Individual differences in encoded neural representations within cortical speech production network

Katherine L. Alfred[1], Justin C. Hayes[1], Rachel G. Pizzie[1,2], Joshua S. Cetron[1,3], & David J. M. Kraemer[1]

[1] Department of Psychological and Brain Sciences, Dartmouth College
6207 Moore Hall
Hanover, NH 03755

[2] Department of Psychology, Georgetown University
305 White-Gravenor Hall
3700 O Street NW
Washington, DC 20057

3 Department of Psychology, Harvard University
William James Hall
33 Kirkland Street
Cambridge, MA 02138

Corresponding Author: Katherine L. Alfred; katherine.l.alfred.gr@dartmouth.edu

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Abstract

Individual differences in patterns of attention and thought can vary so greatly that two individuals presented with the same information may encode distinct representations. When presented with a stimulus to be recalled later, the information an individual encodes is dependent on the features of the stimulus to which one attends. Past studies have shown that, on the group level, verbal and visual information (e.g., words and pictures) are encoded in disparate regions of the brain. However, this account conflates external and internal representational formats, and it also neglects individual differences in attention. In this study, we examined neural and cognitive patterns associated with individual differences in attention to verbal representations—both external and internal. We found that the encoded neural representation of semantic content (meaningful words and pictures) varied as a function of individual differences in verbal attention, independent of the stimulus presentation format. Individuals who demonstrated an attentive bias toward words showed similar multivariate BOLD activity patterns within an *a priori* speech production network when encoding object names as when encoding pictures of objects. This result indicates that these individuals use a common process to encode meaningful words and pictures. These effects were not found for non-semantic stimuli (pronounceable non-words and nonsense pictures). Importantly, as expected, no individual differences in neural representation were found in a separate network of regions known to process semantic content independent of format. These results highlight inter-individual divergence and convergence in internal representations of encoded semantic content.

Significance Statement

This study shows how tendencies towards attending to word or picture representations are associated with individual differences in encoded neural representations. Individuals who selectively attend to words instead of pictures process semantically meaningful information in language regions of the brain, regardless of whether the information was originally presented as a word or a picture. Though all participants encoded words and pictures similarly in regions that are known to represent domain-general semantic information, it was only the individuals who are biased towards word representations who additionally processed both words and pictures in material-specific verbal regions. These results demonstrate both the convergence and divergence between individuals that occurs during encoding of meaningful information.

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Evidence from early studies on the neural basis of encoding supported the theory of material-specific encoding—that image and language representations are localized to separate hemispheres in the brain (Milner et al., 1966). For instance, lesions in the left medial temporal lobe interfered with verbal memory whereas lesions in the right temporal lobe interfered with memory for non-verbal material. Since then, a large body of work has examined the left-hemispheric association with language and the right-hemispheric association with visuospatial processing (Golby et al., 2001; Gross, 1972; Milner, 1971; Milner, 1972; Milner, 1982; Kelley et al., 1998; Kelley et al., 2002). However, more recent research has revealed a high degree of inter-individual variation even at the level of basic information encoding (Casasanto et al., 2002; Kirchoff & Buckner, 2006; Miller et al., 2002; Miller et al., 2009). These patterns are stable across time, demonstrating systematic differences in how individuals encode and retrieve information (Miller et al., 2009; Miller et al., 2012). Differences in information retrieval on a behavioral and neural level have further been linked to self-reported visual and verbal habits of thought, e.g., using a word-based approach versus a mental-imagery-based approach during a memory task in which information is presented via words or pictures (Hsu et al., 2011; Kirchoff & Buckner, 2006; Kraemer, Rosenberg, & Thompson-Schill, 2009; Kraemer et al., 2014; Miller et al., 2012).

The present study uses both words and pictures to examine how individual differences in attentional biases for words affects encoding of information in both formats. When encoding highly imageable words and easily nameable images, participants may encode the material according to their individual habits of thought, e.g., by using verbal labeling. Whereas the typical model of material-specific processing predicts that all participants encode verbal information in left hemispheric language regions and picture information in right hemispheric visual regions, the individual differences research cited above suggests that different patterns of activity may be observed between participants in addition to these group-level similarities. Specifically, we predict that individuals who attend to verbal representations will encode both verbal and visual content similarly, using verbally-associated regions, i.e., a cortical speech production network.

Whereas previous studies have focused on encoding of words (Miller at al., 2011) or pictures (Kirchhoff & Buckner, 2006), participants in this study are presented with both words and picture stimuli. This allows for analysis of the representational similarities of meaningful content, regardless of original presentation format (word or picture). In order to account for differences in individual variability using an objective behavioral measure, we use a novel task to probe habits of thought in terms of attentional bias to visual or verbal information (similar to Amit et al., 2012) instead of traditional self-report measures. The attention bias task used in the current study leverages conflicting verbal and pictorial information during a speeded judgment task to measure implicit bias towards attending to word representations versus picture representations. The representational format to which participants preferentially attend is expected to correspond to their internal representations of the material. For example, participants who are more biased towards attending to words would show similar processing in language network regions for encoding meaningful words and pictures.

In contrast to these individual differences predicted for material-specific neural representations, activation patterns are expected to be more similar between individuals in a network of brain regions associated with semantic retrieval across content (Binder et al., 2005; Frankland & Greene, 2014; Shinkareva et al., 2011; Thompson-Schill, 2003). For example, Shinkareva and colleagues (2011) demonstrated multivariate similarity between neural responses to object pictures and object names, such that semantic category was accurately classified regardless of original presentation format. Therefore, the network of content-independent semantic processing is expected to show similar patterns across participants, whereas material-specific brain regions—specifically the speech production network—is predicted to reflect individual differences in representational format, regardless of how that content was originally presented.

