Decoding Abstract and Concrete Concept Representations Based on Single-Trial fMRI Data

Jing Wang, Laura B. Baucom, and Svetlana V. Shinkareva*

Department of Psychology, University of South Carolina, Columbia, South Carolina

Abstract: Previously, multi-voxel pattern analysis has been used to decode words referring to concrete object categories. In this study we investigated if single-trial-based brain activity was sufficient to distinguish abstract (e.g., mercy) versus concrete (e.g., barn) concept representations. Multiple neuroimaging studies have identified differences in the processing of abstract versus concrete concepts based on the averaged activity across time by using univariate methods. In this study we used multi-voxel pattern analysis to decode functional magnetic resonance imaging (fMRI) data when participants perform a semantic similarity judgment task on triplets of either abstract or concrete words with similar meanings. Classifiers were trained to identify individual trials as concrete or abstract. Cross-validated accuracies for classifying trials as abstract or concrete were significantly above chance ($P < 0.05$) for all participants. Discriminating information was distributed in multiple brain regions. Moreover, accuracy of identifying single trial data for any one participant as abstract or concrete was also reliably above chance ($P < 0.05$) when the classifier was trained solely on data from other participants. These results suggest abstract and concrete concepts differ in representations in terms of neural activity patterns during a short period of time across the whole brain. *Hum Brain Mapp 34:1133–1147, 2013.* © 2012 Wiley Periodicals, Inc.

Key words: fMRI; MVPA; language

INTRODUCTION

Representations of concrete and abstract concepts in the brain are relevant to understanding language function in both healthy and clinical populations [Eviatar et al., 1990; Kuperberg et al., 2008; Mervis and John, 2008]. A series of behavioral advantages of processing concrete compared to abstract concepts have been well documented and referred to as the concreteness effect: concrete words are acquired earlier during development, remembered and recognized more rapidly and accurately, and are less vulnerable to brain damage than abstract words [Kroll and Merves, 1986; Marschark and Cornoldi, 1991; Schwanenflugel, 1991].

Numerous neuroimaging studies have contributed evidence for distinct neural substrates of abstract versus concrete representation. These studies have examined representational differences by using a statistical parametric mapping approach based on data averaged across time. Whether the differences between abstract and concrete concepts can be detected in a single trial remains an open question. A complementary approach to statistical parametric mapping is to use multi-voxel pattern analysis (MVPA), a pattern-based approach that detects neural response by jointly investigating information in multiple voxels. This method is more sensitive compared to univariate statistical parametric mapping that localizes the differences of activation averaged across trials [Haynes and Rees, 2006; Norman et al., 2006; O'Toole et al., 2007].

Additional Supporting Information may be found in the online version of the article.

*Correspondence to: Svetlana V. Shinkareva, Department of Psychology, University of South Carolina, Columbia, SC 29208. E-mail: shinkareva@sc.edu

Received for publication 18 February 2011; Revised 21 September 2011; Accepted 26 September 2011

DOI: 10.1002/hbm.21498

Published online 16 January 2012 in Wiley Online Library (wileyonlinelibrary.com).

MVPA allows focusing on single trials of data, which has a potential future application in brain-computer interface.

MVPA has been successfully used to investigate how semantic information about objects is represented in the brain. Previous studies on concept representation were able to detect the neural responses associated with viewing categories of objects [Carlson et al., 2003; Chan et al., 2011; Cox and Savoy, 2003; Hanson and Halchenko, 2007; Hanson et al., 2004; Haxby et al., 2001; Just et al., 2010; O'Toole et al., 2005; Polyn et al., 2005; Shinkareva et al., 2011; Shinkareva et al., 2008]. Moreover, the category of an object that a participant was viewing [Shinkareva et al., 2008] or a concrete noun that a participant was reading [Just et al., 2010; Shinkareva et al., 2011] can be identified based only on other participants' characteristic neural activation patterns, establishing the commonality in how different people's brains represent the same object.

Most MVPA studies on concept representation used pictorial stimuli [Carlson et al., 2003; Cox and Savoy, 2003; Hanson and Halchenko, 2007; Hanson et al., 2004; Haxby et al., 2001; O'Toole et al., 2005; Polyn et al., 2005; Shinkareva et al., 2008]. Only a few studies have applied MVPA to decode semantic concept representations of concrete objects based on verbal stimuli [Chan et al., 2011; Just et al., 2010; Shinkareva et al., 2011]. Compared to visual depictions of objects, verbal stimuli are more independent of visual perception and can refer to abstract concepts. Whether representation of abstract concepts can be distinguished from concrete concepts using MVPA methods is unclear. In this work we extend the previous MVPA findings on concept representation by including the abstract category that is less dependent on perceptual or motor experiences [for an alternate explanation see Barsalou, 1999; Lakoff and Johnson, 1980]. The purpose of this study was twofold. First, we explored whether MVPA methods could be used to identify single trials as abstract or concrete within each individual by decoding functional patterns of whole brain activity, thus extending previous MVPA studies of concept representation to abstract concepts. We also examined where the discriminating information between abstract and concrete concepts is located in the brain by focusing on the spatially localized anatomical brain regions that contained sufficient information for identification of abstract or concrete concepts on average across participants. Second, we investigated whether the representations of abstract and concrete concepts are similar across individuals by training the classifier on all but one participant and then predicting single trials as abstract or concrete in the left out participant.

METHODS

Participants

Thirteen participants (six female) from the University of South Carolina community participated in this experiment and gave written informed consent in accordance with the Institutional Review Board at the University of South Carolina. Participants were right-handed, healthy adults and native English-speakers.

Materials

Stimuli were word triplets comprised of semantically similar nouns from two concrete (tools and dwellings) and two abstract (cognition and emotion) categories (Supporting Information Table S1). Each category contained four exemplars, with four different words in each exemplar. For instance, the words knife, scalpel, razorblade, and cutlass composed the exemplar cutting object within the concrete category tools. For each exemplar, six different triplets were selected from all possible permutations of the four words. Because the six triplets in each exemplar referred to the same semantic concept, these triplets were regarded as repetitions of the same exemplar. The 16 exemplars were each presented six times, with each repetition composed of a unique list of triplets, generating 96 triplets in total (4 categories $\times$ 4 exemplars $\times$ 6 repetitions). Triplets were balanced between the abstract and concrete categories on word frequency [$M_{\text{Abstract}} = 27.86$ and $M_{\text{Concrete}} = 31.98$, $t(94) = -0.53$, $P = 0.60$] and word length [$M_{\text{Abstract}} = 7.25$ and $M_{\text{Concrete}} = 6.83$, $t(94) = 1.84$, $P = 0.07$].

