Neural similarity at temporal lobe and cerebellum predicts out-of-sample preference and recall for video stimuli

Hang-Yee Chan, Ale Smidts, Vincent C. Schoots, Roeland C. Dietvorst, Maarten A. S. Boksem

NeuroImage 197 (2019) 391–401

Contents lists available at ScienceDirect

NeuroImage

journal homepage: www.elsevier.com/locate/neuroimage

Neural similarity at temporal lobe and cerebellum predicts out-of-sample preference and recall for video stimuli

Hang-Yee Chan [a,*], Ale Smidts [a], Vincent C. Schoots [a], Roeland C. Dietvorst [b], Maarten A.S. Boksem [a]

[a] Department of Marketing Management, Rotterdam School of Management, Erasmus University Rotterdam, the Netherlands
[b] Alpha.One, the Netherlands

A B S T R A C T

The extent to which brains respond similarly to a specific stimulus, across a small group of individuals, has been previously found to predict out-of-sample aggregate preference for that stimulus. However, the location in the brain where neural similarity predicts out-of-sample preference remains unclear. In this article, we attempt to identify the neural substrates in three functional magnetic resonance imaging (fMRI) studies. Two fMRI studies (N = 40 and 20), using previously broadcasted TV commercials, show that spatiotemporal neural similarity at temporal lobe and cerebellum predict out-of-sample preference and recall. A follow-up fMRI study (N = 28) with previously unseen movie-trailers replicated the predictive effect of neural similarity. Moreover, neural similarity provided unique information on out-of-sample preference above and beyond in-sample preference. Overall, the findings suggest that neural similarity at temporal lobe and cerebellum – traditionally associated with sensory integration and emotional processing – may reflect the level of engagement with video stimuli.

1. Introduction

Recent neuroscientific research, using electroencephalography (EEG) (Barnett and Cerf, 2017; Boksem and Smidts, 2015; Dmochowski et al., 2014) or functional magnetic resonance imaging (fMRI) (Berns and Moore, 2012; Couwenberg et al., 2017; Falk et al., 2012; Genevsky et al., 2017; Scholz et al., 2017; Venkatraman et al., 2015), has shown the possibility of using neural signals from a small group of individuals to predict the aggregate preference of a separate and larger group of individuals (hereafter population or out-of-sample preference). In most fMRI studies linking brain signals to out-of-sample preference, researchers have focused on signal *intensity*, i.e. the magnitude of blood oxygenation level dependent (BOLD) signal during exposure to the stimulus. Activation at nucleus accumbens (NAcc), medial prefrontal cortex (mPFC), or a combination of both, was found to be predictive of population preference such as, e.g., song downloads, funding success, and advertising elasticities (Knutson and Genevsky, 2018).

A separate body of neuroimaging studies in recent years is concerned with signal *consistency* across individuals' brains. Referred to as either inter-subject correlation (Nummenmaa et al., 2012), similarity (Barnett and Cerf, 2017), synchronization (Hasson et al., 2004), alignment (Golland et al., 2017), consistency (Lankinen et al., 2014), or reliability (Dmochowski et al., 2014), researchers found that (a) dynamic natural stimuli (such as videos, narratives, or speeches) evoke similar neural responses across individuals, not only at sensory cortices but also temporal and frontal areas (Hasson et al., 2010); and (b) such neural similarity appeared to be modulated by stimulus quality, such as emotional arousal (Nummenmaa et al., 2012), rhetorical strength (Schmälzle et al., 2015), and humor (Jääskeläinen et al., 2016). Recent EEG studies (Barnett and Cerf, 2017; Christoforou et al., 2017; Dmochowski et al., 2014) went further by testing market-level outcomes and found whole-brain neural similarity predicted online ratings of TV commercials, real-time tweet frequency during TV shows, and box office sales of movies.

Why would neural activation and similarity predict preference not only of the individual, but also of the population? Knutson and Genevsky (2018) posit that neural activation in certain parts of the brain (e.g., NAcc) captures positive arousal to stimuli, a reliably predictive component of choice across different individuals. On the other hand, it is less clear which antecedent of aggregate preference neural similarity might be measuring. Previous studies on neural similarity have shown that synchronized activities across individuals at different brain regions can be induced by various conditions. For example, stronger neural similarity is observed at mPFC and anterior insula when receiving shared emotional information (Golland et al., 2017); superior temporal gyrus (STG) when receiving shared linguistic information (Dikker et al., 2014); STG, temporal pole (TP) and parahippocampus when forming episodic memory

* Corresponding author. Department of Marketing Management, Rotterdam School of Management, Burgemeester Oudlaan 50, 3062 PA Rotterdam, the Netherlands.
E-mail address: chan@rsm.nl (H.-Y. Chan).

https://doi.org/10.1016/j.neuroimage.2019.04.076
Received 24 October 2018; Received in revised form 24 April 2019; Accepted 29 April 2019
Available online 1 May 2019

from shared experience (Hasson et al., 2008). Finally, whole-brain similarity, measured by EEG, is higher when individuals pay attention to the same content (Ki et al., 2016) and when the content is less complex (Barnett and Cerf, 2017).

An outstanding question is whether the predictive power of neural similarity on out-of-sample preference is concentrated in particular areas, or distributed all over the brain. Areas typically found to display synchronized activities during video watching (Hasson et al., 2010) involve sensory processing (visual and auditory cortices), comprehension (temporal and parietal cortices), and valuation (prefrontal cortex). However, at which stage (or stages) in mental processing, from perception to integration to evaluation, a relationship between neural similarity and aggregate preference can be observed remains elusive.

In addition, recent studies have shown that neural and self-report information may each contain non-redundant signals predictive of out-of-sample preference, such that neural activation improves market-outcome prediction over using self-report measures alone (Berns and Moore, 2012; Boksem and Smidts, 2015; Genevsky et al., 2017; Venkatraman et al., 2015). It remains an open question whether the same non-redundancy can also be observed for neural similarity.

We aimed at answering these questions with three fMRI studies. We examined whether neural responses, in terms of activation and similarity, predicted out-of-sample preference for videos. We then examined if these responses explained additional variance after taking into account self-reported preference of the participants. Finally, we provided more insight into the potential mechanism of neural similarity as an indicator of preference by looking into the covariation of moment-by-moment neural similarity and activation at the individual level.

2. Materials and methods

We present results from three original studies. The first two involved the same set of 35 commercials (Study 1a and 1b), while the third involved 18 movie-trailers (Study 2), totaling 88 participants in the scanner. In all three studies, participants inside the scanner watched videos once in randomized order, followed by evaluation after each presentation (see Table 1 for an overview of the three studies). Our main dependent variable (DV) is out-of-sample preference reported by a separate and larger group of raters for each set of stimuli (117 raters for TV commercials and 96 raters for movie-trailers). For a subset of TV commercials (24 out of 35), we have obtained contemporaneous aided recall data collected by a marketing research company during the rollouts of the respective commercials, which serves as our secondary DV.

Table 1
Summary of studies.

	Study 1a	Study 1b	Study 2
Stimulus			
N and type	35 previously broadcast TV commercials		18 previously unseen movie-trailers
Length (s)	25-60 (M = 41; SD = 9.4)		66-150 (M = 134; SD = 18.3)
Dependent variable			
Main: Out-of-sample preference	117 external raters on 2 items of 7-point Likert scale		96 external raters on an 11-point scale(5-star rating in half-star increments)
Secondary: Aided recall	Aided recall (%) by online panel at time of broadcast (for a subset of 24 commercials)		–
Scanning participants			
N	40	20	28
Mean age	35.1	39.1	20.9
Sex	56% female	55% female	50% female
Scanning parameters			
Scanner type	1.5T	3T	3T
Repetition time (TR)	3000 ms	2140 ms	2070 ms

2.1. Experimental design and statistical analysis

Our approach to the three studies was (a) to investigate which brain areas were associated with out-of-sample aggregate preference using the first study (Study 1a), and (b) to replicate these findings with the second study (Study 1b). After locating the relevant brain areas in Study 1a and 1b, we extracted neural information from these regions from all three studies (Study 1a, 1b and 2), and investigated to what extent neural similarity information could explain variance in aggregate preference. We then examined to what extent neural similarity in these regions explained additional variance on top of self-report measures and neural activation.

The studies were approved by the institutional review board in line with the Declaration of Helsinki. All participants signed informed consent prior to participation.

2.2. TV commercial study (study 1a and 1b)

2.2.1. Stimuli

Thirty-five commercials from seven well-known telecommunication brands, aired on national TV networks during 2009–2015, were used as stimuli (see supplementary material S1 for details). Their lengths varied from 25s to 60s ($M_{length} = 40.5$s; $SD_{length} = 9.4$s). On average, the commercials appeared on air for 7.4 weeks ($SD_{broadcast} = 2.2$ weeks).

