [self] have a lot of material possessions?
Mental Health
How is [acquaintance_1]'s mental health?
How is [close_friend_1]'s mental health?
How is [family_3]'s mental health?
How is [famous_person_4]'s mental health?
How is [fictional_person_1]'s mental health?
How is [work_colleague_1]'s mental health?
Mental Illness
Has [acquaintance_4] experienced mental illness?
Has [close_friend_4] experienced mental illness?
Has [family_4] experienced mental illness?
Has [famous_person_3] experienced mental illness?
Has [fictional_person_3] experienced mental illness?
Has [work_colleague_1] experienced mental illness?
Modesty- V1
Is [fictional_person_3] likely to believe that they are better than others?
Modesty- V2
Is [work_colleague_1] likely to think highly of themselves?
Modesty- V3
Is [work_colleague_1] likely to have a high opinion of themselves?
Modesty- V4
Is [close_friend_4] likely to boast about their virtues?
Money Growing Up
Was money a concern when [acquaintance_3] was growing up?
Was money a concern when [close_friend_1] was growing up?
Was money a concern when [family_5] was growing up?
Was money a concern when [famous_person_3] was growing up?
Was money a concern when [fictional_person_3] was growing up?
Was money a concern when [self] was growing up?
Was money a concern when [work_colleague_3] was growing up?
Non American
How much does [close_friend_1] identify with non-American cultures?
How much does [famous_person_4] identify with non-American cultures?
How much does [fictional_person_3] identify with non-American cultures?
How much does [self] identify with non-American cultures?
How much does [work_colleague_1] identify with non-American cultures?
Non English Lg
How familiar is [acquaintance_2] with non-English languages?
How familiar is [close_friend_5] with non-English languages?
How familiar is [fictional_person_3] with non-English languages?
How familiar are [self] with non-English languages?
How familiar is [work_colleague_2] with non-English languages?

Num Countries Lived
How many countries has [acquaintance_4] lived in?
How many countries has [close_friend_4] lived in?
How many countries has [family_1] lived in?
How many countries has [famous_person_1] lived in?
How many countries has [fictional_person_4] lived in?
How many countries have [self] lived in?
How many countries has [work_colleague_1] lived in?
Num Places Lived
How many places has [acquaintance_4] lived at?
How many places has [close_friend_3] lived at?
How many places has [family_1] lived at?
How many places has [famous_person_5] lived at?
How many places has [fictional_person_1] lived at?
How many places has [self] lived at?
How many places has [work_colleague_1] lived at?
Num Previous Jobs
How many previous jobs has [acquaintance_2] had?
How many previous jobs has [close_friend_2] had?
How many previous jobs has [family_3] had?
How many previous jobs has [fictional_person_2] had?
How many previous jobs have [self] had?
How many previous jobs has [work_colleague_3] had?
Num Siblings
How many siblings does [acquaintance_3] have?
How many siblings does [close_friend_5] have?
How many siblings does [family_1] have?
How many siblings does [famous_person_1] have?
How many siblings does [fictional_person_5] have?
How many siblings does [work_colleague_2] have?
Num Social Groups
How many social groups is [acquaintance_5] part of?
How many social groups is [close_friend_1] part of?
How many social groups is [family_5] part of?
How many social groups is [famous_person_1] part of?
How many social groups is [fictional_person_2] part of?
How many social groups is [self] part of?
How many social groups is [work_colleague_5] part of?
Number Close Ppl
How many people does [acquaintance_3] feel close to?
How many people does [acquaintance_2] feel close to?
How many people does [close_friend_1] feel close to?
How many people does [close_friend_5] feel close to?
How many people does [family_3] feel close to?
How many people does [family_4] feel close to?
How many people does [famous_person_1] feel close to?
How many people does [fictional_person_3] feel close to?