Method

Participants. Twenty-nine (16 female, M_{AGE} = 20.7) undergraduate and graduate students at Dartmouth College, who were right-handed native English speakers with normal or corrected to normal vision took part in this study. None of the participants had any history of neurological or psychiatric disorders. All participants provided informed written consent and were compensated with a choice of cash or course credit for their participation, in accordance with the Dartmouth's Committee for the Protection of Human Subjects.

Measures of visual and verbal cognitive style. Visual and verbal cognitive styles were assessed through a computerized presentation of the revised Visualizer-Verbalizer Questionnaire (VVQ) (Kirby et al., 1988). Cognitive style was measured on two separate dimensions for the degree to which a person had the verbal cognitive style and the degree to which a person had a visual cognitive style. Participants indicated how much they agreed with each of 20 statements on a 7-point likert scale, from 1 (strongly disagree) to 7 (strongly agree). Half of the questions for each dimension were reverse scored. The "dream vividness" dimension of questions was omitted from the questionnaire because the positive correlation between the visual subscale and visuospatial abilities was only observed after elimination of the questions relating to dream vividness (Kirby, 1988).

Measures of visual and verbal cognitive abilities. Participants took the long form of the Automated Working Memory Assessment (AWMA; Allport, 2007) to obtain measures of visual and verbal working memory, as well as visual working memory. In addition, participants visual and verbal IQ scores (Verbal Comprehension Index (VCI) and Perceptual Reasoning Index (PRI) components respectively) were obtained through the Wechsler Abbreviated Scale of Intelligence (WASI; Weschler, 1999).

Visual and verbal Attention Bias task. This novel task measured the degree to which participants attended to visual and verbal information. In each trial, participants were shown a card suit symbol and an accompanying text label, and were asked to press a key to identify whether they were being shown a club, spade, or heart (Figure 1A). Out of a total of 192 trials, 144 (75%) presented congruent information—i.e., the text labels matched the symbols shown. In 48 (25%) of the trials, however, participants were shown incongruent information, where the picture and the text label had conflicting information (e.g., a picture of a club with text that says "spade"). Word or Picture Attention Bias was calculated as the percentage of incongruent trials for which the participant pressed the key for the picture or text, respectively (Figure 1B). Each of the three suits were the target image an equal number of times, and the location of the text was counterbalanced for presentation above and below the picture. The center of the screen was always between the picture and the text.

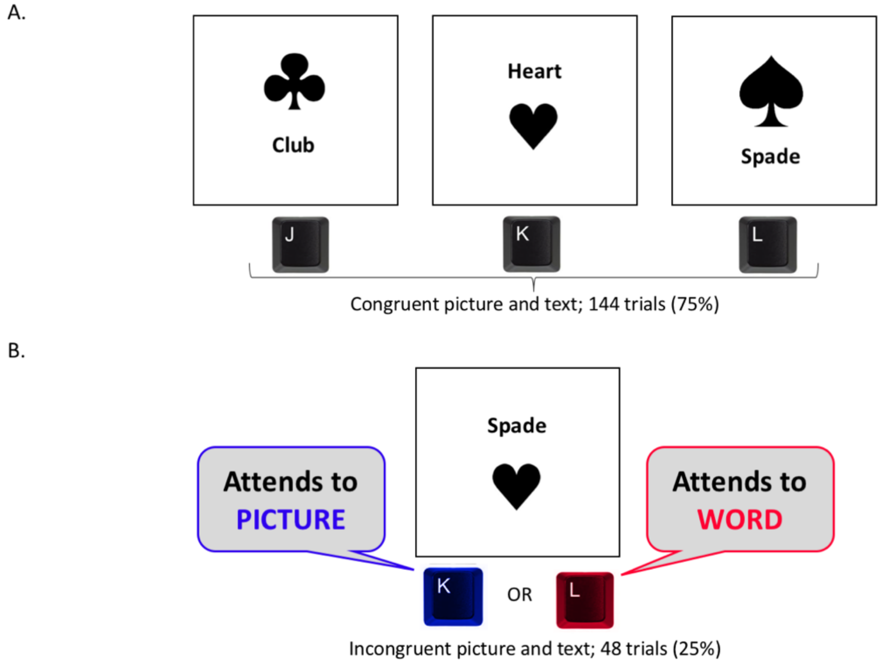

Figure 1. Attention Bias task structure. A. Participants were instructed to press J when shown club, K for heart, and L for spade and respond as quickly and accurately as possible. Most trials (75%) presented congruent word and picture information. B. Some trials (25%) presented a word and picture that were incongruent. Participants had to rapidly decide whether to rely on the picture being correct (in this case, responding K for heart) or word (in this case, responding L for spade).

Word and picture memory task (fMRI task). During fMRI scanning, participants were presented with a series of items to memorize. The items were presented in blocked lists of words, pseudowords, pictures, and abstract pictures to measure neural activity during intentional encoding processes. Participants were instructed to pay attention to the stimuli for a later test. Participants were also instructed to press a button with their right index finger if they saw an item repeat. After memorizing a list of real (English) words and a list of pseudowords, participants took a test on the real words they had studied. In the pictures block, participants studied a set of object pictures and abstract pictures, then took a test on the object pictures. Participants were not given tests on pseudowords or abstract pictures. Each block contained a total of 60 items that would later appear on the test for that block (2.5 seconds each), 6 repeat items that were shown twice (2.5 seconds each), and fixation crosses (72 fixation periods, 2.5 seconds each, with up to 3 fixation periods in a row) interleaved together. In the word block, the words were the names of pictures from the Snodgrass item set (Snodgrass & Vanderwart, 1980). In the picture block, the critical items were easily nameable black line drawings from the same item set. Repeat items were the same type of stimuli, but were not present in the test, and were used to check for continued attention during study phases.