Experimental Paradigm

While being scanned, the participants were asked to make judgments on semantically similar written words, analogous to the synonym judgment paradigm [Breedin et al., 1994; Noppeney and Price, 2004; Sabsevitz et al., 2005]. In each trial, a word triplet was presented for three seconds, followed by a seven-second fixation period. For each triplet, participants were asked to decide during the three-second triplet presentation which of two words at the bottom of the display was more similar to the word shown at the top. During the presentation of the seven-second fixation, the participant was instructed to clear the mind and fixate on the cross at the center of the screen. The task was designed to prompt careful evaluation of each item and its properties, thus implicitly eliciting the semantic representation of the presented exemplar. A long fixation trial of 24 seconds was presented after each repetition of the 16 exemplars. Participants were prompted by the word "Ready?" following the long fixation to indicate the beginning of the next repetition. The whole experiment was completed in two scanning sessions, with three repetitions of the 16 exemplars in each session.

MRI Acquisition

Functional images were acquired with gradient echo EPI on a Siemens 3T Trio scanner at the McCausland Brain Imaging Center at the University of South Carolina with the following parameters: TR = 2200 ms, TE = 30 ms, and 90° flip angle. Thirty-six oblique-axial slices were imaged with no gap. The acquisition matrix was 64 × 64 pixels with 3 × 3 × 3 mm voxels.

fMRI Data Preprocessing

Data were corrected for head movement and then normalized into a standard template in SPM5 (www.fil.ion.ucl.ac.uk/spm). First, head-movement artifacts were corrected based on a six-parameter rigid body transformation. The head movement in any direction of any participant was smaller than 1.5 mm. The first image was used as the reference volume for realignment. The mean functional image was created and coregistered to a standard stereotactic space using the EPI-derived Montreal Neurological Institute (MNI) template, and the registration parameters were used to normalize the realigned functional images.

MVPA Methods

The MVPA analysis steps employed in this work are similar to those that have been successfully used in other MVPA studies [Mitchell et al., 2008; Shinkareva et al., 2011; Shinkareva et al., 2008]. Classifiers were trained on the mean percent signal change (PSC) of functional activity for each word triplet in the training set to identify the cognitive states associated with processing abstract and concrete concepts. For each participant's data, the mean PSC of each voxel was the ratio of signal difference between word triplets and the baseline to the baseline signal. The baseline was computed from the averaged signal in the long fixation trials. The signal of each triplet was computed by averaging two volumes offset 4.4 s away from the stimulus onset (the third and fourth volumes of one trial) to account for the delay of hemodynamic response function. Furthermore, the PSCs in each voxel were normalized across triplets to have mean 0, and variance 1, to equate variations in different voxels [Pereira et al., 2009].

Feature selection

To reduce the size of the data prior to classification, relevant features were extracted by using voxels with the most consistent responses toward different conditions across cross-validation folds [Pereira et al., 2009]. Response stability was computed by averaging pairwise correlation coefficients between vectors of repetitions of all exemplars [Shinkareva et al., 2011]. The voxels with lowest response stability were removed. The rationale of stability-based feature selection was that if a voxel responded unsystematically between repetitions across conditions, it was unlikely to contain information that is associated with different conditions. This procedure was based on training data only to avoid over-fitting. We explored different numbers of voxels retained by feature selection instead of deciding upon an arbitrary threshold.

Classification within participants

A logistic regression classifier was used for abstract versus concrete two-way classification. As a commonly used classifier, logistic regression directly estimates its parameters from the training data [Bishop, 2006]. This classifier was chosen because it is simple, less likely to generate over-fitting compared to non-linear classifiers, and has been successfully applied in previous studies [Mitchell et al., 2004; Pereira et al., 2009]. To ensure the evaluation of classification performance was unbiased, classification accuracy was evaluated using six-fold cross validation procedure, where each fold corresponded to one repetition of all exemplars. The repetitions were separated by the long fixation period, thus the independence between training and test sets was ensured.

For each cross-validation fold, the trained classifiers were applied to each trial in the test set to classify it as abstract or concrete, and the proportion of trials that were correctly classified was reported. For each participant, the obtained accuracy was compared to an empirically generated null distribution, formed by 1000 classification accuracies obtained from the same dataset, but with randomly permuted labels.

To locate the voxels that contributed most to classifying individual trials as abstract or concrete (henceforth, informative voxels), voxels with the highest and lowest five percent of logistic regression weights were identified for each cross-validation fold. A union of such voxels across cross-validation folds was visualized for each participant. To investigate the consistency of informative voxel locations across individuals, a voxel location probability map was generated across participants after convolving each voxel with a 4 mm Gaussian kernel [Kober et al., 2008]. The probability map was further thresholded by a simulated null hypothesis distribution at $P = 0.05$ (FWE corrected).

In addition, the multinomial logistic regression classifiers were used to identify each of the 16 exemplars. For simplicity, the number of voxels from a feature selection step in this analysis was set to 400. Feature selection, cross-validation, and significance testing were as described above.

Region of interest (ROI) analysis

To investigate how the discriminating information is distributed in the brain, the classifiers were trained on data from one of the 90 anatomically defined regions at a time [Shinkareva et al., In press]. ROIs were defined by Automated Anatomical Labeling [AAL; Tzourio-Mazoyer et al., 2002]. Mean PSC in all gray matter voxels in each ROI was used to train the logistic regression classifiers. To access if an anatomical region contained sufficient information to decode abstract or concrete concepts on average across participants, the classification accuracy for each region was compared to a binomial distribution $B(n, p)$, where n is the number of triplets, and p is the probability