How many people do [self] feel close to?
How many people does [work_colleague_1] feel close to?
Number Friends
How many friends does [famous_person_2] have?
How many friends does [fictional_person_3] have?
Number Partners
How many partners does [acquaintance_4] have?
How many partners does [acquaintance_1] have?
How many partners does [close_friend_5] have?
How many partners does [close_friend_3] have?
How many partners does [family_3] have?
How many partners does [family_2] have?
How many partners does [famous_person_1] have?
How many partners does [fictional_person_3] have?
How many partners do [self] have?
How many partners does [work_colleague_3] have?
Order+ V1
Is [acquaintance_2] likely to enjoy tidying up?
Order- V3
Is [famous_person_4] likely to leave their belongings around?
Is [fictional_person_1] likely to leave their belongings around?
Parent Alive
Are [acquaintance_5]'s parent(s) alive?
Are [close_friend_4]'s parent(s) alive?
Are [family_5]'s parent(s) alive?
Are [famous_person_1]'s parent(s) alive?
Are [fictional_person_1]'s parent(s) alive?
Are [work_colleague_3]'s parent(s) alive?
Parent Edu
How educated are [acquaintance_5]'s parent(s)?
How educated are [close_friend_3]'s parent(s)?
How educated are [family_5]'s parent(s)?
How educated are [fictional_person_5]'s parent(s)?
How educated are [self]'s parent(s)?
Parent Wealth
How wealthy are [acquaintance_4]'s parent(s)?
How wealthy are [famous_person_1]'s parent(s)?
How wealthy are [fictional_person_5]'s parent(s)?
How wealthy are [work_colleague_1]'s parent(s)?
Physical Health
How is [acquaintance_4]'s physical health?
How is [close_friend_4]'s physical health?
How is [family_5]'s physical health?
How is [fictional_person_4]'s physical health?
How is [self]'s physical health?
Play Instrument
Does [acquaintance_3] play an instrument?

Does [close_friend_5] play an instrument?
Does [family_1] play an instrument?
Does [famous_person_1] play an instrument?
Does [fictional_person_3] play an instrument?
Does [work_colleague_4] play an instrument?

Play Sport
Does [acquaintance_5] play a sport?
Does [close_friend_1] play a sport?
Does [family_4] play a sport?
Does [fictional_person_4] play a sport?
Do [self] play a sport?

Politics
How interested is [close_friend_1] in politics?
How interested is [famous_person_1] in politics?
How interested is [fictional_person_3] in politics?
How interested are [self] in politics?
How interested is [work_colleague_1] in politics?

Popularity
How popular is [close_friend_2]?
How popular is [family_2]?
How popular is [famous_person_4]?
How popular is [fictional_person_3]?
How popular are [self]?

Positive Emotions+ V1
Is [family_1] likely to radiate joy?

Positive Emotions+ V3
Is [work_colleague_3] likely to love life?

Positive Emotions+ V4
Is [self] likely to look at the bright side of life?

Power
How much does [acquaintance_2] value controlling others?
How much does [close_friend_5] value authority?
How much does [family_3] value controlling others?
How much does [work_colleague_2] value authority?

Power Over Others
How much power does [acquaintance_4] have over others?
How much power does [close_friend_3] have over others?
How much power does [family_3] have over others?
How much power does [famous_person_1] have over others?
How much power does [fictional_person_4] have over others?
How much power do [self] have over others?
How much power does [work_colleague_2] have over others?

Pride City
Is [acquaintance_3] proud to live in their city?
Is [close_friend_4] proud to live in their city?
Is [family_3] proud to live in their city?
Is [famous_person_3] proud to live in their city?

Is [fictional_person_2] proud to live in their city?
Are [self] proud to live in [self]r city?
Is [work_colleague_3] proud to live in their city?
Pride Generation
How proud is [acquaintance_4] of their generation?
How proud is [family_1] of their generation?
How proud is [famous_person_1] of their generation?
How proud is [fictional_person_2] of their generation?
How proud is [self] of their generation?
How proud is [work_colleague_5] of their generation?
Pride Work
Is [acquaintance_3] proud to be a member of their workplace?
Is [close_friend_1] proud to be a member of their workplace?
Is [family_1] proud to be a member of their workplace?
Is [famous_person_5] proud to be a member of their workplace?
Is [fictional_person_3] proud to be a member of their workplace?
Are [self] proud to be a member of [self]r workplace?
Is [work_colleague_2] proud to be a member of their workplace?
Recent Stress
How stressed has [acquaintance_5] been in the past couple weeks?
How stressed has [close_friend_4] been in the past couple weeks?
How stressed has [family_5] been in the past couple weeks?
How stressed has [famous_person_4] been in the past couple weeks?
How stressed has [fictional_person_2] been in the past couple weeks?
How stressed has [self] been in the past couple weeks?
How stressed has [work_colleague_5] been in the past couple weeks?
Recent Trauma
Has [acquaintance_4] recently experienced a traumatic event?
Has [close_friend_5] recently experienced a traumatic event?
Has [family_2] recently experienced a traumatic event?
Has [famous_person_3] recently experienced a traumatic event?
Has [fictional_person_5] recently experienced a traumatic event?
Has [self] recently experienced a traumatic event?
Has [work_colleague_2] recently experienced a traumatic event?
Reputation
Does [acquaintance_4] have a good reputation?
Does [close_friend_2] have a good reputation?
Does [family_5] have a good reputation?
Does [fictional_person_3] have a good reputation?
Do [self] have a good reputation?
Does [work_colleague_2] have a good reputation?
Romantic Attraction
How strongly does [acquaintance_5] experience romantic attraction?
How strongly does [close_friend_1] experience romantic attraction?
How strongly does [family_2] experience romantic attraction?
How strongly does [famous_person_4] experience romantic attraction?
How strongly does [fictional_person_3] experience romantic attraction?