After completing the study of either words or pictures, participants took a questionnaire about the strategy they used to learn the items. Participants then completed another block of trials identical to the procedure outlined above, except with abstract pictures if they saw pictures first, or non-words if they saw words. Abstract pictures were black line drawings with both straight and curved lines, but did not resemble an object that could be named. Non-words were drawn from the Deacon (2004) set of non-words without English roots. After participants completed the strategy questionnaire again for the abstract picture or non-word condition, they were tested on the real pictures or words learned in the first block. During the test, participants saw a total of 120 items, half of which were the critical items that were studied in the first block, and half of which were new items. Participants were asked if they had seen the item before, and were asked to rate their confidence as, “high,” “low,” or, “guess.” The test trials were self-paced. After the test, the procedure was repeated, except with words and non-words if pictures and abstract pictures were used previously, or vice versa. With the exception of repeat trials, none of the words or pictures were repeated between conditions (i.e., a word studied in one block would not be the name of a picture studied in a later block). The task was counterbalanced both for the half of the stimuli used first as well as the material format (word/picture) that set was presented in. An overview of the fMRI design can be seen in Figure 2.

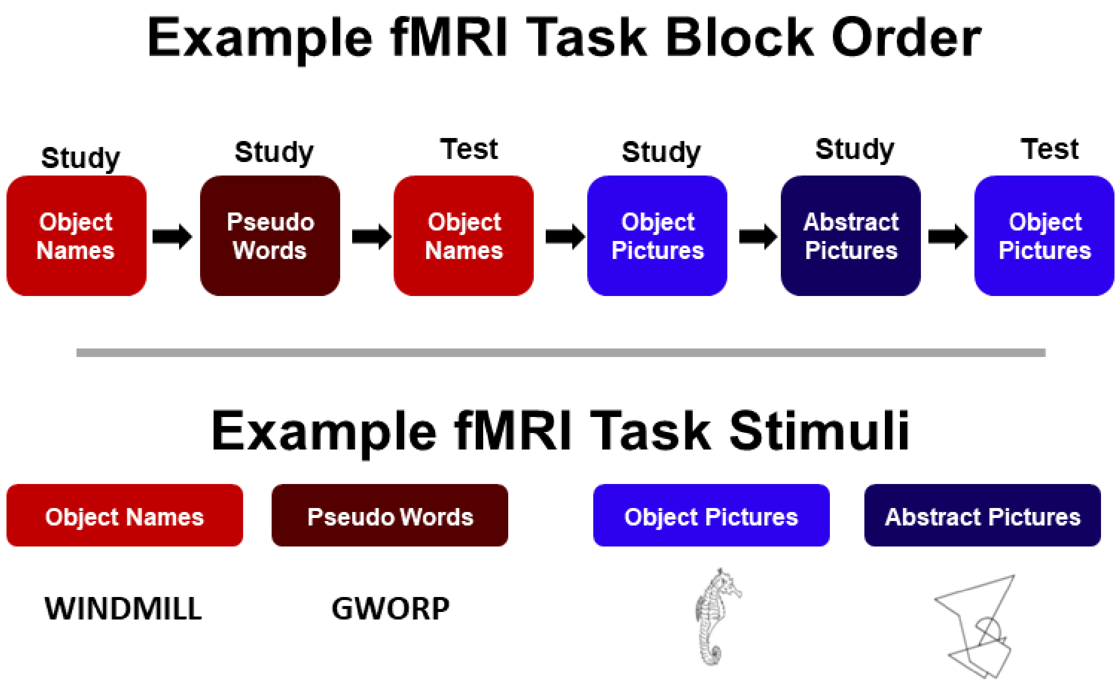

Figure 2. Overview of fMRI task design. Participants were first presented with a block of object names, such as "windmill", followed by a block of pseudo-words, such as "gworp". Participants were then tested on the object names they had studied. The procedure was repeated with object pictures and abstract pictures, and a test on the object pictures. Word and picture block order was counterbalanced between participants.

Scanner information. All scans took place at the Dartmouth Brain Imaging Center. The scanner used to obtain the imaging data was a Phillips 3 T Achieva Intera with a 32 channel sense head coil. For the functional runs, there were four runs of 150 volumes per run for a total of 600 functional (T2*) volumes with a TR of 2.5s. The functional scans were a gradient-echo EPI with 42 transverse slices at 3 mm per slice. TE was 35, flip angle was 90 degrees. The scan acquisition order was Philips interleaved.

Univariate Functional Imaging Analysis: Neural data were preprocessed with FSL tools for motion correction and registration (Jenkinson et al., 2002). Each participant's neural data set was modeled using the canonical 6 second HRF after onset of the display of the items (words, pseudo-words, pictures, or abstract pictures) during the encoding task, and were smoothed using a 5 mm FWHM Gaussian kernel. Regressor covariance estimates generated by FSL confirmed that these portions of the trial were statistically separable due to the jittered fixation periods inserted in between sections of each trial. The beta values used in the representational similarity analysis (described below) were drawn from the contrast of studied item (separated by study block) compared to jittered fixation baseline. Anatomical data for the searchlight portion of the analysis were prepared from participants' T1 images using FreeSurfer (Fischl, 2012).