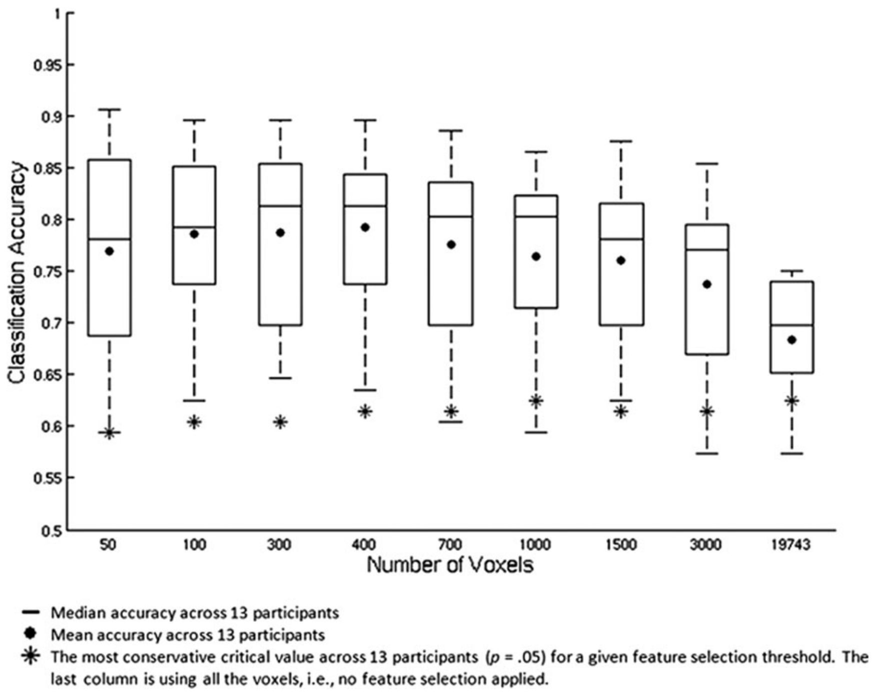

Figure 1.
Within-participant classification accuracies for identifying trials as abstract or concrete, summarized across 13 participants by box plots, are shown as a function of different number of voxels.

of successfully identifying a triplet as abstract or concrete under the hypothesis that triplets are randomly assigned to the two categories [Pereira et al., 2009]. *P*-values (computed using a normal approximation) were obtained for the mean classification accuracy, computed across participants for each region. The *P*-values for anatomically defined regions were compared to 0.05 level of significance using the Bonferroni correction for multiple comparisons.

Classification across participants

To test for a commonality in the neural representation of abstract and concrete concepts across individuals, classifiers were trained on data from all but one participant to identify trials as abstract or concrete in the left-out participant. An entropy-based feature selection was applied to retain the voxels containing most stable information across individuals. For each voxel, the Shannon entropy was computed from the data of twelve individuals in the training set ordered by individual exemplars within abstract and concrete categories. Entropy-based feature selection has been validated as an efficient index of the voxel sensitivity toward the variation of conditions [Poldrack et al., 2009]. For simplicity, the top 20% of most stable voxels, that is, voxels with the lowest entropy values, were selected. For each cross-validation fold, the classifier was trained on the PSC data from all but one participant, which was the test dataset. This procedure was repeated for all participants. Classification accuracy was compared to the empirically generated distribution, formed by 1000 classification accuracies obtained from the same dataset, but with randomly permuted labels. Accuracies with *P*-values smaller than 0.05 were considered significant.

RESULTS

Behavioral Results

There were no significant differences in the mean reaction times across participants between judgments on abstract and concrete triplets [$M_{\text{Abstract}} = 1.66$ and $M_{\text{Concrete}} = 1.69$, $t(12) = -0.85$, $P = 0.41$]. Moreover, none of the individual participants showed significantly different reaction times between abstract and concrete triplets (p ranged from 0.08 to 0.94). These results suggest making judgments on abstract or concrete triplets did not differ in difficulty.

Within-Participant Classification Based on the Whole Brain

When classifiers were trained to identify word triplets as abstract or concrete, the mean accuracies across participants were significantly greater than chance ($P < 0.05$) for all threshold levels (Fig. 1). Classification accuracies for one participant were as high as 90.62% (87 out of 96 triplets correctly identified as abstract or concrete). The

