Overlapping semantic representations of sign and speech in novice sign language learners

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Abstract

The presence of semantic information in multivariate patterns of neural activity has been explored as a method of measuring knowledge and learning. Using fMRI, we investigated whether novice learners of American Sign Language (ASL) showed overlapping representations of semantic categories for words presented in a well-known (English) or newly learned (ASL) language. We find evidence of neural patterns that were partially shared between sign and speech in novice participants. This result provides evidence for the influence of even brief learning on neural representations in cross-modality language processing.

Keywords: cognitive neuroscience; learning; knowledge representations; fMRI; semantics of language

Introduction

A fundamental concern of educational neuroscience is the ability to detect and characterize changes in knowledge and understanding over the course of learning. While traditional methods of quantifying learning include a wide array of behavioral measures (multiple-choice tests, essay exams, oral exams, etc.), prior work has found that data-driven neuroimaging methods such as multivariate representational similarity analysis (RSA) (Kriegeskorte et al., 2008) and other multivariate pattern analysis techniques can complement traditional methods of assessing an individual's knowledge, for example by identifying cortical areas where neural response patterns correlate with the semantic structure between stimuli. Multivariate patterns of brain activity which are associated with understanding or expertise have been investigated in a number of conceptual domains, including physics and engineering (Cetron et al., 2019; Cetron et al., 2020; Mason & Just 2015), computer science (Meshulam et al., 2020), and foreign language (Qu et al., 2019; Zinszer et al., 2016).

Furthermore, studies of semantic processing suggest that neural representations of real-world semantic concepts are to some extent "modality-independent": the same concept presented in two different modalities such as pictures and text (Shinkareva et al., 2011) or cued with homologous words in two different languages (Correia et al., 2014; Honey et al., 2012) can evoke similar neural patterns associated with the underlying semantic meaning. Evans et al. (2019) found evidence of partially shared semantic representations across languages even when the languages in question were of different modalities (spoken British English and British Sign Language). This suggests that language cues from two different modalities may evoke a shared underlying semantic concept. However, these studies focus on fluent bilingual participants, who have extensive training in both studied languages. Another study (Zinzer et al., 2012) found that neural pattern similarity between responses evoked by participants' first and second languages correlated with proficiency in the second language (e.g. spoken English and spoken Chinese).

Here, we sought to investigate whether overlapping conceptual representations across modality (i.e., expressed in spoken compared to signed language) could be observed in *novice* learners after brief exposure to a small set of words in an unfamiliar language. If so, this overlap of neural patterns in response to familiar and newly-learned languages could serve as a useful measure of learning. We recruited two groups of participants who were fluent English speakers with no prior training in either American Sign Language (ASL) or Russian.

Each group completed three brief trainings in one of the two target languages (ASL or Russian), learning a total of 24 concrete nouns. All participants underwent fMRI scanning while watching short video clips in ASL, Russian, and English and completing a semantic task. Using multivariate analytical methods which leverage meaningful dimensions of similarity between the ASL signs, including semantic distance and conceptual categories, we decoded neural patterns which were partially shared between sign and speech for the ASL group. Importantly, similar evidence of cross-language decoding was not found for the unstudied language, Russian. This result provides a proof of concept for research concerning the influence of even brief learning on neural representations of cross-modality language processing.

Method

Participants

Twenty-two Dartmouth College students participated in this study. Data from two participants were excluded due to incomplete scans, resulting in a sample of N = 20 (13 female, mean age = 20 years, SD = 1.70). All participants were fluent English speakers who reported no prior knowledge of American Sign Language or Russian. Participants provided informed consent prior to participation in each day of data collection and were compensated either with curricular extra credit points or a gift card. All protocols were approved by the Dartmouth Committee for the Protection of Human Subjects.

Stimuli and Design

Stimuli for the behavioral and scanner tasks (i.e. the language lessons and semantic task, detailed in the section "Procedure") were short audiovisual clips each containing one vocabulary word in ASL, Russian, or English. The ASL videos were provided by ASL-LEX, a database of lexical and phonological properties of ASL signs (Caselli et al., 2017). The Russian and English videos were created with efforts to mimic the style of the ASL-LEX videos by lab volunteers who are fluent in the respective languages. Each video clip consisted of the presenter seated before a neutral background, demonstrating a single vocabulary word. Of the 24 words, 12 were members of the semantic categories of interest (animals, fruits, and vehicles), while another 12 were selected as distractor items to obscure the intended categories from participants. To ensure that participants would not be able to guess the meanings of the words without training, ASL signs which were rated greater than average in iconicity (the extent to which a sign's form and meaning are non-arbitrarily related) by a sample of 950 hearing nonsigners collected by the creators of the ASL-LEX corpus were excluded from the stimulus set. Additionally, all ASL and Russian stimuli were pilot tested on Amazon Mechanical Turk to confirm that native English speakers with no training in ASL or Russian were not able to guess the meanings of the words and that subjective ratings of visual similarity (for ASL) and auditory similarity (for Russian) between the words did not correlate with object category.