2.2.2. Main DV

Out-of-sample aggregate preference was measured by obtaining responses from 117 individuals not involved in the fMRI scanning ($M_{age} = 32.9$; $SD_{age} = 12.3$; 56% female). They watched the commercials in randomized order, and then gave a general evaluation ('how much did you like this video?') and rated them on four aspects on a 7-point Likert scale: whether they were entertaining, informative, relevant, and convincing. To find out if the five items measured the same latent construct, we used factor analysis, which revealed two factors – a first factor consisting of the general evaluation and the entertaining score, and a second factor with the remaining three items. Since the second factor involves more cognitive judgment instead of preference, we used the average of the general evaluation and the entertaining score as the liking score (responses to the two items were highly correlated, $r = 0.85$). Converting the score onto a 0–1 scale with a mid-point at .5, the mean rating of the 35 commercials was 0.575 ($SD_{rating} = 0.115$, range = 0.322–0.697). (We present results of the analysis of the remaining items in supplementary material S2.)

2.2.3. Secondary DV

For a subset of commercials (24 out of 35), contemporaneous market level data on aided recall at the time of broadcast (2009–2015) were available. A marketing research company systematically tracked aided recall for each of the subset commercials over the duration of their broadcasts. In each given week when a certain commercial was aired, a fresh panel of 100 online respondents aged 16–65 drawn from a representative national sample saw a few screenshots of that commercial and were asked to report if they had definitely seen it, might have seen it, or did not recall seeing it in the past 4 weeks. Aided recall was the ratio of all respondents who reported having definitely seen the commercial during its entire broadcast period.

2.2.4. Participants and procedure

Participants (Study 1a: N = 40; $M_{age} = 35.1$; $SD_{age} = 9.7$; 56% female; Study 1b: N = 20; $M_{age} = 39.1$; $SD_{age} = 11.1$; 55% female) were recruited from the general public by a marketing research company. Potential subjects responded to an online MRI screening questionnaire which ensured they had no history of neurological illness or damage, were not

using drugs or psychiatric medication, and had normal or corrected-to-normal vision. Those who were found suitable for scanning were contacted, and written informed consent was obtained in advance. For their participation, each participant was paid €60. They were invited to the scanning facility, where they watched the 35 commercials, presented in randomized order, during fMRI scanning. Immediately after each commercial, participants indicated their liking via button presses without time limit, then waited for 6–10s with a blank screen before another commercial began. (See supplementary material S3 for detailed task procedure.) The scanning lasted about 35 min. Within three days after scanning, they completed an online survey which contained the same 5-item questionnaire for each of the commercials, again presented in random order. We used their responses to the same 2 items (entertaining and general evaluation) to compute their individual rating for each of the 35 commercials (in-sample preference).

2.2.5. FMRI acquisition

For Study 1a, the functional magnetic resonance images were obtained using a 1.5T (Siemens) MRI system. Functional scans were acquired by a T2*-weighted gradient-echo, echo-planar pulse sequence in ascending interleaved order (35 slices, 3.0 mm slice thickness, 0.6 mm slice gap, 3.0 × 3.0 mm in-plane resolution, 80 × 80 voxels per slice, flip angle = 90°). Echo time (TE) was 40 ms and repetition time (TR) was 3000 ms. A T1-weighted image was acquired for anatomical reference (1.0 × 1.0 × 1.0 mm resolution, 176 sagittal slices, flip angle = 15°, TE = 3.93 ms, TR = 2040 ms).

In Study 1b, a different scanner was used with modified acquisition parameters. The functional magnetic resonance images were obtained using a 3T (Siemens) MRI system. Functional scans were acquired by a T2*-weighted gradient-echo, echo-planar pulse sequence in ascending interleaved order (35 slices, 3.0 mm slice thickness, 0.6 mm slice gap, 3.0 × 3.0 mm in-plane resolution, 64 × 64 voxels per slice, flip angle = 90°). Different echo time (TE = 25 ms) and repetition time (TR = 2140 ms) were used. A T1-weighted image was acquired for anatomical reference (1.0 × 1.0 × 1.0 mm resolution, 192 sagittal slices, flip angle = 9°, TE = 2.98 ms, TR = 2300 ms).

2.3. Movie-trailer study (study 2)

2.3.1. Stimuli

The stimuli were 18 movie trailers selected from a larger database of 168 movies (see supplementary material S1 for more details on movie trailers). In short, the movies were released in the US between 2000 and 2010 with varying levels of commercial success (box office receipts between $4.4 million and $121 million; $M_{boxoffice}$ = $47 million). The trailers of these movies are 66–150s long (M_{length} = 134s; SD_{length} = 18.3s). Importantly, a screening procedure during subject recruitment confirmed that none of the movies had been seen by any of the participants.

2.3.2. Main DV

Out-of-sample ratings were collected from a separate group of university students from the same population (N = 96) who watched the movie trailers in a randomized order. Immediately after each movie-trailer, they rated liking on a 5-star rating scale (from 0 to 5 stars in half-star increments). The average rating was 2.45 stars (range = 1.16–3.51 stars; SD_{star} = 0.71).

2.3.3. Participants and procedure

Thirty-one participants were recruited from the university population and paid a fixed fee of €10 per hour for their participation in the fMRI scanning session. Potential subjects responded to an online MRI screening questionnaire which ensured they had no history of neurological illness or damage, were not using drugs or psychiatric medication, and had normal or corrected-to-normal vision. One participant had to be excluded due to falling asleep, and two more due to excessive head movements. These are omitted from all behavioral and neural analyses. The final sample consisted of 28 participants (M_{age} = 20.9; SD_{age} = 3.2; 14 female).

Participants underwent fMRI scanning while watching the 18 movie trailers, presented in randomized order, together with one practice video at the beginning (30s). For each movie-trailer, the poster of that movie appeared before and after the video for 3.5s. After that, they had to provide different ratings immediately after viewing, such as liking, willingness to pay, valence and arousal without time limit. A blank screen would appear for 3.5s before the next movie-trailer. (See supplementary material S3 for detailed task procedure.) We used their responses to the 5-star liking scale (same as the main DV) as in-sample preference for each of the movie-trailers.

2.3.4. FMRI acquisition

The functional magnetic resonance images were obtained using a 3T MRI system (Siemens). Functional data was acquired with a T2*-sensitized parallel imaging multi-echo sequence with echo times (TE) at 9, 19.3, 30 and 40 ms in ascending order (34 slices, 3.0 mm slice thickness, 0.5 mm slice gap, 3.5 × 3.5 mm in-plane resolution, 64 × 64 voxels per slice, flip angle = 90°). Repetition time (TR) was 2070 ms. Prior to preprocessing, the four read-outs acquired via the multi-echo sequence were combined and realigned by using standard procedures described by Poser et al. (2006). A T1-weighted image was acquired for anatomical reference (1.0 × 1.0 × 1.0 mm resolution, 192 sagittal slices, flip angle = 8°, TE = 3.03 ms, TR = 2300 ms).

2.4. Data preprocessing, extraction and visualization

We preprocessed the neuroimaging data using standard software (SPM12, Wellcome Department of Cognitive Neurology, London, UK). To correct for head motion, the functional images were realigned to the mean image. Functional images were slice-time corrected, coregistered to the anatomical image, spatially normalized to the Montreal Neurological Institute (MNI) template and lightly smoothed with a Gaussian kernel (3 × 3 × 3 mm full width at half maximum). In all studies, we verified that acquired images cover the whole brain, including cerebellum (supplementary material S4). Whole-brain activation analysis was conducted with SPM12. Neural similarity analysis was conducted with the PyMVPA toolbox (Hanke et al., 2009) and custom Python scripts. In both cases, spatially normalized neuroimaging data were regressed with average global signals and white matter signals. A high-pass filter implemented by discrete cosine transform (1/128 Hz for TV commercials and 1/256 Hz for movie-trailers) was applied, and each voxel was *z*-scored within the scanning session. We extracted brain volumes during stimuli viewing between 3s after stimulus onset and 3s after stimulus offset. To ensure the onset time relative to the acquisition time of the first extracted volume was the same across participants, temporal interpolation between volumes was carried out. Resultant brain maps are visualized using the Caret software (Van Essen et al., 2001), with additional images produced by Nilearn (Abraham et al., 2014).