Searchlight Representational Similarity Analysis: We used a surface-based searchlight mapping technique (Oosterhof et al., 2011) to produce a whole-brain map for each subject that reflected the Pearson correlation between local neural representational structure and a target similarity structure. The target similarity structure was created to probe for semantic similarity, looking for brain regions that process meaningful words and pictures similarly (in the vein of Shinkareva et al., 2011). Specifically, a dissimilarity matrix (DSM) for the stimuli was created using the similarity of semantic content, where each of the studied content types (words, pseudo-words, pictures, and abstract pictures) was assigned 0 dissimilarity to itself (Figure 4A). Words and pictures had 1 level of dissimilarity with each other, given that they were not identical to each other, but both contained semantically meaningful content. All other comparisons had 5 levels of dissimilarity from each other, as words have very little similarity to psuedowords (for example) in terms of semantically meaningful content. The values chosen are category markers- that is, the values were chosen to indicate low and high levels of dissimilarity, but do not represent a strict 4 units of dissimilarity between them. At each searchlight location (5 mm radius), the local neural dissimilarity matrix was computed using correlation distance between activity patterns for all pairs of stimuli (120 pairwise distances). Activity patterns were defined by the voxel-wise estimated hemodynamic responses from GLM analysis of the functional data collected during the four encoding sessions. These analyses were performed using Python and PyMVPA (http://www.pymvpa.org; Hanke et al., 2009), SciPy (http://scipiy.org), and NumPy (http://numpy.scipy.org).

The resultant DSMs at each searchlight location were correlated with the semantic content model DSM, yielding a whole-brain correlation map for each participant. These maps were then averaged at the group level. To determine the likelihood that the observed correlations occurred due to chance, we conducted a permutation test to compare our observed results to a distribution of possible results based on a distribution of 10,000 random permutations of the target labels. The probabilities associated with our results were thus calculated as the number of times the average correlation at a given searchlight across subjects for permuted observations exceeded the actual observed average correlation, divided by 10,000.

Results

Attention Bias Task. The task was designed to assess Word or Picture Attention Bias based on the percentage of trials where, when given conflicting verbal and visual information, participants relied on the word or picture to respond. A subtraction score was calculated for each participant where the percent of times a participant relied on pictures was subtracted from the percent of time participants relied on words (Attention Bias score: % Word trials - % Picture trials). This created single score for each participant, ranging from -1 (only selected pictures during incongruent trials) to 1 (only selected words during incongruent trials). The participants were split at the 0 point (indicating no preference for words or pictures). Participants with negative scores, indicating a reliance on visual information, were classified in the “Picture Bias” group. Participants with positive scores, indicating a bias for verbal information, were classified in the “Word Bias” group. These attention bias scores indicated both the type of content that each participant selectively attended to as well as how consistently each participant was drawn to that type of content. Trials where participants gave an invalid response (e.g., pressing the "spade" key when the trial was a picture of "heart" labeled "club") were discarded. Overall, participants preferred to rely on the picture instead of the word, though there are clear individual differences, as indicated by the high variability ($\text{PictureBias}_{N} = 18$, $\text{PictureBias}_{MEAN} = .58$, $\text{PictureBias}_{SD} = .33$; $\text{WordBias}_{N} = 10$, $\text{WordBias}_{MEAN} = .38$, $\text{WordBias}_{SD} = .31$). The WordBias-PictureBias subtraction score results indicate that while Picture Bias seems more common, there is a high degree of variability ($\text{Word-Pic}_{MEAN} = -.20$, $\text{Word-Pic}_{SD} = .64$). Though participants were split on whether they preferred words or pictures, each participant was relatively consistent in their Attention Bias across trials (Figure 3). Even the three participants with the least consistent biases still tended to choose one content type 10-20% more often than the other.