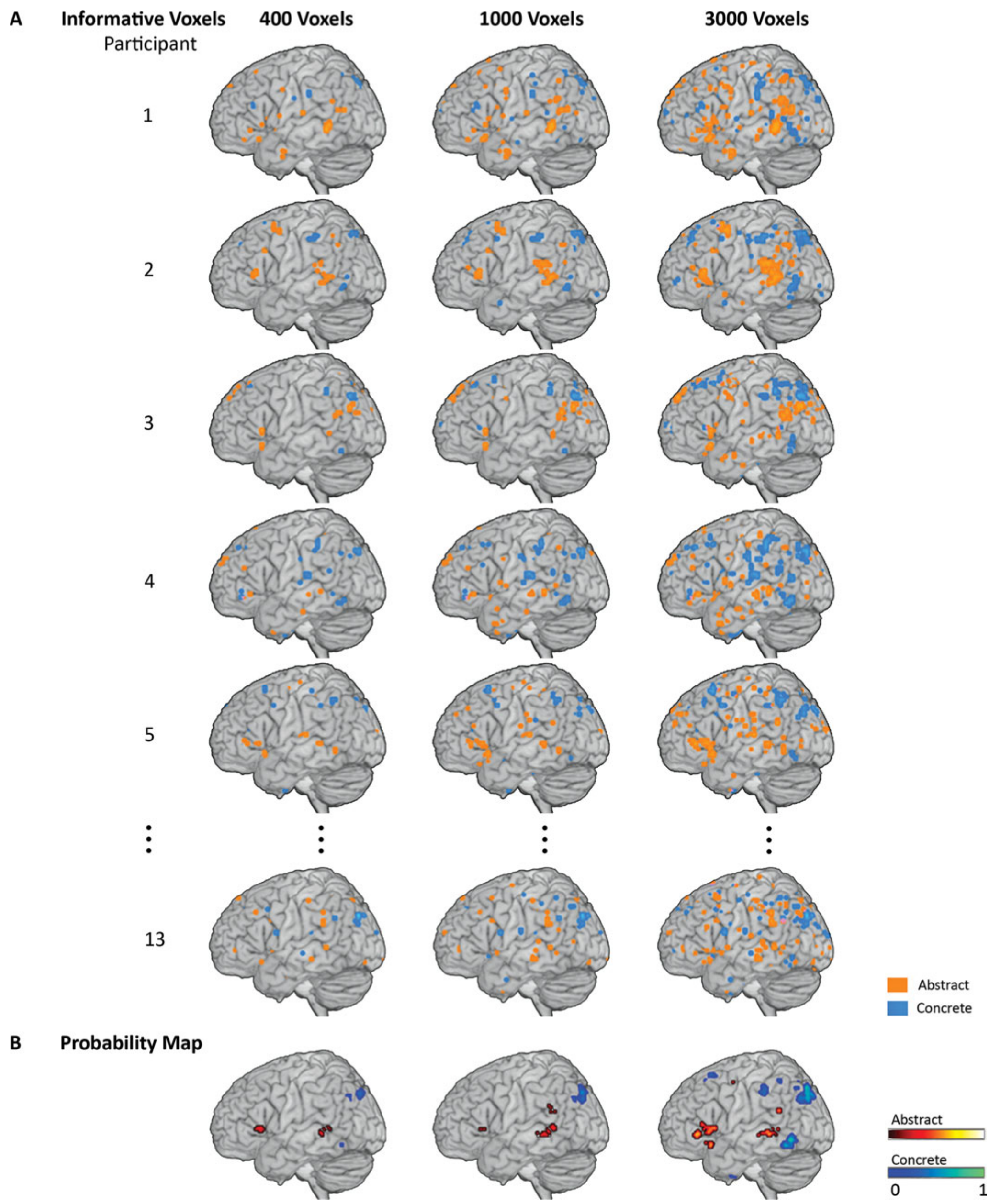

Figure 2.

Consistency of informative voxels across participants. Panel **A**: Most informative voxels for decoding abstract versus concrete concepts representation within participants are shown on a surface rendering at three feature selection thresholds: retaining 400, 1000, or 3000 voxels. Participants were ordered by within-participant classification accuracy. The warm color indicates the top 5% of voxels that were most informative for identifying abstract trials. The cool color indicates the top 5% of voxels that were most informative for identifying concrete trials. Panel **B**: The thresholded probability maps ($P = 0.05$, FWE corrected) of the informative voxels that were consistently identified across all 13 participants. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

classification accuracies were highest when the numbers of voxels used for classification ranged from 50 to 3000. The accuracies were reliably above chance for most participants even when all the voxels were included in the analysis.

The locations of voxels with largest classifier weights for identifying trials as abstract or concrete were distributed in multiple areas in the brain and were similar across participants. For example, when feature selection retained 400

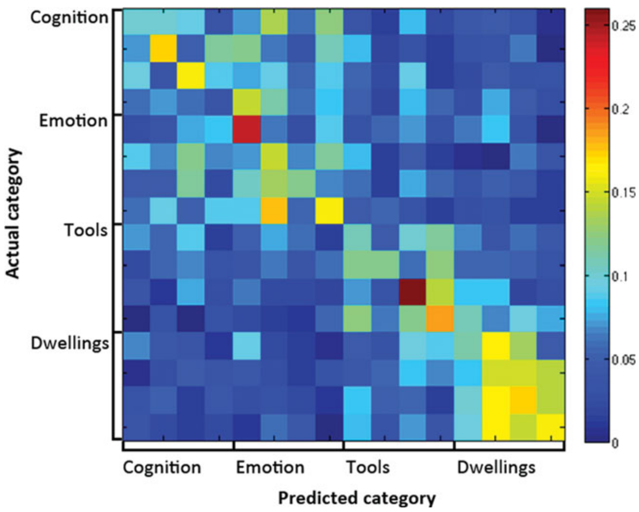

Figure 3.
Exemplar classification confusion matrix averaged across participants. The value of each element indicates the proportion of exemplars identified as the corresponding label. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

voxels, the most informative voxels for identifying abstract concepts, consistently detected across participants, were located in the left inferior frontal gyrus, middle temporal gyrus, and posterior cingulate cortex; the most consistent informative voxels for identifying concrete concepts were located in the left angular gyrus, fusiform gyrus, inferior temporal gyrus, middle frontal gyrus, posterior cingulate cortex, and precuneus (Fig. 2).

In addition, classifiers were trained to identify a specific exemplar about which a participant was making similarity judgments. Classification reached mean accuracy of 14.4% across participants for classifying an exemplar into one of the 16 categories (compared to 9.38% at $P = 0.05$ level of significance). Exemplars were reliably ($P < 0.05$) identified for 11 out of 13 participants. Most of the mistakes that the classifier was making were within the same abstract or concrete category (Fig. 3). Thus, the brain activity patterns associated with making similarity judgments with either abstract or concrete concepts can be decoded on a single-trial basis, suggesting the distinct representations of abstract and concrete concepts.

Within-Participant Classification Based on Single ROIs

To investigate whether individual regions contain sufficient information for decoding abstract and concrete concepts, classifiers were trained using voxels from only one anatomical region at a time. Fifty-two out of the 90 ROIs showed reliable ($P < 0.05$) classification accuracies on average across participants. These regions were distributed across temporal, frontal, parietal, and occipital lobes bilaterally, whereas the regions with the highest accuracies were mostly in the left hemisphere (Fig. 4). Out of the 52 informative ROIs, 30 were in the left hemisphere, including the top 15 ROIs with highest average accuracies across participants. For all informative right-hemisphere ROIs the left homologues also contained information for successful identification. Among these bilateral region pairs, the average classification accuracies across participants were higher in the left hemisphere, with an exception of the lingual gyrus. Five ROIs, including left middle temporal gyrus, left precuneus, left angular gyrus, left middle occipital gyrus, and left precentral gyrus, showed significant accuracy for all of the participants (Fig. 5). These results were consistent the locations of the informative voxels from the whole brain analysis (Fig. 2). Thus multiple brain regions contain information sufficient to decode abstract versus concrete concept representation.

Across-Participant Classification Based on the Whole Brain

Classifiers were trained on data from 12 participants to determine if it was possible to identify individual trials as abstract or concrete in the left-out participant. The average accuracy across participants of identifying triplets as abstract or concrete when the classifier was trained on data from other participants was 84.13% ($P < 0.001$). Word triplets were reliably ($P < 0.05$) identified for all 13 participants, with the accuracies ranging from 62.50% to 93.75% (Fig. 6). This result indicates the commonality of abstract versus concrete concept representation across individuals.

DISCUSSION

We were able to successfully identify brain activity patterns as abstract or concrete based on single-trial data. This study has extended previous results on concrete words representation [Chan et al., 2011; Just et al., 2010; Shinkareva et al., 2011] to abstract concepts. Compared with studies that examined activation differences in abstract and concrete concept representation, this study suggests neural responses during abstract and concrete semantic concepts processing can be identified from distributed patterns of activity on an individual trial basis.