2.5. Calculating neural similarity

We calculated neural similarity for each stimulus as follows (Fig. 1). For a stimulus v seen by n participants, we had spatiotemporal matrices $M_{v,1} \cdots M_{v,n}$, each with t volumes × k voxels. Scaling was first performed by subtracting the mean (voxel-wise) and then dividing by the matrix norm (i.e., the root of sum of squares of all elements) within each matrix. The neural similarity s_v of that stimulus is defined as the negative of the average pairwise Euclidean distance (i.e., the root of sum of squares of differences of all elements) of matrices $M_{v,1} \cdots M_{v,n}$, i.e.,

$$s_v = -\frac{2}{n(n-1)} \sum_{i=1}^{n} \sum_{j=i+1}^{n} \| M_{v,i} - M_{v,j} \| \# \quad (1)$$

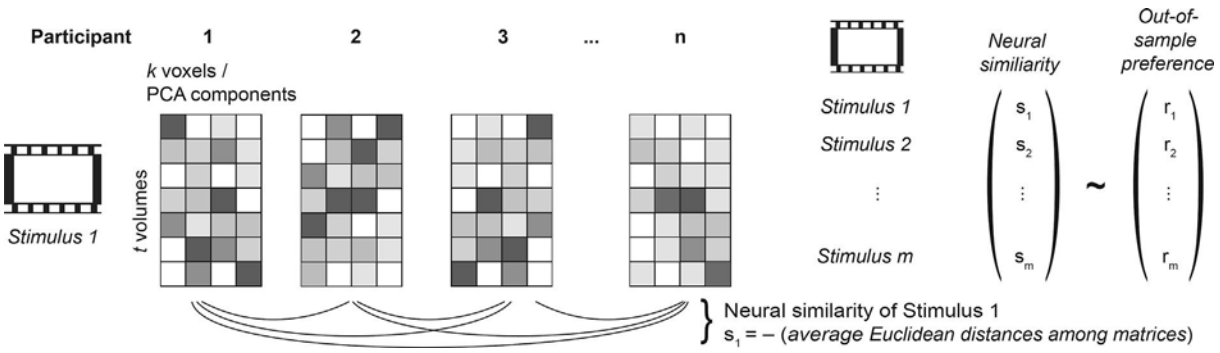

Fig. 1. Schematic diagram of neural similarity calculation.

2.6. Whole-brain analysis of neural similarity

To create whole-brain maps of neural similarity for each stimulus, we used the searchlight approach, employing a spherical searchlight of 2-voxel radius ($k = 33$ voxels). At each voxel, we extracted from participants the spatiotemporal matrices of neural responses using the spherical searchlight mask, then calculated neural similarity using the above equation (Equation (1)). Each stimulus had therefore a whole-brain similarity map.

In order to determine which brain areas had a significant similarity score during stimulus presentation (i.e., exhibited synchronized neural activities across participants), we implemented the following testing procedure: As we calculated the inter-subject pairwise distances ($-\| M_{v,i} - M_{v,j} \|$, for a given pair of participants i and j) for each stimulus v, we also randomly rolled one of the matrices along the time-axis ($M^*_{v,j}$) then calculated the similarity ($s_{v,\text{null}}$) again under this null condition ($-\| M_{v,i} - M^*_{v,j} \|$). Out of the $\frac{1}{2}n(n-1)$ inter-subject pairwise distances, a paired t-test ($s_v - s_{v,\text{null}}$) was conducted at each voxel for each stimulus. The t maps were then averaged across stimuli.

To investigate whether neural similarity correlates with out-of-sample preference, we calculated at each voxel a Pearson's correlation while partialling out stimulus length to minimize potential confounding effect of time. Similarly, we estimated statistical significance by permutation testing. We shuffled the stimuli ratings 10,000 times and obtained null correlation maps, then derived the empirical p value at each voxel from the voxel's own null distribution.

2.7. Whole-brain analysis of neural activation

To study the relationship between neural activation and out-of-sample preference, we estimated for each participant a general linear model (GLM) containing the following: a boxcar regressor to indicate whenever a video was presented, and an additional parametrically modulated regressor of out-of-sample preference. The design matrix was then convolved with canonical hemodynamic response function (HRF), and average global signal and white matter signal were entered as regressors of no interest. Based on these estimated beta images, second-level random-effects group contrast maps were then created in both directions (i.e., positive and negative correlation between activation and out-of-sample preference).

2.8. Region-of-interest (ROI) analysis of neural similarity and activation

Having identified voxels in whole-brain analysis, we proceeded to use the areas identified in Study 1a and 1b as regions-of-interest (ROIs) and recalculated neural similarity and activation. Given the high spatial correlation among voxels, we first reduced the data dimension by conducting principal component analysis (PCA) on time series data from Study 1a. Specifically, we concatenated ROI-extracted fMRI time series from all 40 participants, choosing only sections where the stimuli were presented (mean-centering was done within each stimulus), resulting in a time series of 20,680 volumes. The first 100 PCA components (explaining 62.8% of the total variance) were selected. Component weights obtained in Study 1a were used to transform the data in Study 1b and 2. (Additional PCA analyses showed component weights obtained within each dataset were highly similar.) Neural similarity was calculated using the Euclidean distances of the PCA-transformed matrices (t volumes $\times$ 100 components, c.f. Equation (1)). Same as in whole-brain analysis, neural similarity and activation scores were first adjusted for stimulus length (obtaining residuals by regression) to minimize potential confounding effect of time.

Knowing that the ROIs were themselves derived from the results obtained in Study 1a and 1b, we then attempted to replicate the effect with secondary DV (aided recall) and a new set of stimuli (Study 2). We also entered neural similarity, neural activation and in-sample preference into a regression model to see if neural similarity provides a unique contribution in explaining the variance of out-of-sample preference.

2.9. Robustness analysis on neural similarity calculation

Calculation of neural similarity involves determining the number of PCA components and the choice of distance metric. We have redone the analysis using 50 and 200 components (accounting for 45% and 82% of the total variance, respectively), and also untransformed raw voxels; we have also tested different distance metrics (cosine and city block).

2.10. Code accessibility and data availability

The data that support the findings of this study, including preprocessing and analysis scripts, are available in an open repository.[1]

3. Results

Since we did not have *a priori* assumptions about whether, or where, we might find (a) significant neural similarity during stimulus presentation, and (b) significant relationship between this neural similarity and out-of-sample aggregate preference, we first conducted a whole-brain analysis on Study 1a. We then repeated the analysis on Study 1b. With a conjunction analysis of Study 1a and 1b, we located brain regions where neural similarity was found to have a significant effect on out-of-sample aggregate preference. We then extended the analysis, using the brain areas identified in Study 1, to a different stimulus type (Study 2). For neural activation, we repeated the same approach (whole-brain analysis and conjunction analysis in Study 1a and 1b, then replication in Study 2). (Scatterplots and correlations of variables are shown in supplementary material S5.)

[1] https://github.com/chanhangyee/neural_similarity.

3.1. Synchronized neural activities during video viewing

Similar to previous studies of video viewing, we observed synchronized neural activity at visual and auditory cortices, as well as superior temporal cortex, anterior and posterior cingulate cortices and cerebellum (Fig. 2). In addition, amygdala and thalamus also displayed synchronized neural activity. Results found in both Study 1a and 1b were largely comparable; the resultant t maps from the two studies were highly correlated ($r = 0.905$, $p < .001$). These areas were also highly similar to past studies involving naturalistic stimulus viewing (Lahnakoski et al., 2017; Nummenmaa et al., 2012).

3.2. Neural similarity and activation correlate with out-of-sample preference

With whole-brain analysis of the TV commercials (Study 1a), we located anatomical areas where neural similarity and activation correlated with out-of-sample aggregate preference. We then replicated the findings in Study 1b, and further tested the robustness with movie trailers in Study 2.

3.2.1. Whole-brain analysis

We investigated if there were brain regions where neural similarity in spatiotemporal neural patterns during video watching covaried with out-of-sample aggregate preference. We conducted whole-brain analysis in both Study 1a and 1b, then obtained an intersection of the thresholded statistical maps ($p < .05$ FDR corrected) to look for conjunction voxels (Nichols et al., 2005). Conjunction analysis revealed that neural similarity at bilateral temporal poles (TPs), temporoparietal junctions (TPJs) and cerebellum was positively associated with out-of-sample aggregate preference (Fig. 3, left panel). Conjunction of significant brain areas from Study 1a and 1b encompasses 653 voxels, or 21.2 cm^3 (Table 2A). In other words, when participants showed more similar spatiotemporal neural patterns at those regions during watching of a certain video, that video tended to be more preferred by out-of-sample raters. Largely overlapping results were found between Study 1a and 1b, and the resultant Fisher-transformed z maps were highly correlated between the two studies ($r = 0.561$, $p < .001$), despite the fact that the two studies differed in scanner type (1.5T vs 3T) and repetition time (3.0s vs 2.14s).

Conjunction analysis of the whole-brain activations in Study 1a and 1b revealed regions where stronger neural activation among participants was associated with greater out-of-sample aggregate preference (Fig. 3, right panel). Significant voxels were found in bilateral superior temporal gyri (STG), as well as precuneus and the left inferior frontal cortex (pars triangularis, Broca's area). Conjunction of significant brain areas from Study 1a and 1b encompasses 723 voxels, or 23.4 cm^3 (Table 2B). The resultant group contrast z maps were again highly correlated between the two studies ($r = .624$, $p < .001$). In a supplementary analysis we performed a significance test on both similarity and activation conjunction sizes by permutation (see supplementary material S6 for details).