How strongly does [self] experience romantic attraction?
How strongly does [work_colleague_5] experience romantic attraction?
Same Gender
How attracted is [acquaintance_4] to people of the same gender?
How attracted is [close_friend_4] to people of the same gender?
How attracted is [family_1] to people of the same gender?
How attracted is [famous_person_1] to people of the same gender?
How attracted is [fictional_person_5] to people of the same gender?
How attracted are [self] to people of the same gender?
How attracted is [work_colleague_5] to people of the same gender?
Science And Tech
How interested is [acquaintance_3] in science and tech?
How interested is [close_friend_3] in science and tech?
How interested is [fictional_person_1] in science and tech?
How interested are [self] in science and tech?
How interested is [work_colleague_3] in science and tech?
Security
How much does [acquaintance_5] value security?
How much does [close_friend_1] value security?
How much does [family_4] value cleanliness?
How much does [famous_person_1] value security?
How much does [self] value security?
How much does [work_colleague_3] value social order?
Seen As Self
Do others see [acquaintance_5] as they see themselves?
Do others see [close_friend_4] as they see themselves?
Do others see [family_1] as they see themselves?
Do others see [fictional_person_2] as they see themselves?
Do others see [self] as they see themselves?
Self-direction
How much does [acquaintance_2] value independence?
How much does [close_friend_3] value independence?
How much does [family_1] value independence?
How much does [famous_person_2] value independence?
How much does [fictional_person_5] value curiosity?
How much do [self] value creativity?
How much does [work_colleague_4] value curiosity?
Self Discipline+ V2
Is [close_friend_4] likely to carry out their plans?
Self Discipline- V1
Is [famous_person_3] likely to waste their time?
Self Discipline- V2
Is [work_colleague_3] likely to have difficulty starting tasks?
Self Esteem Level
How high is [acquaintance_1]'s self-esteem?
How high is [close_friend_3]'s self-esteem?
How high is [family_1]'s self-esteem?

How high is [famous_person_3]'s self-esteem?
How high is [fictional_person_2]'s self-esteem?
How high is [work_colleague_4]'s self-esteem?
Self Satisfaction
Is [acquaintance_5] satisfied with themselves?
Is [close_friend_3] satisfied with themselves?
Is [family_4] satisfied with themselves?
Is [famous_person_3] satisfied with themselves?
Is [fictional_person_1] satisfied with themselves?
Is [work_colleague_2] satisfied with themselves?
Selfconsciousness+ V1
Is [acquaintance_5] likely to find it difficult to approach others?
Selfconsciousness+ V2
Is [family_4] likely to be afraid to draw attention to themselves?
Selfconsciousness+ V3
Is [self] likely to only feel comfortable with friends?
Sexual Attraction
How strongly does [acquaintance_4] experience sexual attraction?
How strongly does [acquaintance_2] experience sexual attraction?
How strongly does [close_friend_1] experience sexual attraction?
How strongly does [close_friend_5] experience sexual attraction?
How strongly does [family_5] experience sexual attraction?
How strongly does [family_1] experience sexual attraction?
How strongly does [famous_person_1] experience sexual attraction?
How strongly does [fictional_person_4] experience sexual attraction?
How strongly do [self] experience sexual attraction?
How strongly does [work_colleague_2] experience sexual attraction?
Show Feelings
Does [close_friend_5] show their feelings?
Does [family_4] show their feelings?
Does [famous_person_3] show their feelings?
Does [fictional_person_5] show their feelings?
Does [work_colleague_3] show their feelings?
Skin Dark
How dark is [acquaintance_5]'s skin?
How dark is [famous_person_5]'s skin?
How dark is [fictional_person_3]'s skin?
How dark is [self]'s skin?
Skin Light
How light is [acquaintance_1]'s skin?
How light is [close_friend_4]'s skin?
How light is [famous_person_5]'s skin?
How light is [self] skin?
Social Conservative
How socially conservative is [acquaintance_3]?
How socially conservative is [close_friend_5]?
How socially conservative is [family_2]?