Moreover, whether a participant was making similarity judgments about abstract or concrete concepts was identifiable solely based on data from other participants, in spite of the anatomical and functional variability across individual brains [Fedorenko and Kanwisher, 2009]. It supports the cross-individual principles of processing semantic concepts. Classification of mental states across individuals has been previously shown for visually depicted objects [Shinkareva et al., 2008], concrete nouns referring to physical objects [Just et al., 2010; Shinkareva et al., 2011], lie detection [Davatzikos et al., 2005], attentional tasks [Mourão-Miranda et al., 2005], cognitive tasks [Poldrack et al., 2009], and voxel-by-voxel correspondence across individuals has

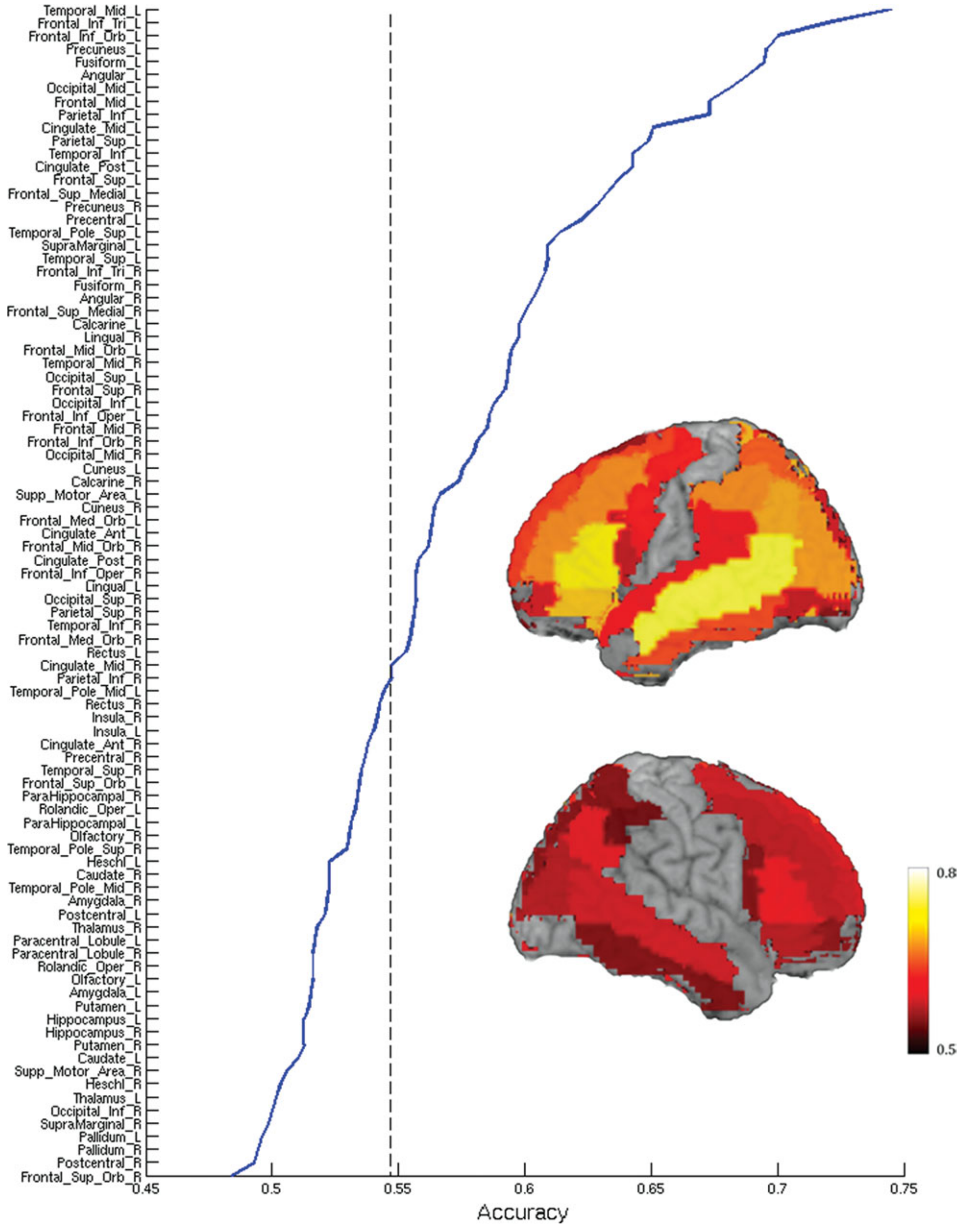

Figure 4.

Mean classification accuracies across participants, for trial identification as abstract or concrete, are shown for each anatomically defined ROI. Regions with significant mean accuracy across participants ($P = 0.05$) are shown on a surface rendering of a brain template (http://www.cabiatl.com/mricro/mricron/index. html). ROIs are ordered by the mean classification accuracy across participants. The dashed line indicates the threshold of significant accuracy. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

been demonstrated during movie-watching [Hasson et al., 2004]. The current study for the first time demonstrates the ability to identify the mental states of a participant as processing abstract or concrete concepts based on neural activation data from other participants.

Classification within individual anatomically defined regions showed that activity patterns in even single regions were sufficient for identifying trials as abstract or concrete. The present results of regions with discriminating information show considerable overlap with the meta-analysis results based on previous statistical parametric mapping studies locating the differences between abstract versus concrete semantic concept representation [Binder et al., 2009; Wang et al., 2010]. All but one region that