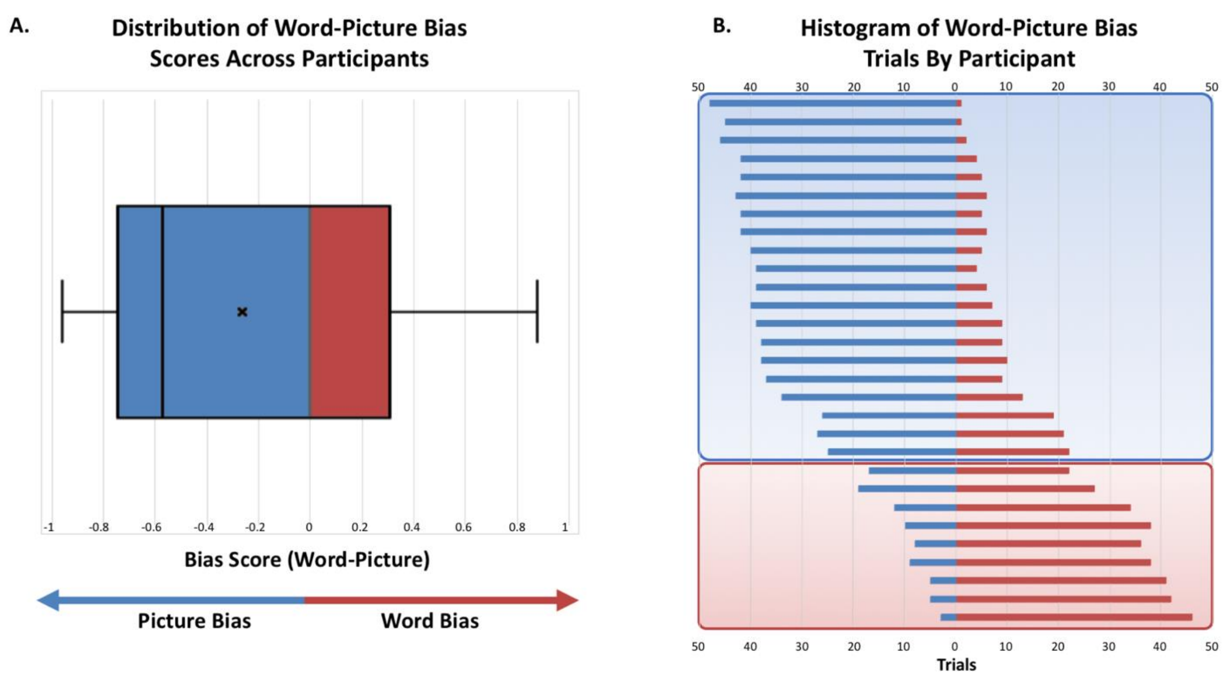

Figure 3. Variability across and within participants on the Attention Bias task. A. Box and whisker plot of Word Bias scores (Word-Picture) indicates the range (-.96 – .88), interquartile range (-.73 – .16), median (-.57), and mean (-.26, marked by **x**) values. There were no outliers.

More participants responded with a bias towards Pictures (blue) than to Words (red). B. Histogram of Word Bias by participant, indicating on how many trials individual participants responded to the picture or to the word. Though there were individual differences in the strength and direction of this bias, the majority of participants demonstrated a strong bias for one content type relative to the other. Groupings are indicated by the shaded boxes (Word Bias > Picture Bias in red; Picture Bias > Word Bias in blue).

Overall, group-level t-tests indicated that participants with Word Attention Bias and Picture Attention Bias scored similarly on measures of working memory, short term memory, and the WASI measures of VCI and PCI. A higher level of Picture Attention Bias was significantly correlated with higher accuracy during the picture memory test, $r(27) = .44$, $p < .05$. Importantly, neither verbal nor visual cognitive style significantly correlated with any behavioral measure in the intentional encoding task. This indicates that this measure of Attention Bias was able to predict behavioral outcomes which were not predicted by any other measure.

Representational Similarity Analysis Results: The searchlight representational similarity analysis (RSA) looked for regions of the brain where the neural signal reflecting semantic similarity (i.e., where words and object pictures are similar to each other but dissimilar to pseudo-words and abstract pictures; Figure 4A). This semantic content RSA revealed different locations where the model correlated with neural representations for the Word Attention Bias and Picture Attention Bias groups (Figure 4B). Specifically, the Word Bias group showed significant correlations with the semantic model in linguistically associated regions, such as the supramarginal gyrus (SMG) and the left insula, as well as some bilateral primary visual cortex and the right parietal lobe. By contrast, the Picture Bias Group showed significant correlations with the semantic model in visually associated regions such as the inferior temporal cortex (IT), ventral visual processing stream, frontal eye fields, as well as the left dorsolateral prefrontal cortex (DLPFC). The main region of overlap between the two groups for the semantic model RSA was the medial temporal gyrus (MTG), which is associated with semantic processing.

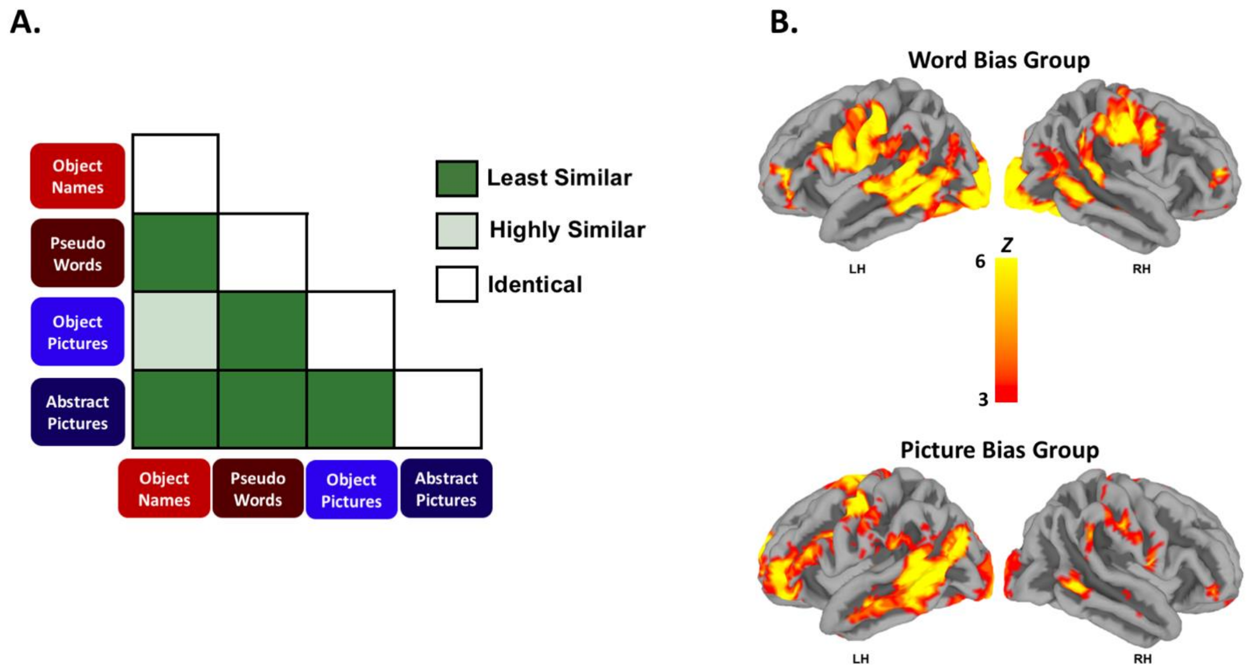

Figure 4. Semantic content RSA results by Attention Bias group. A. The dissimilarity matrix for the semantic content model. This DSM was used in a searchlight to identify regions of the brain where real words and real pictures were represented with similar patterns of neural activity. In this model, words and pictures had low dissimilarity with each other, but high dissimilarity with pseudo words and abstract pictures (to control for low level visual or linguistic processing). B. The raw average z-maps of the permuted semantic RSA for each of the Word and Picture Bias groups. Unlike in Figure 5, these maps show regions such as the medial temporal gyrus (MTG), which are generally associated with semantic activity and would not be specific to either attention bias group.