Comparing the whole-brain maps of similarity and activation (both transformed to z) yields only moderate correlations of 0.306 and 0.323 for Study 1a and 1b respectively (both $ps < .001$). In addition, it should also be noted that whole-brain analysis of similarity and activation uncovered largely distinct brain regions (similarity region = 20.5 cm^3, activation region = 26.3 cm^3, overlap = 5.7 cm^3 or 13.8%, see supplementary material S7 for the extent of overlap).

3.2.2. ROI analysis

We examined to what extent neural information, in terms of both activation and similarity, could predict out-of-sample aggregate preference for different stimuli (movie-trailers). Selecting the voxels in the conjunction areas of the two TV commercial studies (i.e., red in Fig. 3A encompassing bilateral TP, TPJ and cerebellum; and blue in Fig. 3B encompassing STG and precuneus), we re-calculated neural similarity (using the red voxels) and activation (using the blue voxels) for the third dataset involving movie-trailers (Study 2). (For the sake of completeness, the whole-brain analysis on Study 2 is included in supplementary material S8.)

Across the three studies, neural similarity at TP/TPJ/cerebellum correlated with out-of-sample preference. Notably, the effect was robust for using different stimuli (movie-trailers) using the voxels identified in TV commercials. Correlation between neural activation at STG/precuneus and out-of-sample preference for the movie-trailers were similar to the commercials ($r = 0.434$), but just failed to reach the 0.05 significance level, $p = .072$. We also extended the findings to a market level DV, i.e., aided recall, for a subset of TV commercials. Both neural similarity in TP/TPJ/cerebellum and activation in STG/precuneus correlated with aided recall ($r = 0.617$–0.805, all $ps < .005$, see Fig. 4 for a summary of findings).

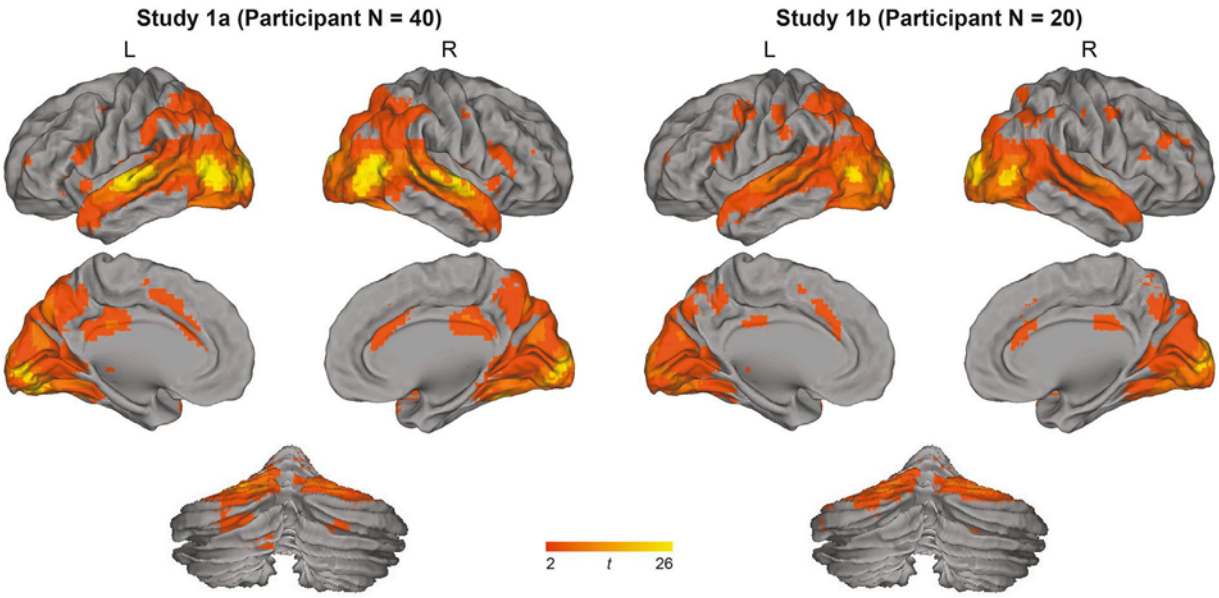

Fig. 2. Brain regions showing significant synchronized activities during TV commercial watching ($p < .05$ FDR corrected).

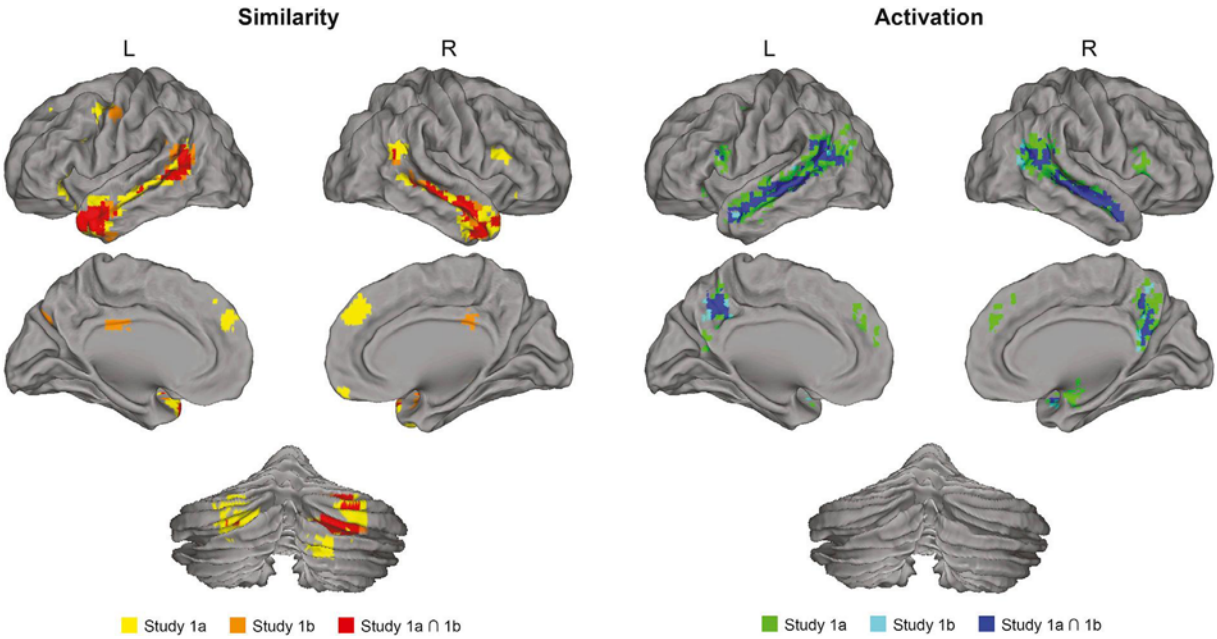

Fig. 3. Voxels with significant correlation between neural similarity and out-of-sample preference (left); and between neural activation and out-of-sample preference (right) ($p < .05$ FDR corrected).

Table 2
Coordinates and sizes of conjunction clusters (only cluster size $k > 5$ shown here).

A. Similarity (Study 1a ∩ 1b)	Cluster size		Cluster center		
	in voxel	in cm^3	*x*	*y*	*z*
Temporal Pole R	229	7.42	52	−5	−21
Temporal Pole L	172	5.57	−54	−53	12
Temporoparietal Junction L	165	5.35	−49	9	−28
Cerebellum R	56	1.81	23	−76	−35
Cerebellum L	11	0.36	−23	−75	−32
Temporal Mid L	9	0.29	−49	−25	−8
Temporal Mid R	7	0.23	57	−52	17
B. Activation (Study 1a ∩ 1b)	**Cluster size**		**Cluster center**		
	in voxel	in cm^3	*x*	*y*	*z*
Superior Temporal Gyrus R	338	10.95	53	−31	2
Superior Temporal Gyrus L	304	9.85	−53	−36	4
Precuneus	172	5.57	0	−54	40
Frontal Inf Tri L	9	0.29	−49	19	18

In a supplementary ROI analysis (supplementary material S9), we did not obtain a consistent relationship between out-of-sample preference and activation at known subjective valuation areas, such as amygdala, anterior insula, anterior cingulate cortex (ACC), mPFC and NAcc (Bartra et al., 2013; Samanez-Larkin and Knutson, 2015).

Robustness analysis (supplementary material S10) shows that findings were robust to changing both PCA component number and metric choice. In addition, our neural similarity measure incorporates all voxels from the bilateral regions of TP, TPJ and cerebellum. To understand the importance of individual areas, we calculated neural similarity for each separate cluster (using raw voxels instead of component weights) and found similar results (see supplementary material S11), underlining the role of each of the three areas in the processing and evaluation of videos.