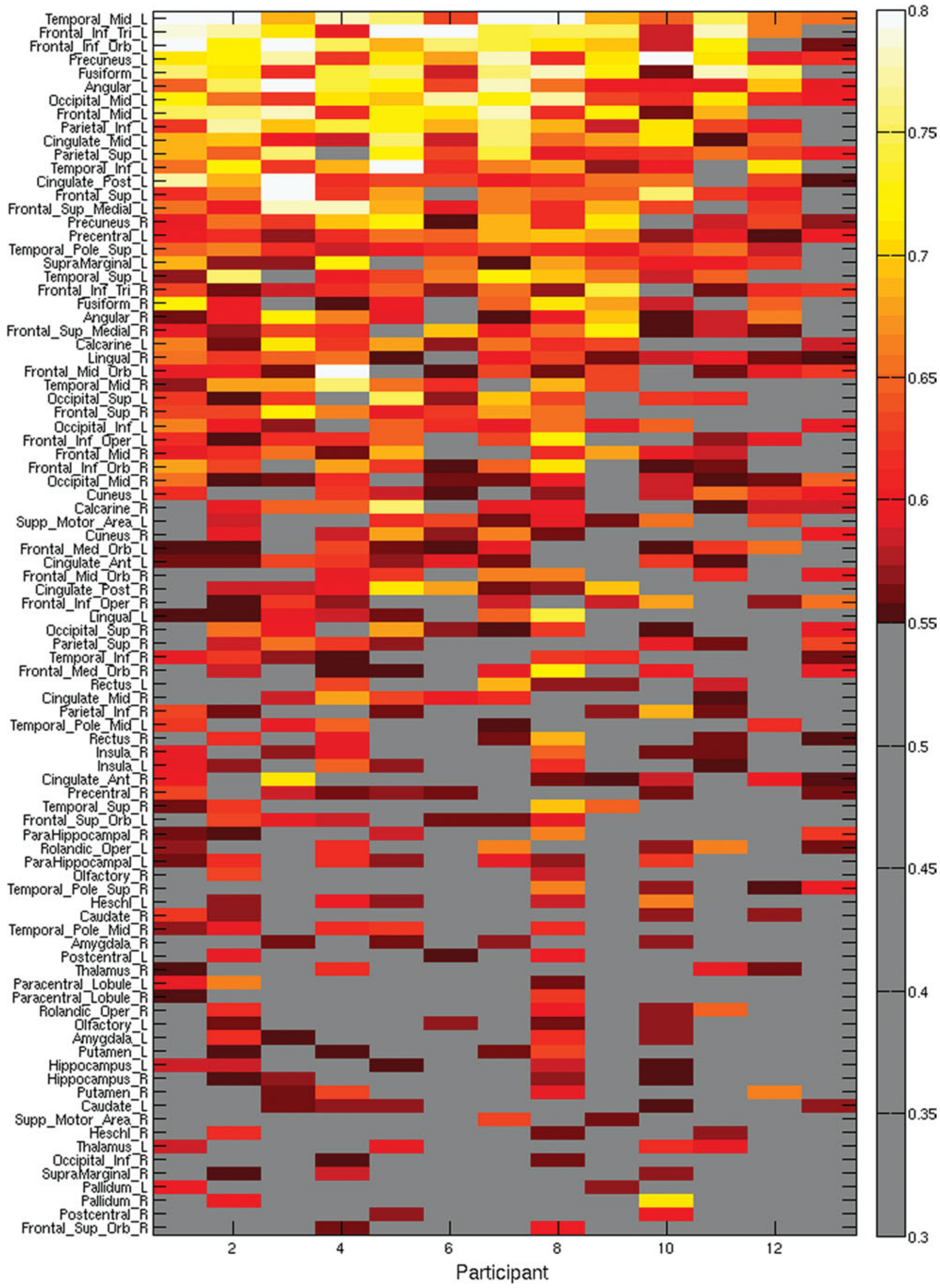

Figure 5.

Classification accuracies for identification of trials as abstract or concrete are shown for each ROI and each participant. Significant accuracies ($P = 0.05$) are shown in color. ROIs are ordered by the mean classification accuracy across participants. Participants are ordered by within-participant accuracy based on 400 voxels. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

were previously identified by the meta-analysis (Table I) were also found to contain information sufficient for identification of trials as abstract or concrete in the current study (Fig. 4). The top six ROIs with the highest average accuracy were also identified by the meta-analyses results. However, this single study identified more informative areas compared to the combined results of early lesion and neuroimaging studies. In fact, the current results are

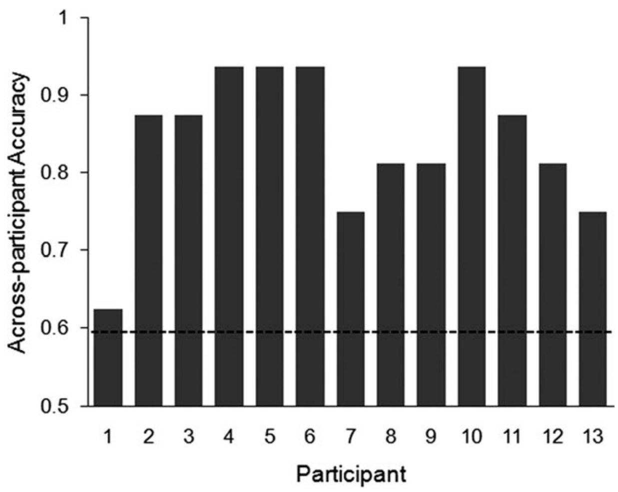

Figure 6.

High across-participants classification accuracies for identifying single trials as abstract or concrete based on data from other participants. Dashed line indicates $P = 0.05$ level of significance. Participants are ordered by within-participant accuracy based on 400 voxels.

more comparable to the collection of previous univariate results (Fig. 7).

The left hemisphere was engaged in abstract versus concrete concept identification to a very large extent. Thirty out of the 45 left hemisphere ROIs showed significant accuracies on average across participants. A number of right hemisphere regions also held information of abstract versus concrete differentiation. Previous studies have found the activation differences in some of these right hemisphere regions but with low cross-study consistency [Binder et al., 2005; D'Esposito et al., 1997; Fliessbach et al., 2006; Grossman et al., 2002; Harris et al., 2006; Jessen et al., 2000; Mellet et al., 1998; Perani et al., 1999a; Sabsevitz et al., 2005; Tettamanti et al., 2008; Wallentin et al., 2005; Whatmough et al., 2004]. A specific investigation of the informative ROIs shows some of these areas have been considered typical for differences between abstract versus concrete concept representations, whereas other regions were not consistently found in previous literature. For example, the results of at least one of the quantitative meta-analyses on semantic processing have identified the left inferior frontal gyrus, left middle temporal gyrus and left superior temporal gyrus and sulcus for being engaged more in abstract than concrete concept processing; whereas the bilateral angular gyrus, left fusiform gyrus, left parahippocampal gyrus, left posterior cingulate, and left precuneus have been identified to be consistently more engaged in concrete than in abstract concept processing [Binder et al., 2009; Wang et al., 2010].