A t-test was performed between the Word Bias and Picture Bias participant RSA z-maps to reveal areas that were significantly more likely to correlate with the semantic model for the Word or Picture Bias groups (Figure 5). This t-test more clearly demonstrated the differences in the representation of semantic content (regardless of initial presentation format) between word and Picture Bias groups. Clusters for the Word Bias group were centered around the left supramarginal gyrus (SMG) and insula as well as left primary visual cortex. The left SMG has previously been reported as important for people with a verbal cognitive style during a picture memory task that involved translating pictures into word labels (Kraemer et al., 2014). The stronger a person's verbal cognitive style, the more impaired they were by the repetitive Transcranial Magnetic Stimulation to this region. The left insula has also previously been shown to be associated with language, such as with speech production (Ackermann & Riecker, 2004; Ardila, 1999) which was commonly reported by participants with a Word Bias during the memory task.

Conversely, clusters for the Picture Bias group were evident in the left IT and frontal eye fields. Inferior temporal cortex is strongly associated with object recognition and processing in the ventral visual stream, necessary for processing semantically relevant objects (Mishkin, Ungerleider, & Macko, 1983; Kriegeskorte et al. 2008; Ungerleider & Haxby, 1994). Frontal eye fields have previously been shown to be associated with visual attention and planned saccades to details in an image (Fischer & Breitmeyer, 1987; Muggleton et al., 2003). Given that more regions showed higher correlations with the semantic model in the Word Bias group compared to the Picture Bias group, a t-test was performed to confirm that the Word Bias group did not simply correlate better with the semantic model overall. That t-test indicated that there was no significant difference between the Word and Picture Bias groups in terms of overall level of activity, $t(27) = 1.38$, $p = .18$, indicating that the groups differ only in the localization of their semantic representations, and not in the overall level of semantic content represented.

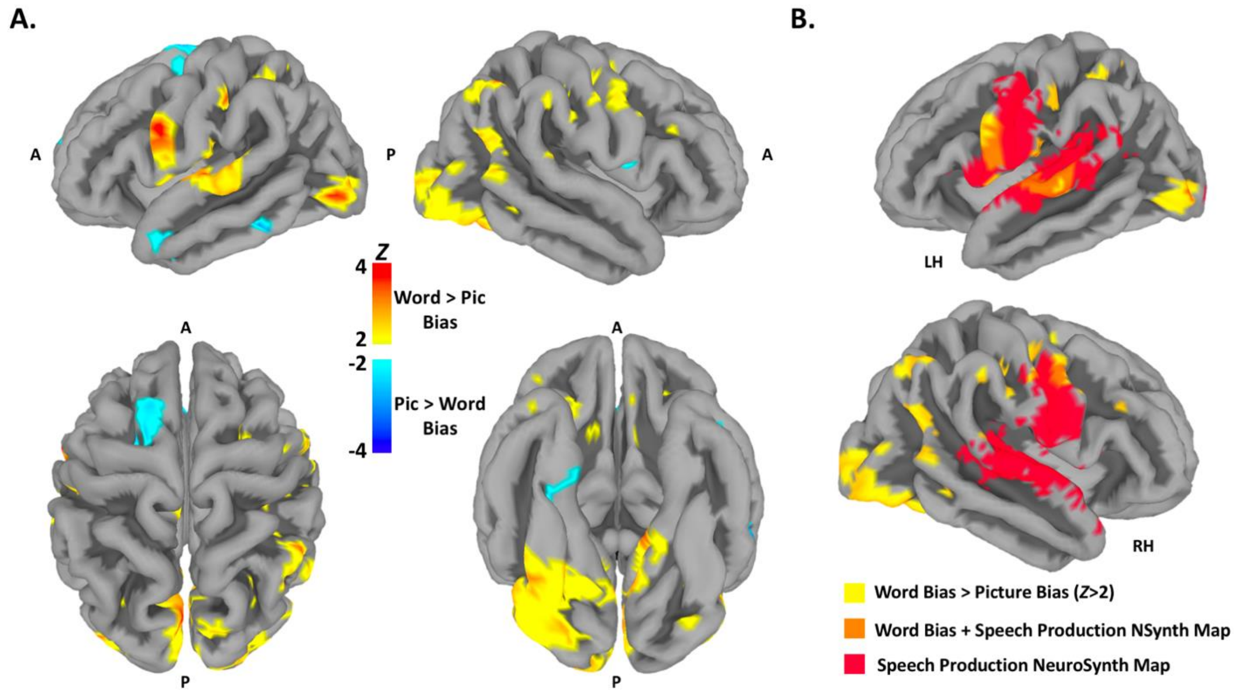

Figure 5. Brain regions where the Word Bias participants had more similarity between pictures and words than the Picture Bias participants. A. The z-map of the permuted t-test between the average RSA results for the Word Bias and Picture Bias groups. Positive values indicate regions where the Word Bias group showed significantly greater semantic similarity than the Picture Bias group. Negative values indicate regions where the Picture Bias group showed significantly greater semantic similarity than the Word Bias group. B. An overlap map of the NeuroSynth Speech Production reverse inference map and the regions where the Word Bias participants showed greater semantic similarity than the Picture Bias participants.