To illustrate how neural similarity differs between stimuli of high and low out-of-sample preference, Fig. 5 shows the time-course plots of the most- and least-liked stimuli using the first two PCA components. In both Study 1a and 1b, inter-subject time-course Euclidean distances of the most-liked commercial were significantly smaller than those of the least-liked commercial, indicating that participants on average had more similar neural responses during the viewing of the most-liked commercial.

3.3. Additional variance in out-of-sample preference explained by neural signals

Next, we examined whether neural similarity and activation provided distinct information in addition to in-sample self-report preference in predicting out-of-sample preference (Table 3). We combined results from the three studies and conducted mixed-effect regression models, using study as random intercept. We compared a reduced regression model with stimulus length and self-report preference entered as regressors (Model 1), and a full model with the additional neural regressors. When either neural similarity (Model 2) or activation (3) or both (4) were entered into the regression model, model performance improved significantly, showing that both neural similarity and activation independently contribute to improved prediction of out-of-sample preference, above and beyond in-sample self-reported preference.

3.3.1. Potential confounding effects of previous exposure and memory for TV commercials

In Study 1a and 1b, like a previous study (Dmochowski et al., 2014), we used previously broadcasted materials. Contemporaneous aided recall data might be confounded by the size of the advertising campaigns at that time (such that bigger campaigns had more media exposure thus might lead to higher recall in the population); current out-of-sample preference might be confounded by the campaign size, and the time lapsed since first exposure (such that more recently broadcast commercials might be liked more). We attempted to find out their potential effects by repeating the analysis with two additional regressors: weeks since initial broadcast, and gross rating points for age group 20–49 (i.e., number of cumulative impressions as a percentage of target population during the advertising campaign). Regression results were robust to the two additional regressors (see supplementary material S12).

4. Discussion

Across different participants, scanning parameters, video lengths and types, we uncovered neural information that predicted out-of-sample aggregate preference of naturalistic dynamic stimuli. With respect to the research questions set forth in the introduction, we present the following findings:

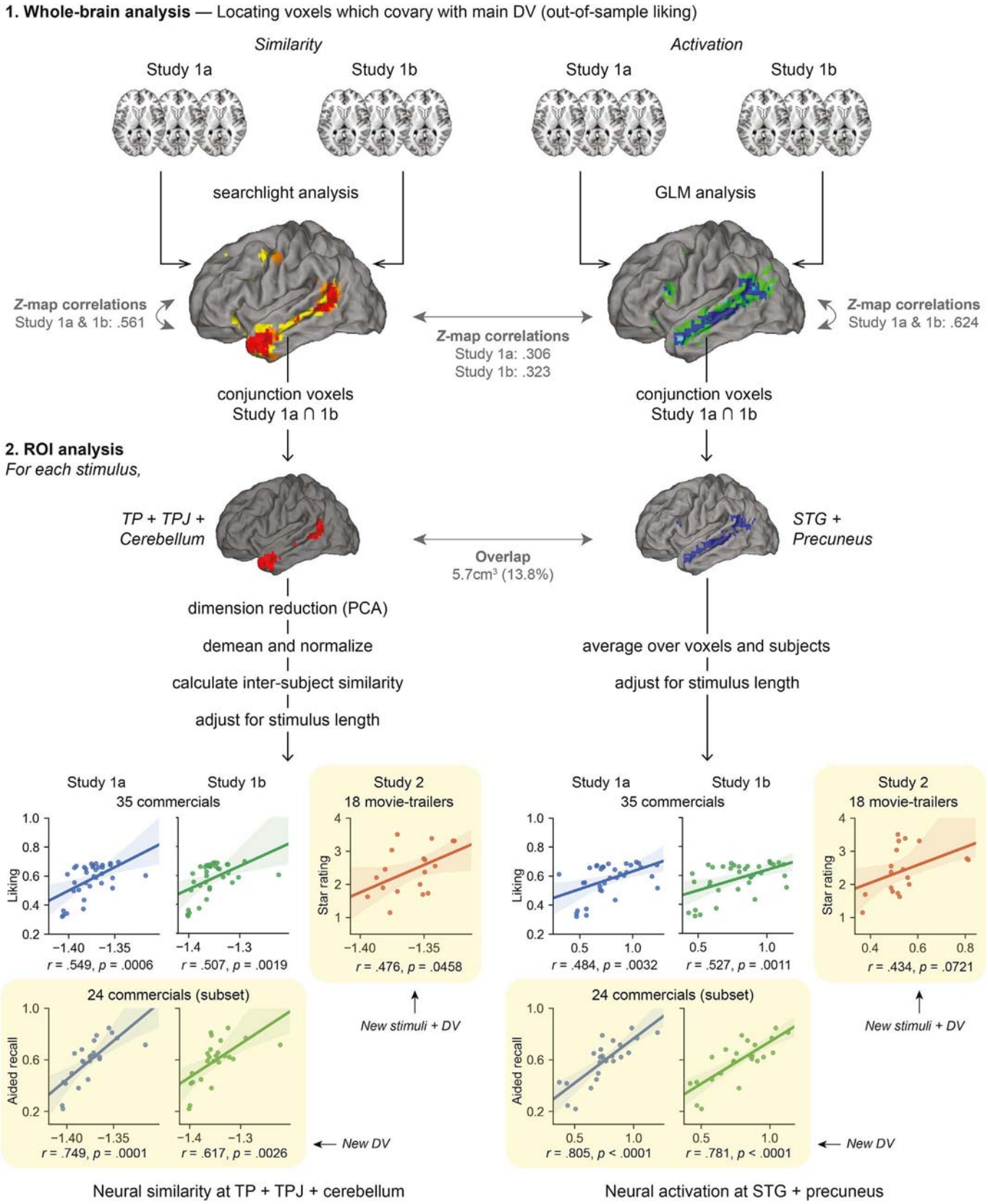

Fig. 4. Schematic diagram of analysis and summary of results. TP = temporal pole; TPJ = temporoparietal junction; STG = superior temporal gyrus.