How socially conservative is [famous_person_1]?
How socially conservative is [fictional_person_2]?
How socially conservative is [work_colleague_2]?
Social Groups Importance
Is [acquaintance_4] an important member of their social groups?
Is [close_friend_2] an important member of their social groups?
Is [family_3] an important member of their social groups?
Is [famous_person_5] an important member of their social groups?
Is [fictional_person_4] an important member of their social groups?
Are [self] an important member of [self]r social groups?
Is [work_colleague_4] an important member of their social groups?
Social Liberal
How socially liberal is [acquaintance_4]?
How socially liberal is [close_friend_2]?
How socially liberal is [family_5]?
How socially liberal is [fictional_person_3]?
How socially liberal are [self]?
Socializing
How good is [acquaintance_4] at socializing with others?
How good is [famous_person_1] at socializing with others?
How good is [fictional_person_5] at socializing with others?
How good is [work_colleague_3] at socializing with others?
Socioeconomic Class
Which socioeconomic class is [acquaintance_5] in?
Which socioeconomic class is [famous_person_5] in?
Which socioeconomic class is [fictional_person_5] in?
Which socioeconomic class is [work_colleague_4] in?
Spend Evening Alone
How often does [close_friend_1] spend the evening alone?
How often does [famous_person_3] spend the evening alone?
How often does [fictional_person_1] spend the evening alone?
How often do [self] spend the evening alone?
How often does [work_colleague_4] spend the evening alone?
Spend Evening Family
How often does [acquaintance_3] spend the evening with family?
How often does [close_friend_2] spend the evening with family?
How often does [fictional_person_4] spend the evening with family?
How often do [self] spend the evening with family?
How often does [work_colleague_3] spend the evening with family?
Spend Evening Friend
How often does [acquaintance_5] spend the evening with friends?
How often does [family_1] spend the evening with friends?
How often does [famous_person_3] spend the evening with friends?
How often does [fictional_person_3] spend the evening with friends?
How often does [self] spend the evening with friends?
How often does [work_colleague_3] spend the evening with friends?
Spirituality Importance

How important is spirituality to [acquaintance_4]?
How important is spirituality to [famous_person_3]?
How important is spirituality to [fictional_person_2]?
Sports
How interested is [acquaintance_5] in sports?
How interested is [family_1] in sports?
How interested is [famous_person_5] in sports?
How interested is [fictional_person_4] in sports?
How interested is [self] in sports?
How interested is [work_colleague_3] in sports?
Stimulation
How much does [acquaintance_2] value excitement?
How much does [self] value adventure?
How much does [work_colleague_3] value adventure?
Straightforwardness- V1
Is [fictional_person_3] likely to use others for their own ends?
Straightforwardness- V3
Is [self] likely to take advantage of others?
Is [work_colleague_4] likely to take advantage of others?
Strength And Comfort Religion
Does [acquaintance_4] find strength and comfort in relgion?
Does [close_friend_2] find strength and comfort in relgion?
Does [family_5] find strength and comfort in relgion?
Does [famous_person_4] find strength and comfort in relgion?
Does [fictional_person_4] find strength and comfort in relgion?
Does [self] find strength and comfort in relgion?
Does [work_colleague_4] find strength and comfort in relgion?
Strong Political Beliefs
Does [acquaintance_1] have strong political beliefs?
Does [famous_person_4] have strong political beliefs?
Does [fictional_person_4] have strong political beliefs?
Does [work_colleague_2] have strong political beliefs?
Tendermindedness- V1
Is [close_friend_1] likely to be uncaring about other people's problems?
Therapist
Has [acquaintance_5] seen a therapist?
Has [famous_person_5] seen a therapist?
Has [fictional_person_3] seen a therapist?
Has [work_colleague_4] seen a therapist?
Think Self No Good
How often does [acquaintance_2] think they are no good?
How often does [close_friend_1] think they are no good?
How often does [family_5] think they are no good?
How often does [fictional_person_4] think they are no good?
How often does [self] think they are no good?
Time At Work
How much time does [acquaintance_4] spend on work?

How much time does [close_friend_3] spend on work?
How much time does [work_colleague_1] spend on work?

Time Interest Group
How much time does [acquaintance_5] spend in clubs or interest groups?
How much time does [close_friend_4] spend in clubs or interest groups?
How much time does [family_1] spend in clubs or interest groups?
How much time does [famous_person_5] spend in clubs or interest groups?
How much time does [fictional_person_5] spend in clubs or interest groups?
How much time do [self] spend in clubs or interest groups?
How much time does [work_colleague_5] spend in clubs or interest groups?