In order to determine whether the regions of high semantic content for the Word Bias group include linguistic processing regions for items presented in both word and picture format, a network of regions of interest was isolated using the NeuroSynth (www.neurosynth.org; Yarkoni et al., 2011) reverse inference map for "speech production". This map can be used to indicate areas that are selectively active for speech production (created through meta-analysis of 86 studies, thresholded at FDR corrected .01), and it is an alternative method to generate networks based on keywords rather than selecting anatomical ROIs. These masks were used to identify networks of regions used in material-specific processing to determine if there are significant differences in how similarly words and pictures are represented in those regions depending on a preference for verbal or visual information. The “speech production” network map was overlaid onto each participant’s z-map from their individual RSAs with the semantic model, and the average z-value from within that mask was taken from each participant. These values were then correlated with their Attention Bias subtraction score, (the degree to which a participant is more biased towards words over pictures). This correlation was significant, $r(27) = .55$; $p < .001$ (Figure 6), indicating that being more biased towards verbal information predicts higher levels of semantic processing in regions of the brain associated with speech production.

As a control, the NeuroSynth reverse inference map for “semantic” (844 studies) was used to get the average *z*-value for each participant. Notably, this meta-analytic map highlights, among other regions, a large portion of lateral mid-temporal cortex which has been implicated across a number of studies as playing a critical role in the retrieval of semantic information (Binder et al., 2005; Frankland & Greene, 2014; Shinkareva et al., 2011; Thompson-Schill, 2003). RSA results within this network were expected to show equal correlation with the semantic dissimilarity matrix for all subjects, and therefore should not correlate with Word Attention Bias. As expected, the semantic map did not significantly correlate with either Picture or Word Bias, $r(27) = .12$, $p = .54$, in contrast to the significant correlation between the speech production map and Word Bias (Figure 6). Further, a slope test revealed that the two correlations are significantly different from each other, $z = 5.233$, $p < .001$. This reinforces the result that the participants who are more biased towards words show a higher level of similarity in processing words and pictures in regions known to selectively process speech production.

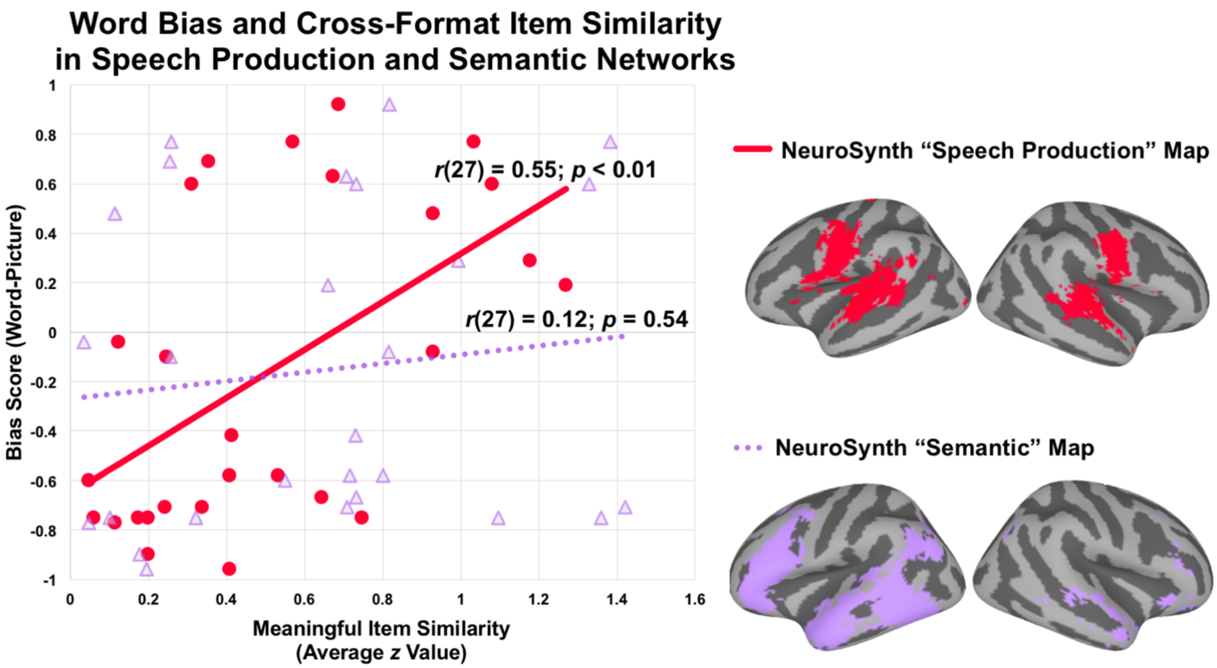

Figure 6. Correlations between average *z*-value in "speech production" and "semantic" reverse inference maps and Attention Bias score. The more biased a participant was towards verbal information, the more similarly words and pictures were represented in areas selectively active during speech production. This relationship was not seen with the semantic network, used as a control.

Discussion

Regardless of whether information was originally presented as words or pictures, that information is represented in the same way in areas related to speech production in participants with verbal habits of thought. Because this similarity of representation is specifically seen in speech production regions, it is likely individuals with a word bias are intentionally encoding material by mentally repeating the names of the objects to themselves. This study contributes to a growing body of work that shows that habits of thought have a sizeable effect on cognitive processes (Kraemer et al., 2009; Kraemer et al., 2014; Shin and Kim, 2015; Thomas and McKay, 2010; Zarnhofer et al., 2012; Zarnhofer et al., 2013). Even further, the relationship between patterns of neural activity while studying meaningful words and pictures and Word Bias score is specific to the speech production NeuroSynth map; there was no such relationship within the semantic NeuroSynth map. The regions contained in the semantic map, specifically across a large area of the lateral mid-temporal cortex, has been previously implicated as being central to the retrieval of semantic information (Binder et al., 2005; Frankland & Greene, 2014; Shinkareva et al., 2011; Thompson-Schill, 2003). Because there is no correlation between Word Bias score and the patterns of activity for meaningful words and pictures in this region, this effect is not simply due to participants with a Word Bias processing words and pictures more similarly than participants with a Picture Bias. In other words, whereas all participants encode words and pictures similarly in semantic processing regions, participants with a Word Attention Bias encode words and pictures more similarly in speech production regions compared to participants with a Picture Attention Bias.