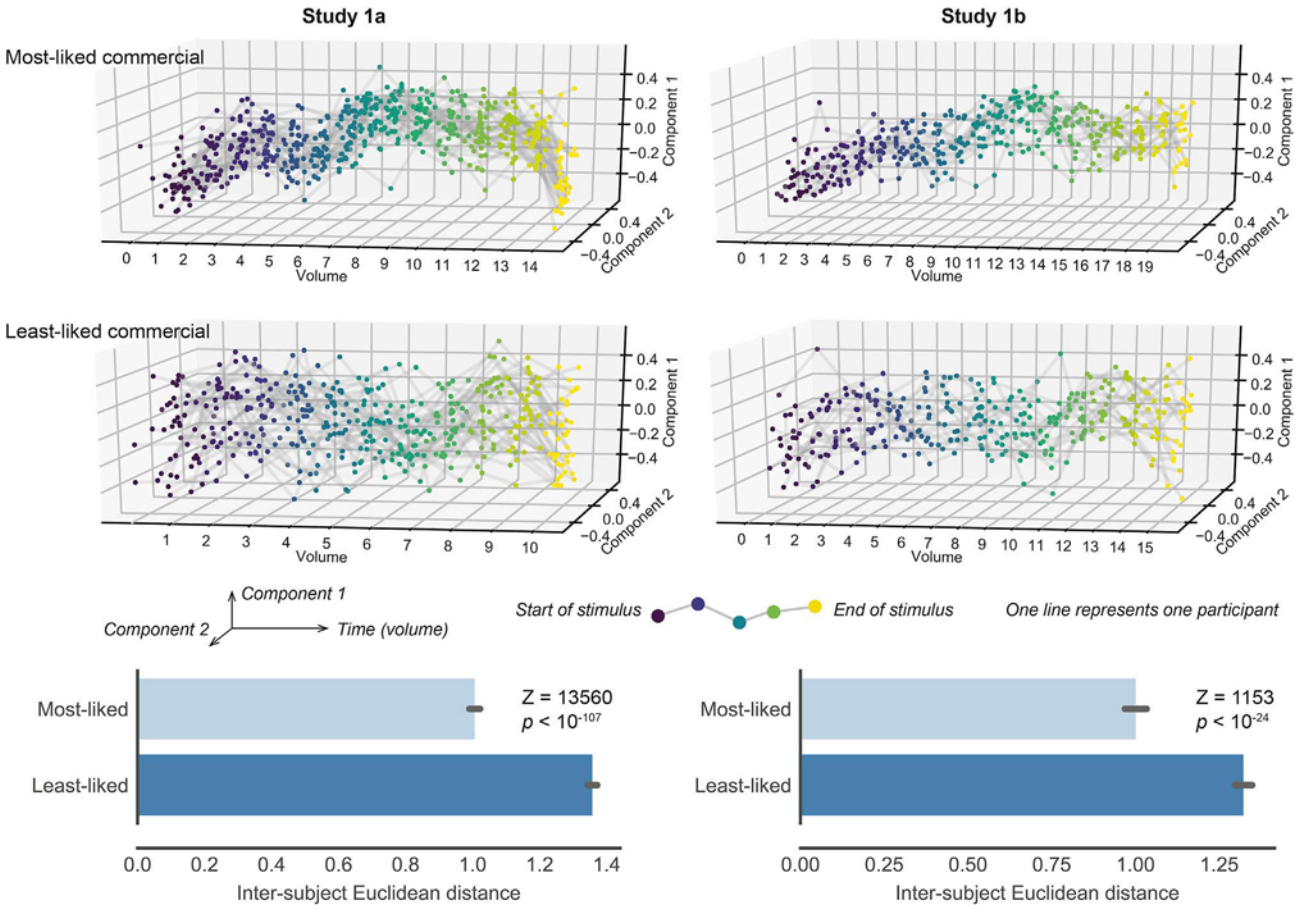

Fig. 5. Time-course plots of neural activities at TP/TPJ/cerebellum for most- and least-liked commercials. Statistical comparisons between most- and least-liked commercials are Wilcoxon signed-rank tests. TP = temporal pole; TPJ = temporoparietal junction.

Table 3
Mixed-effect regression models predicting out-of-sample preference with different regressors, with study entered as random intercepts. Model comparisons were done with the baseline model (1).

DV: Out-of-sample preference (N = 88[a])	(1)		(2)		(3)		(4)	
	β	*p*	β	*p*	β	*p*	β	*p*
Video length	0.238	.001	0.339	<.001	0.197	.001	0.261	<.001
In-sample preference	0.686	<.001	0.522	<.001	0.558	<.001	0.499	<.001
Neural similarity			0.288	<.001			0.153	.028
Neural activation					0.331	<.001	0.257	<.001
AIC	158.1		142.1		132.9		130.1	
χ^2			18.0	<.001	27.2	<.001	32.0	<.001

[a] N denotes total number of stimuli (Study 1a: 35, Study 1b: 35, Study 2: 18)

4.1. Neural similarity in the TP, TPJ and cerebellum predicts out-of-sample preference

We found that the synchronized neural activity across participants at the TP, TPJ and cerebellum was associated with out-of-sample preference for videos, in terms of liking and recall. TP and TPJ have been described as the association cortex (Olson et al., 2007), due to their extensive connections with the sensory systems. TP is interconnected with the amygdala and orbital frontal cortex, and the suggested role of TP as a midway station between multi-modal perceptual inputs and emotional responses (Wong and Gallate, 2012) is consistent with our current findings that video watching evoked similar neural responses in these areas. A meta-analytic review of activation-based studies also found the involvement of bilateral temporal poles in the evaluation of emotional content from stimuli (Lindquist et al., 2012). TPJ, on the other hand, has been linked to multiple functions pertinent to the emotional processing of complex stimuli, from general cognitive functions (e.g., attention, language processing, and episodic memory encoding) to more selective ones (e.g., mentalizing and social cognition) (Carter and Huettel, 2013).

In the smaller body of literature on neural similarity, right TP was found to be part of the brain network whose inter-subject synchronicity covaried with self-report arousal during film watching (Nummenmaa et al., 2012), while left TP synchronicity correlated with syntactic complexity during story listening (Brennan et al., 2012). There is also evidence that neural activities at TPs and TPJs during narrating and listening to the same story are synchronized (Silbert et al., 2014); more interestingly, neural similarity at TP and TPJ has previously been found to predict successful content recall after watching a video (Hasson et al., 2008). In brief, neural similarity at those areas may signal engagement and effective/successful communication.

Lastly, the inclusion of cerebellum in our findings provides further evidence on its role in emotional processing (Schmahmann and Caplan,

2006). In fact, a number of studies found the involvement of cerebellum during video watching (Franklin and Adams, 2011; Han et al., 2011; Mathiak and Weber, 2006). We considered the possibility that synchronized cerebellar activities might be driven by perceptual processes such as eye movement. In a supplementary analysis (supplementary material S13), we compared activation maps associated with movement and emotion obtained from Neurosynth (Yarkoni et al., 2011), and found that the cerebellum ROI in the current study contains voxels included in the emotion-related association map but not the movement-related map, suggesting that the effect is likely to be driven by emotional processing at cerebellum.

In the current study, we revealed for the first time that neural similarity at TP, TPJ and cerebellum within a small group can predict out-of-sample preference. This finding, together with the fact that we found no significant effect in sensory or prefrontal cortices, suggests that aggregate preference of the population may be related to the interpersonal consistency in higher-order comprehension, instead of sensory processing or valuation. This echoes past findings on neural activation that, while video advertisements with more attention-grabbing features produced higher activation in occipital cortex, they were associated with decreased activation in temporal and prefrontal cortices, and lower recall rate (Langleben et al., 2009).

4.2. Neural activation in the STG and precuneus predicts out-of-sample preference

In addition to our findings on neural similarity, we found that neural activation at STG and precuneus consistently predicted preference across stimulus types. Precuneus is known to be associated with self-consciousness (Cavanna and Trimble, 2006) and valuation (Litt et al., 2011). On the other hand, the role of STG in the integration of sounds and images in audiovisual stimuli, especially those involving speech, is well-documented (Beauchamp et al., 2004; Noesselt et al., 2012). One plausible interpretation may be that preference is related to attention, which in turn modulates STG activation during audiovisual integration (Morís Fernández et al., 2015). On the other hand, precuneus has long been associated with self-consciousness (Cavanna and Trimble, 2006), and a recent study suggested it may also have a role in attention (Klasen et al., 2012). These findings point to the speculation that neural activation in STG and precuneus may be an indication of engagement, although further study is needed before any definitive conclusion can be drawn.

Our study did not find activation at known subjective valuation areas, such as amygdala, anterior insula, anterior cingulate cortex (ACC), mPFC and NAcc (Bartra et al., 2013; Samanez-Larkin and Knutson, 2015) to be predictive of out-of-sample preference. Among studies involving dynamic stimuli, there are conflicting findings on the relationship between self-report enjoyment and activation in these areas. For example, the amygdala was found to correlate with liking in comedy movies (Franklin and Adams, 2011; Jääskeläinen et al., 2016) and TV commercials (Venkatraman et al., 2015), while no such effect was found for liking of dance video clips (Cross et al., 2011). In one study, decreased mPFC activity was related with humor rating of comedy videos (Franklin and Adams, 2011), while increased NAcc activity was found to predict market-level success of songs (Berns and Moore, 2012) and TV commercials (Venkatraman et al., 2015) but not in others that measured self-report liking (Cross et al., 2011; Franklin and Adams, 2011; Jääskeläinen et al., 2016). Overall, it seems that activations at brain areas traditionally associated with reward such as NAcc and mPFC may not offer a reliable signal of out-of-sample preference for dynamic stimuli.

4.3. Overlap in ROIs associated with similarity and activation

While studies on neural similarity and activation often identify different but overlapping brain regions involved in the same task or observation (e.g., Hasson et al., 2008; Nummenmaa et al., 2014), it is unclear whether the similarity- and activation-based measurements offer the same or distinct information. In a supplementary analysis (supplementary material S14) we computed both similarity and activation within each individual ROI and found that both similarity and activation in the temporal lobe (TP, TPJ and STG) predict out-of-sample preference, while only similarity (but not activation) measured at cerebellum and only activation (but not similarity) measured at precuneus predicts out-of-sample preference. These findings are perhaps not that surprising, given the close proximity of the ROIs situated in the temporal lobe, and the smoothing kernel used in preprocessing of the data. Importantly, they do not take away from the result that there is unique information in similarity measures that is not present in activation measures (see Table 3), even if similarity and activation are observed in the same/similar brain areas. Indeed, the finding that aggregate preference can be predicted from similarity and activation in areas that are at least partly distinct supports the view that information from pattern similarities and magnitude differences may have separate neural substrates.

4.4. Neural similarity as a distinct information source

We replicated past findings that neural activation offers unique information about aggregate preference in addition to self-report responses (Berns and Moore, 2012; Boksem and Smidts, 2015; Genevsky et al., 2017; Venkatraman et al., 2015). Here, we showed that neural similarity also provides unique information, above and beyond self-report. As such, it adds to the growing literature of neural prediction which demonstrates that brain imaging provides additional predictive power on top of self-report measures.