This is the first time that such a large number of informative brain areas for abstract versus concrete concept representation were identified in a single experiment. The extensive spatial distribution of discriminating information may reflect the lack of semantic context restriction during single word processing. Compared to the word specified in a meaningful sentence, single word processing in a semantics-related task may stimulate the rich contexts of the word more extensively [Price, 2010]. However the MVPA results do not directly reveal the properties of the information reflected in the data [Hanke et al., 2010]. What do these results suggest about the underlying processes driving the neural differences between abstract and concrete concept processing? The following sections will discuss this question first based on the most consistently identified brain regions, then based on the areas that were less consistently reported.

TABLE I. Consistent brain regions of abstract versus concrete distinction (based on Wang et al., 2010)

Abstract > Concrete
Left inferior frontal gyrus
Left middle temporal gyrus
Left superior temporal gyrus
Concrete > Abstract
Left fusiform
Left parahippocampalgyrus
Left posterior cingulate gyrus
Left precuneus

Left middle temporal gyrus

Classification accuracy of this single region reached 74.52% across participants, which is striking considering the 79.17% accuracy based on voxels distributed across the whole brain gray matter. A number of studies have reported greater activation in the left middle temporal gyrus for abstract than concrete concept representations [Grossman et al., 2002; Harris et al., 2006; Noppeney and Price, 2004; Pexman et al., 2007; Sabsevitz et al., 2005;

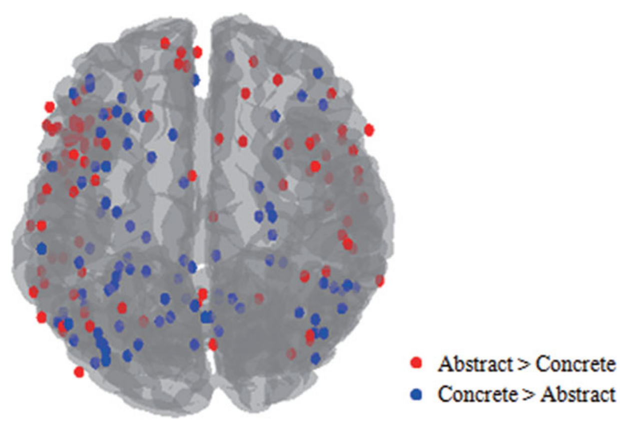

Figure 7.

Activation peaks for abstract versus concrete representation from 19 studies are shown on the brain template (See Wang et al., 2010 for the list of studies and meta-analysis results). [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

Tettamanti et al., 2008; Wallentin et al., 2005]. Multiple aspects of language processing have been shown to relate to activity in this area, including explicit or implicit word reading [Paulesu et al., 2001], speech comprehension [Binder, et. al., 2000; Crinion et al., 2003; Davis et al., 2007; Davis and Johnsrude, 2003], word memorization [Ojemann et al., 1988], and executively demanding semantic judgment [Whitney et al., 2011]. Increasing activation in this area is also related to processing higher lexical frequency words in implicit semantic processing [Graves et al., 2010]. One of the most likely associations of this region with the current results is its pivotal role in mapping semantic concepts to words, which is usually reflected in the object naming or picture identification tasks [Boatman et al., 2000; Perani et al., 1999b; Schwartz et al., 2009]. Moreover, the left middle temporal gyrus is also engaged in retrieving conceptual knowledge related to object manipulation [Jastorff et al., 2010], suggesting a property-based, "transmodal" way of encoding or retrieving concepts of this area [Binder et al., 2009; Mesulam, 1998]. Thus, the highly discriminating activity patterns in this region may be due to the different association strengths with physical objects, or concreteness, between abstract and concrete concepts.

Another probable reason for the middle temporal gyrus to be exceptionally informative for classification is its involvement in context-dependent encoding of word meanings. The left middle temporal gyrus, along with inferior frontal gyrus and parahippocampal gyrus, has been identified in acquiring new word meaning [Mestres-Missé et al., 2008]. Studies manipulating syntactic ambiguities suggest this region may be involved in disambiguating word meanings based on sentence contexts [Gennari et al., 2007; Rodd et al., 2010]. Because the similarity judgment requires the participant to make subtle distinctions in the context of synonymous triplets, the left middle temporal gyrus might be one of the most important areas to represent semantic information, thus being more sensitive to the abstract versus concrete differences.

Left inferior frontal gyrus

Pars triangularis and pars orbitalis of the left inferior frontal gyrus are highly informative for abstract versus concrete decoding. This result is not surprising given the fact that left inferior frontal gyrus is one of the most canonical regions found in abstract > concrete contrast in previous literature [Binder et al., 2005; Fiebach and Friederici, 2004; Fliessbach et al., 2006; Friederici et al., 2000; Jessen et al., 2000; Noppeney and Price, 2004; Perani et al., 1999a; Pexman et al., 2007; Sabsevitz et al., 2005; Tettamanti et al., 2008; Wallentin et al., 2005]. The roles of the left inferior frontal gyrus are suggested to be multifold. Left pars triangularis and pars orbitalis along with other prefrontal areas have been found to be sensitive to increasing abstractness of a concept in a semantic decision task [Goldberg et al., 2007] and explicit requirement of semantic retrieval [Friederici et al., 2000; Petersen et al., 1988; Wagner et al., 2001]. Several studies suggest that the left inferior frontal gyrus activity does not reflect a semantic retrieval process per se, but rather reflects a specific executive for the demand of semantic selection [Demb et al., 1995; Nagel et al., 2008; Thompson-Schill et al., 1997]. According to these conclusions, the successful classification within the left inferior frontal gyrus in the current study may be attributed to strategic verbal retrieval in abstract concept representation. Verbal representation of word meanings is not given priority during semantic processing, but when the available prior information, for example, perceptual and imagery details, is insufficient, the verbal representation will step in to facilitate the semantic processing.

Another line of evidence suggests the importance of phonological processing in the left inferior frontal gyrus for the abstract versus concrete differentiation. Left pars opercularis, an area with a moderate but still significant classification accuracy, has been associated with phonological working memory [Binder et al., 2005; Burton, 2001; Zatorre et al., 1992], and sequencing of phonemes and hummed notes [Gelfand and Bookheimer, 2003]. The activity pattern differences in this region may relate to how long the information is held in the phonological loop. This is in line with the hypothesis that processing abstract words occupies the working memory to a greater extent than concrete words, because it requires additional semantic processing [Binder et al., 2005]. Thus, this area may implicate a natural difficulty of representing abstract concepts even when no difference is found in behavioral responses.