Attention bias, like cognitive style, falls under the broader umbrella of an individual's habits of thought- the way that an individual consistently experiences and represents the world. When an individual attempts to commit information to memory, what is ultimately encoded depends on what the individual attends to. While habits of thought refer to the internal representation that an individual constructs, this representation is made up of the information that the individual selectively pays attention to. Both the Attention Biases and internal preferences are part of an individual's habits of thought, and these constructs have been shown to interact in previous research. For example, a related line of research has examined how the construct of cognitive style, which refers to ways that individuals consistently prefer to process material (e.g., visually or verbally), is in turn linked to inter-individual differences in the modality in which information is encoded (Kraemer et al., 2009; Kraemer et al., 2014; Miller et al., 2011). Participants' cognitive styles influence whether participants attend to (and therefore, encode) nameable landmarks or spatial information (relative directions) while navigating a virtual environment (Kraemer et al., 2016). Landmarks were easier to label verbally than judgments of relative direction, and therefore participants with a more verbal cognitive style were also more likely to focus their attention on landmarks. This interaction between cognitive style and Attention Bias demonstrates that individuals have consistent habits of thought that both changes what sorts of information an individual focuses on, as well as the internal representation they build of that information.

Alternative methods to access individual differences in habits of thought, such as the Attention Bias task that we introduce here, are a promising way to study what information participants are actually relying on. Although a large body of work has highlighted individual differences in verbal and visual processing (see Alfred & Kraemer, 2017 for review), self-report measures can be unreliable. Behavioral measures, such as measuring preferential attending to a particular material type, allow for the ability to capture these habits of thought directly. These results using Attention Bias to reflect these habits of thought lend further support to the argument that differing preferences for verbal or visual material can lead to significant changes in neural patterns of activity during intentional memory encoding tasks.

One limitation of the Attention Bias task in the current design is that it does not separate between object visualizers and object spatializers—two distinct categories of people typically lumped together in the "visual" cognitive style (Blajenkova, Kozhevnikov, and Motes, 2006; Blajenkova & Kozhevnikov, 2009; Kozhevnikov, Kosslyn, & Shephard, 2005). Given that the participants with Word Bias showed a more consistent pattern of results compared to participants with Picture Bias, it is possible that object visualizers and object spatializers are not adequately captured by this task. Further, Attention Bias did not significantly correlate with cognitive style,

(r = .27, p = 0.15), though this not necessarily problematic. Though both measures are attempting to tap into the same construct, Attention Bias significantly correlates with performance on memory tasks, whereas cognitive style only correlates with itself (i.e. verbal and visual cognitive style positively correlate with each other, and not with anything else). Therefore, it's not clear that cognitive style as measured by the VVQ is superior to the Attention Bias measure of habits of thought. Further research can clarify the relationship between Attention Bias and traditionally measured cognitive style, as well as try to build alternative behavioral measures of cognitive style.

It remains an open question whether having specific habits of thought would improve an individual's performance on a given task or make it worse. Benefits could potentially come from translating labels from the given format to the preferred format (Fiorella & Mayer, 2018). Even when a task can be completed solely through visual information (e.g. novel category learning), participants were faster to learn the categories when given a redundant verbal label (Lupyan, Rakison, & McClelland, 2007). This relationship was beneficial only when assigning verbal labels to visual information and not vice versa (Lupyan, Rakison, & McClelland, 2007). Alternatively, it is possible that verbal overshadowing could lead to worse performance on a task if a participant is creating verbal labels for visual material (Dodson, Johnson, & Schooler, 1997; Meissner, Christian, & Brigham, 2001; Schooler & Engstler-Schooler, 1990), and that cognitive style may interact with the verbal overshadowing effect (Ryan & Schooler, 1998). While this study cannot make any specific claims about which is more likely, participants who were biased towards preferring words ultimately performed slightly worse on the picture memory task. Ultimately, future work should continue to include a variety of individual difference measures, especially measures designed to capture the ways that individuals preferentially process different types of material. Not only can a preference for processing specific materials lead to processing other materials in the preferred format, these preferences can predict memory performance on tasks not in the preferred format. This study confirms that patterns of behavioral responses and neural activity are highly idiosyncratic and this variation should not be averaged away as noise. Rather, when the variation is studied and carefully parcellated, it can reveal consistent changes in the neural patterns of activity between participants, which are necessary for understanding the factors that contribute to individual differences in thought.

Finally, this study puts a finer point on the results of previous work demonstrating broad associations between left-hemispheric processing of verbal content and right-hemispheric processing of visuospatial content. It is not simply the case that visual information is processed in the right hemisphere. Rather, depending on that individual’s bias towards processing verbal or visual information, content originally presented in the form of a picture may be represented linguistically. This study demonstrates that material presented in a specific format is not necessarily represented in that format, but rather that processing of specific materials is dynamic and depends on individual differences in cognitive habits of thought. These individual differences must be accounted for when examining the neural representations of the concepts that comprise human thought.

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