Why does neural similarity from a group of individuals improve out-of-sample preference prediction, even after taking into account the stated preference of those individuals? We posit that similar to the case of neural activation (Knutson and Genevsky, 2018), neural similarity may capture aspects of individual choice that scale better to forecast aggregate choice. Specifically, neural similarity at TP/TPJ/cerebellum may measure the level of sustained engagement with the videos, which results in enhanced understanding of the content ('I understand what the video is about'), one of the components for liking that may generalize more across individuals compared to more idiosyncratic components such as personal values ('I find the video suits my needs/tastes').

4.5. Measuring spatiotemporal similarity in neural activities

Unlike many studies on temporal synchronization of brain activities (Golland et al., 2017; Hasson et al., 2004; Lankinen et al., 2018, 2014; Nummenmaa et al., 2012; Silbert et al., 2014), we did not compute our neural similarity measure using single-voxel time series. Instead, we made use of BOLD signals spanning across both space and time to calculate a multi-voxel, spatiotemporal similarity measure. We believe that this type of approach is particularly well suited for analysis of neural responses when complex, dynamic stimuli are involved. In a supplementary analysis, we indeed found that using single-voxel time series to compute neural similarity failed to uncover significant brain areas, and we observed similar anatomical findings with varying searchlight radius. (Results are available upon request.) Discussions about ways to find out the optimal shape and size of searchlight for this type of multi-voxel analysis have not reached a consensus yet (Etzel et al., 2013), and it is likely to be dependent on the nature of the stimuli and the task. Further research is required to determine the best practice.

4.6. Further research questions

To further extend this line of research, there are two questions that would be of interest. First, can neural similarity be applied to static stimuli (i.e., spatial instead of spatiotemporal similarity)? Recent advances in representational similarity analysis (Kriegeskorte et al., 2008) allow researchers to apply this kind of analysis in studies involving consumer ratings or choosing products based on static stimuli. Second,

beyond aggregate preference, can neural similarity predict actual choices made by consumers in the market (as measured by, for example, sales)? Again, more data on market-level effectiveness is needed before we understand the potential and limits of neural similarity.

Lastly, our three studies used video stimuli (TV commercials and movie trailers) originally designed to appeal to a broad audience. While we found that popular videos were the ones which evoked most similar responses among individuals, it is unclear if such findings are restricted to a certain genre of stimuli. For example, one may speculate that for cultural products meant to provoke discussion and stimulation (such as documentaries or debates), neural *dis*similarity may actually a more suitable predictor of preference.

4.7. Conclusion

In summary, across multiple studies we found that neural similarity is a robust signal of preference, and that it provides meaningful information in addition to both neural activation and self-report measures. This study provides several novel contributions. First, we found that neural similarity at temporal lobe and cerebellum – areas involved in sensory integration and emotional processing – predicted out-of-sample preference. Second, while prior research demonstrated the link between neural similarity and preference, this is the first study that demonstrates its robustness across scanning settings, outcome measurements and video types. Third, it showed the additional predictive power of neural similarity above and beyond self-report measures, and showed the value of harnessing this measure for the purpose of 'neuroforecasting' (Knutson and Genevsky, 2018). More research is needed in order to shed light on the interplay between activation and similarity within an individual. Whether the predictive effect of neural similarity on aggregate preference is specific to a certain type of stimuli (e.g., genre catered to mass entertainment) remains to be studied.

Conflicts of interest

The authors declare no competing financial interests.

Acknowledgement

The authors would like to thank the editor and anonymous reviewers for their insightful comments. We also gratefully acknowledge financial support from the Erasmus Research Institute of Management and the Dutch national e-infrastructure with the support of SURF Cooperative.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.neuroimage.2019.04.076.

References

Abraham, A., Pedregosa, F., Eickenberg, M., Gervais, P., Mueller, A., Kossaifi, J., Gramfort, A., Thirion, B., Varoquaux, G., 2014. Machine learning for neuroimaging with scikit-learn. Front. Neuroinf. 8. https://doi.org/10.3389/fninf.2014.00014.

Barnett, S.B., Cerf, M., 2017. A ticket for your thoughts: method for predicting content recall and sales using neural similarity of moviegoers. J. Consum. Res. 44, 160–181. https://doi.org/10.1093/jcr/ucw083.

Bartra, O., McGuire, J.T., Kable, J.W., 2013. The valuation system: a coordinate-based meta-analysis of BOLD fMRI experiments examining neural correlates of subjective value. Neuroimage 76, 412–427. https://doi.org/10.1016/j.neuroimage.2013.02.063.

Beauchamp, M.S., Argall, B.D., Bodurka, J., Duyn, J.H., Martin, A., 2004. Unraveling multisensory integration: patchy organization within human STS multisensory cortex. Nat. Neurosci. 7, 1190–1192. https://doi.org/10.1038/nn1333.

Berns, G.S., Moore, S.E., 2012. A neural predictor of cultural popularity. J. Consum. Psychol. 22, 154–160. https://doi.org/10.1016/j.jcps.2011.05.001.

Boksem, M.A.S., Smidts, A., 2015. Brain responses to movie trailers predict individual preferences for movies and their population-wide commercial success. J. Mark. Res. 52, 482–492. https://doi.org/10.1509/jmr.13.0572.

Brennan, J., Nir, Y., Hasson, U., Malach, R., Heeger, D.J., Pylkkänen, L., 2012. Syntactic structure building in the anterior temporal lobe during natural story listening. Brain Lang. 120, 163–173. https://doi.org/10.1016/j.bandl.2010.04.002.

Carter, R.M., Huettel, S.A., 2013. A nexus model of the temporal-parietal junction. Trends Cognit. Sci. 17, 328–336. https://doi.org/10.1016/j.tics.2013.05.007.

Cavanna, A.E., Trimble, M.R., 2006. The precuneus: a review of its functional anatomy and behavioural correlates. Brain 129, 564–583. https://doi.org/10.1093/brain/awl004.

Christoforou, C., Papadopoulos, T.C., Constantinidou, F., Theodorou, M., 2017. Your brain on the movies: a computational approach for predicting box-office performance from viewer's brain responses to movie trailers. Front. Neuroinf. 11. https://doi.org/10.3389/fninf.2017.00072.

Couwenberg, L.E., Boksem, M.A.S., Dietvorst, R.C., Worm, L., Verbeke, W.J.M.I., Smidts, A., 2017. Neural responses to functional and experiential ad appeals: explaining ad effectiveness. Int. J. Res. Mark. 34, 355–366. https://doi.org/10.1016/J.IJRESMAR.2016.10.005.

Cross, E.S., Kirsch, L., Ticini, L.F., Schütz-Bosbach, S., 2011. The impact of aesthetic evaluation and physical ability on dance perception. Front. Hum. Neurosci. 5, 102. https://doi.org/10.3389/fnhum.2011.00102.

Dikker, S., Silbert, L.J., Hasson, U., Zevin, J.D., 2014. On the same wavelength: predictable language enhances speaker-listener brain-to-brain synchrony in posterior superior temporal gyrus. J. Neurosci. 34, 6267–6272. https://doi.org/10.1523/JNEUROSCI.3796-13.2014.

Dmochowski, J.P., Bezdek, M.A., Abelson, B.P., Johnson, J.S., Schumacher, E.H., Parra, L.C., 2014. Audience preferences are predicted by temporal reliability of neural processing. Nat. Commun. 5. https://doi.org/10.1038/ncomms5567.

Etzel, J.A., Zacks, J.M., Braver, T.S., 2013. Searchlight analysis: promise, pitfalls, and potential. Neuroimage 78, 261–269. https://doi.org/10.1016/J.NEUROIMAGE.2013.03.041.

Falk, E.B., Berkman, E.T., Lieberman, M.D., 2012. From neural responses to population behavior: neural focus group predicts population-level media effects. Psychol. Sci. 23, 439–445. https://doi.org/10.1177/0956797611434964.

Franklin, R.G., Adams, R.B., 2011. The reward of a good joke: neural correlates of viewing dynamic displays of stand-up comedy. Cognit. Affect Behav. Neurosci. 11, 508–515. https://doi.org/10.3758/s13415-011-0049-7.

Genevsky, A., Yoon, C., Knutson, B., 2017. When brain beats behavior: neuroforecasting crowdfunding outcomes. J. Neurosci. 37, 8625–8634. https://doi.org/10.1523/JNEUROSCI.1633-16.2017.

Golland, Y., Levit-Binnun, N., Hendler, T., Lerner, Y., 2017. Neural dynamics underlying emotional transmissions between individuals. Soc. Cognit. Affect Neurosci. 12, 1249–1260. https://doi.org/10.1093/scan/nsx049.

Han, D.H., Bolo, N., Daniels, M.A., Arenella, L., Lyoo, I.K., Renshaw, P.F., 2011. Brain activity and desire for Internet video game play. Compr. Psychiatr. 52, 88–95. https://doi.org/10.1016/j.comppsych.2010.04.004.