Time Relax
How much time does [close_friend_5] have to relax?
How much time does [famous_person_2] have to relax?
How much time does [fictional_person_2] have to relax?
How much time does [self] have to relax?
How much time does [work_colleague_4] have to relax?

Time With Family
How much time does [acquaintance_3] spend with their family?
How much time does [acquaintance_2] spend with their family?
How much time does [close_friend_1] spend with their family?
How much time does [close_friend_5] spend with their family?
How much time does [family_3] spend with their family?
How much time does [family_1] spend with their family?
How much time does [famous_person_5] spend with their family?
How much time does [fictional_person_3] spend with their family?
How much time do [self] spend with [self]r family?
How much time does [work_colleague_2] spend with their family?

Tradition
How much does [family_1] value cultural customs?
How much does [fictional_person_5] value tradition?
How much does [self] value tradition?

Treat With Respect
Do others generally treat [acquaintance_5] with respect?
Do others generally treat [famous_person_1] with respect?
Do others generally treat [fictional_person_5] with respect?
Do others generally treat [work_colleague_5] with respect?

Trust+ V1
Is [close_friend_4] likely to trust others?

Trust+ V2
Is [famous_person_4] likely to believe that others have good intentions?
Is [fictional_person_1] likely to believe that others have good intentions?

Trust+ V3
Is [work_colleague_3] likely to trust what people say?

Trust- V1
Is [acquaintance_5] likely to distrust people?
Is [close_friend_2] likely to distrust people?
Is [family_1] likely to distrust people?

Is [famous_person_1] likely to distrust people?
Is [self] likely to distrust people?

Universalism
How much does [acquaintance_5] value tolerance of others?
How much does [family_3] value protecting the environment?
How much does [famous_person_5] value tolerance of others?
How much does [fictional_person_4] value protecting the environment?
How much does [work_colleague_1] value protecting the environment?

Values+ V1
Is [acquaintance_1] likely to vote for liberal political candidates?
Is [close_friend_5] likely to vote for liberal political candidates?

Values- V2
Is [close_friend_1] likely to believe that we should be tough on crime?
Is [fictional_person_5] likely to believe that we should be tough on crime?
Is [work_colleague_3] likely to believe that we should be tough on crime?

Vulnerability+ V1
Is [acquaintance_3] likely to panic easily?
Is [close_friend_4] likely to panic easily?

Vulnerability- V1
Is [close_friend_1] likely to remain calm under pressure?
Is [fictional_person_2] likely to remain calm under pressure?
Is [work_colleague_4] likely to remain calm under pressure?

Warmth+ V1
Is [close_friend_1] likely to make friends easily?
Is [work_colleague_2] likely to make friends easily?

Warmth+ V2
Is [close_friend_4] likely to feel comfortable around people?
Is [fictional_person_4] likely to feel comfortable around people?

Warmth- V2
Are [self] likely to keep others at a distance?

Weight
How much does [close_friend_5] weigh?
How much does [family_2] weigh?
How much does [famous_person_1] weigh?
How much does [fictional_person_2] weigh?
How much does [work_colleague_4] weigh?

Well Connected
How well-connected is [acquaintance_3]?
How well-connected is [fictional_person_5]?
How well-connected are [self]?
How well-connected is [work_colleague_5]?

Well Known
How well-known is [acquaintance_5]?
How well-known is [close_friend_5]?
How well-known is [family_3]?
How well-known is [famous_person_1]?
How well-known are [self]?

How well-known is [work_colleague_3]?

Work Pride

Is [acquaintance_2] proud of their work?
Is [close_friend_5] proud of their work?
Is [fictional_person_1] proud of their work?
Is [self] proud of their work?
Is [work_colleague_2] proud of their work?

Work Satisfaction

How much satisfaction does [acquaintance_1] get from work?
How much satisfaction does [family_3] get from work?
How much satisfaction does [famous_person_1] get from work?
How much satisfaction does [fictional_person_5] get from work?
How much satisfaction do [self] get from work?
How much satisfaction does [work_colleague_1] get from work?

Worth Compare Others

Does [acquaintance_5] believe that they are worth as much as others?
Does [famous_person_5] believe that they are worth as much as others?
Does [fictional_person_3] believe that they are worth as much as others?
Does [work_colleague_3] believe that they are worth as much as others?