Precuneus and posterior cingulate

These two structures in the left hemisphere have been consistently identified in the concrete > abstract contrast in previous literature [e.g., Binder et al., 2005; Harris et al., 2006; Mellet et al., 1998; Pexman et al., 2007; Sabsevitz et al., 2005]. Due to their adjacency in location as well as their structural and functional connectivity [Castellanos et al., 2008; Cavanna and Trimble, 2006; Fransson and Marrelec, 2008; Mizelle and Wheaton, 2010; Vogt et al., 2006], we discuss them in a combined section. The precuneus has been shown to be involved in different tasks that require mental image generation, such as mental rotation [Butler et al., 2006; Cohen et al., 1996; Gauthier et al., 2002] and visuospatial episodic memory encoding and retrieval [Aggleton and Pearce, 2001; Fletcher et al., 1995; Ghaem et al., 1997; Mellet et al., 2000; but also see Krause et. al. 1999]. Bilateral precuneus has also been associated with motor imagery [Hanakawa et al., 2003; Malouin et al., 2003]. Similarly, the posterior cingulate has been found in spatial representation and episodic retrieval of places [Sugiura et al., 2005], happy event imagery [Mantani et al., 2005], name recognition [Sugiura et al., 2009], and memorizing route [Katayama et al., 1999], suggesting its engagement in imagery generation during memory tasks. These findings, together with the results of abstract versus concrete word classification, are in agreement with the dual-coding hypothesis: the concrete concepts representation is facilitated by an additional imagery coding system because of the more detailed perceptual information compared to the abstract concepts.

Left fusiform gyrus

Left fusiform gyrus has been associated with object recognition, naming colors and reading words in visual and auditory forms [see Price and Devlin, 2003 for a review]; the functions of representing specific categories of objects have been finely localized within subareas of this region [Martin and Chao, 2001]. The frequent identification of the fusiform gyrus in the contrast of concrete > abstract representation has been attributed to the easiness of mental generation of object features represented by concrete concepts [D'Esposito et al., 1997; Mellet et al., 1998; Mestres-Missé et al., 2009; Wise et al., 2000]. In addition to the previous assumption of modality-specific area for visual input [e.g., Cohen et al., 2002; Kanwisher et al., 1997], the left fusiform gyrus has recently also been recognized to integrate sensory information from other input modalities, and even associate visual form stimuli with higher-order properties [Devlin et al., 2006; Doehrmann et al., 2010]. The left posterior portion of fusiform gyrus has been characterized as semantically processing words representing objects [Wheatley et al., 2005]. The involvement of perceptual areas in distinguishing abstract and concrete word processing implicates the perceptual grounding of representing concrete semantic concepts.

Angular gyrus and inferior parietal lobule

The bilateral angular gyrus is another region with high classification accuracy that has been consistently identified by neuroimaging studies for greater activation in concrete compared to abstract word representations [Binder et al., 2005; Fliessbach et al., 2006; Sabsevitz et al., 2005]. It is noteworthy that most of its surrounding areas in the left hemisphere, including the superior temporal gyrus, middle temporal gyrus and inferior parietal lobule, are among the most informative regions of abstract versus concrete classification. The left angular gyrus has been suggested to be critical to the transfer and organization of multi-modal sensory-motor information for higher-level conceptualizations [Geschwind, 1965] and to the assembly of verbal information in auditory working memory for integrative comprehension tasks [Dronkers et al., 2004; Pugh et al., 2000], thereby it is not surprising that the angular gyrus is one of the centers for integrative semantic processing and knowledge retrieval [Binder et al., 2009]. The left inferior parietal lobule has been linked with integrating features for semantic categorization [Koenig et al., 2005]. The information content sufficient for decoding abstract versus concrete concept representations in these regions, especially in the left hemisphere, may reflect the abstract versus concrete distinction on a semantic comparison level, which is a consequence of the differences in either perceptual-motor information from mental imagery or associate verbal contexts.

Left superior temporal gyrus

The left superior temporal gyrus has been recognized for greater activation in abstract than concrete concept representation in several previous studies [Grossman et al., 2002; Perani et al., 1999a; Pexman et al., 2007]. This region has been linked to the assembly of phonology in perception [Booth et al., 2004; Scott et al., 2000] and production [Buchsbaum et al., 2001; Hickok et al., 2000]. Activity in the bilateral superior temporal gyri has also been associated with the effect of semantic context [Friederici et al., 2003; Van Petten and Luka, 2006] and semantic judgment task [D'Esposito et al., 1995]. Therefore, the significant classification accuracy of this area might be caused by the longer processing of abstract than concrete concepts in the phonological loop, or the stronger reliance of abstract concepts on semantic context.

It is quite striking that single regions contain, on their own, enough information to decode the presented concepts. It is likely to be the case that sufficient information for category identification is represented in several different regions. Several of the discriminating regions, as discussed above, have been associated with functions other than semantic processing, thus raising questions of whether the successful classification results were driven solely by the representational differences of abstract and concrete concepts. The balanced lexical features of the stimuli and the behavioral results suggest that task difficulty is unlikely to be the confounder. We believe that this wide involvement of regions is due to the multiple mechanisms engaged in processing semantic concepts. The processing of abstract and concrete concepts may differ on several aspects, such as richness of semantic context, coding system, retrieval strategy, or the occupation of working memory. A number of regions identified in the current study have been shown in previous studies using statistical parametric mapping, but not in the same experiment, for a single task and a limited number of stimuli. One of the reasons, based on the current results, may be the lack of sensitivity in detecting the differences. These results suggest that the representation of abstract and concrete concepts were differentiated on various aspects rather than a single mechanism. Further studies may help illuminate the representational content in regions that support category identification across stimulus formats, such as studies using item-repetition priming [Grill-Spector et al., 1999; James et al., 2002; Vuilleumier et al., 2002] or Dynamically Adaptive Imaging [Cusack et al., 2011].

By using multi-voxel pattern analysis, this study successfully identified brain activity patterns as abstract or concrete based on single-trial data, suggesting participants' mental states during processing of abstract and concrete semantic concepts were identifiable from distributed patterns of activity on an individual trial basis. The ability to identify whether a participant was representing abstract or concrete concepts solely from other participants' data suggests the cross-individual principles of processing this type of knowledge are similar.

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