Hanke, M., Halchenko, Y.O., Sederberg, P.B., Olivetti, E., Fründ, I., Rieger, J.W., Herrmann, C.S., Haxby, J.V., Hanson, S.J., Pollmann, S., 2009. PyMVPA: a unifying approach to the analysis of neuroscientific data. Front. Neuroinf. 3, 3. https://doi.org/10.3389/neuro.11.003.2009.

Hasson, U., Furman, O., Clark, D., Dudai, Y., Davachi, L., 2008. Enhanced intersubject correlations during movie viewing correlate with successful episodic encoding. Neuron 57, 452–462. https://doi.org/10.1016/j.neuron.2007.12.009.

Hasson, U., Malach, R., Heeger, D.J., 2010. Reliability of cortical activity during natural stimulation. Trends Cognit. Sci. 14, 40–48.

Hasson, U., Nir, Y., Levy, I., Fuhrmann, G., Malach, R., 2004. Intersubject synchronization of cortical activity DuringNatural vision. Science 303, 1634–1640 (80-.). https://doi.org/10.1126/science.1089506.

Jääskeläinen, I.P., Pajula, J., Tohka, J., Lee, H.-J., Kuo, W.-J., Lin, F.-H., 2016. Brain hemodynamic activity during viewing and re-viewing of comedy movies explained by experienced humor. Sci. Rep. 6, 27741. https://doi.org/10.1038/srep27741.

Ki, J.J., Kelly, S.P., Parra, L.C., 2016. Attention strongly modulates reliability of neural responses to naturalistic narrative stimuli. J. Neurosci. 36, 3092–3101. https://doi.org/10.1523/JNEUROSCI.2942-15.2016.

Klasen, M., Weber, R., Kircher, T.T.J., Mathiak, K.A., Mathiak, K., 2012. Neural contributions to flow experience during video game playing. Soc. Cognit. Affect Neurosci. 7, 485–495. https://doi.org/10.1093/scan/nsr021.

Knutson, B., Genevsky, A., 2018. Neuroforecasting aggregate choice. Curr. Dir. Psychol. Sci. 27, 110–115. https://doi.org/10.1177/0963721417737877.

Kriegeskorte, N., Mur, M., Bandettini, P. a., 2008. Representational similarity analysis - connecting the branches of systems neuroscience. Front. Syst. Neurosci. 2, 4. https://doi.org/10.3389/neuro.06.004.2008.

Lahnakoski, J.M., Jääskeläinen, I.P., Sams, M., Nummenmaa, L., 2017. Neural mechanisms for integrating consecutive and interleaved natural events. Hum. Brain Mapp. 38, 3360–3376. https://doi.org/10.1002/hbm.23591.

Langleben, D.D., Loughead, J.W., Ruparel, K., Hakun, J.G., Busch-Winokur, S., Holloway, M.B., Strasser, A.A., Cappella, J.N., Lerman, C., 2009. Reduced prefrontal and temporal processing and recall of high "sensation value" ads. Neuroimage 46, 219–225. https://doi.org/10.1016/j.neuroimage.2008.12.062.

Lankinen, K., Saari, J., Hari, R., Koskinen, M., 2014. Intersubject consistency of cortical MEG signals during movie viewing. Neuroimage 92, 217–224. https://doi.org/10.1016/j.neuroimage.2014.02.004.

Lankinen, K., Saari, J., Hlushchuk, Y., Tikka, P., Parkkonen, L., Hari, R., Koskinen, M., 2018. Consistency and similarity of MEG- and fMRI-signal time courses during movie viewing. Neuroimage 173, 361–369. https://doi.org/10.1016/j.neuroimage.2018.02.045.

Lindquist, K.A., Wager, T.D., Kober, H., Bliss-Moreau, E., Barrett, L.F., 2012. The brain basis of emotion: a meta-analytic review. Behav. Brain Sci. 35, 121–143. https://doi.org/10.1017/S0140525X11000446.

Litt, A., Plassmann, H., Shiv, B., Rangel, A., 2011. Dissociating valuation and saliency signals during decision-making. Cerebr. Cortex 21, 95–102. https://doi.org/10.1093/cercor/bhq065.

Mathiak, K., Weber, R., 2006. Toward brain correlates of natural behavior: fMRI during violent video games. Hum. Brain Mapp. 27, 948–956. https://doi.org/10.1002/hbm.20234.

Morís Fernández, L., Visser, M., Ventura-Campos, N., Ávila, C., Soto-Faraco, S., 2015. Top-down attention regulates the neural expression of audiovisual integration. Neuroimage 119, 272–285. https://doi.org/10.1016/j.neuroimage.2015.06.052.

Nichols, T., Brett, M., Andersson, J., Wager, T., Poline, J.-B., 2005. Valid conjunction inference with the minimum statistic. Neuroimage 25, 653–660. https://doi.org/10.1016/j.neuroimage.2004.12.005.

Noesselt, T., Bergmann, D., Heinze, H.-J., Münte, T., Spence, C., 2012. Coding of multisensory temporal patterns in human superior temporal sulcus. Front. Integr. Neurosci. 6, 64. https://doi.org/10.3389/fnint.2012.00064.

Nummenmaa, L., Glerean, E., Viinikainen, M., Jaaskelainen, I.P., Hari, R., Sams, M., Jääskeläinen, I.P., Hari, R., Sams, M., 2012. Emotions promote social interaction by synchronizing brain activity across individuals. Proc. Natl. Acad. Sci. 109, 9599–9604. https://doi.org/10.1073/pnas.1206095109.

Nummenmaa, L., Saarimäki, H., Glerean, E., Gotsopoulos, A., Jääskeläinen, I.P., Hari, R., Sams, M., 2014. Emotional speech synchronizes brains across listeners and engages large-scale dynamic brain networks. Neuroimage 102, 498–509. https://doi.org/10.1016/j.neuroimage.2014.07.063.

Olson, I.R., Plotzker, A., Ezzyat, Y., 2007. The Enigmatic temporal pole: a review of findings on social and emotional processing. Brain 130, 1718–1731. https://doi.org/10.1093/brain/awm052.

Poser, B.A., Versluis, M.J., Hoogduin, J.M., Norris, D.G., 2006. BOLD contrast sensitivity enhancement and artifact reduction with multiecho EPI: parallel-acquired inhomogeneity-desensitized fMRI. Magn. Reson. Med. 55, 1227–1235. https://doi.org/10.1002/mrm.20900.

Samanez-Larkin, G.R., Knutson, B., 2015. Decision making in the ageing brain: changes in affective and motivational circuits. Nat. Rev. Neurosci. 16, 278–289. https://doi.org/10.1038/nrn3917.

Schmahmann, J.D., Caplan, D., 2006. Cognition, emotion and the cerebellum. Brain 129, 290–292. https://doi.org/10.1093/brain/awh729.

Schmälzle, R., Häcker, F.E.K., Honey, C.J., Hasson, U., 2015. Engaged listeners: shared neural processing of powerful political speeches. Soc. Cognit. Affect Neurosci. 10, 1137–1143. https://doi.org/10.1093/scan/nsu168.

Scholz, C., Baek, E.C., O'Donnell, M.B., Kim, H.S., Cappella, J.N., Falk, E.B., 2017. A neural model of valuation and information virality. Proc. Natl. Acad. Sci. 114, 2881–2886. https://doi.org/10.1073/pnas.1615259114.

Silbert, L.J., Honey, C.J., Simony, E., Poeppel, D., Hasson, U., 2014. Coupled neural systems underlie the production and comprehension of naturalistic narrative speech. Proc. Natl. Acad. Sci. U. S. A 111, E4687–E4696. https://doi.org/10.1073/pnas.1323812111.

Van Essen, D.C., Drury, H.A., Dickson, J., Harwell, J., Hanlon, D., Anderson, C.H., 2001. An integrated software suite for surface-based analyses of cerebral cortex. J. Am. Med. Inform. Assoc. 8, 443–459. https://doi.org/10.1136/jamia.2001.0080443.

Venkatraman, V., Dimoka, A., Pavlou, P.A., Vo, K., Hampton, W., Bollinger, B., Hershfield, H.E., Ishihara, M., Winer, R.S., 2015. Predicting advertising success beyond traditional measures: new insights from neurophysiological methods and market response modeling. J. Mark. Res. 52, 436–452. https://doi.org/10.1509/jmr.13.0593.

Wong, C., Gallate, J., 2012. The function of the anterior temporal lobe: a review of the empirical evidence. Brain Res. 1449, 94–116. https://doi.org/10.1016/j.brainres.2012.02.017.

Yarkoni, T., Poldrack, R.A., Nichols, T.E., Van Essen, D.C., Wager, T.D., 2011. Large-scale automated synthesis of human functional neuroimaging data. Nat. Methods 8, 665–670. https://doi.org/10.1038/nmeth.1635.