Procedure

Participants completed three short (approx.. 30 min) online behavioral sessions on the two days preceding and the day of the fMRI scan. Half of the participants (N=10) were assigned to learn the set of 24 concrete nouns in ASL, while the other half learned the same nouns in Russian. The lessons were administered through Qualtrics (Qualtrics, Provo, UT). During each of the first two learning sessions, participants learned 12 new words in their target language through watching and mimicking the expert videos. They then completed a set of multiple-choice questions, a free recall task, and finally used their computer's webcams to record videos of themselves practicing each word. In the third practice session, which occurred on the same day as the fMRI scan, participants reviewed all 24 words that they had previously learned, created a final set of webcam recordings of themselves performing each word, and completed another free recall quiz before arriving for the fMRI scan session.

During the fMRI session, participants watched the same audiovisual clips followed by questions which probed either the semantic meaning of each noun (such as "Is this object colorful?" or "Would it be easy to cause this object to move?") or non-semantic perceptual features of the clip ("Has this word been presented already in this block?"). They answered this question by pressing a button with their right index finger or middle finger. All participants, regardless of which language they had studied in the learning period, saw clips in ASL, Russian, and English. ASL and Russian were presented in counterbalanced blocks of 16 trials each during the first two functional runs. The English stimuli were presented in similar blocks of 16 trials during the third functional run, due to concern that knowledge that the same 24 nouns were presented in each language might help participants "guess" the words in the unstudied language. The non-semantic question trials were included to encourage participants to pay attention even during blocks when they did not know the semantic meanings of the words. Each target word was presented twice in each language.

fMRI Data Acquisition

Brain images were acquired using a 3 Tesla Siemens PRISMA fMRI scanner with a 32-channel head coil. A single high-resolution T1-weighted anatomical scan and three 8-minute functional runs were performed for each participant. Each 2D EPI sequence consisted of 192 measurements with a 240 mm^2 field of view to provide full brain coverage over 46 slices (Flip angle = 79°; TE = 32 ms; TR = 2500 ms; 3mm^3 voxels). In the scanner, stimuli were presented using PsychoPy (Pierce et al., 2019) version 2021.2.3 (using Python 3.6).

Image Preprocessing and Univariate Analyses

Brain images were preprocessed using the FSL FEAT software package (Jenkinson et al., 2012). Each high-resolution T1-weighted anatomical image was first skull-stripped using the FSL brain-extraction tool. Skull-stripping, motion correction, slice timing correction, and highpass temporal filtering were then applied to each functional EPI volume. Finally, the functional EPIs were registered to the participant's individual anatomical volume using the FSL linear registration tool (Smith 2002).

A univariate regression model using the GLM was then calculated at the trial level, such that beta-value estimates for each stimulus were generated separately for each run. For each trial, brain activity was sampled from the initial presentation of the video stimulus through a short intra-trial fixation and a 4 s response period. Trials were separated by a jittered fixation interval to allow for an unconfounded estimate of BOLD signal. For stimuli which appeared in more than one run (ASL and Russian words), beta estimates were additionally combined across runs with an item-level regression model, yielding a single contrast estimate for each word in each language. All beta-value estimates were then aligned to the individual's T1 volume and resampled to 2 mm^3 using the FSL mathematical manipulation tool.

Finally, cortical surface reconstructions were generated for each subject's T1-weighted anatomical image using FreeSurfer's recon-all toolbox (Fischl & Dale, 2000) and transformed to Surface Mapping (SUMA) format (Saad & Reynolds, 2012). Formatted cortical surface maps were fitted to standard mesh grids based on an icosahedron with 32 linear divisions, yielding 20,484 nodes for the whole-brain cortical surface. Sulcal alignment of each participant's cortical surface to the FreeSurfer average brain (Fischl et al., 1999) allowed for anatomical correspondence between surface nodes across participants.

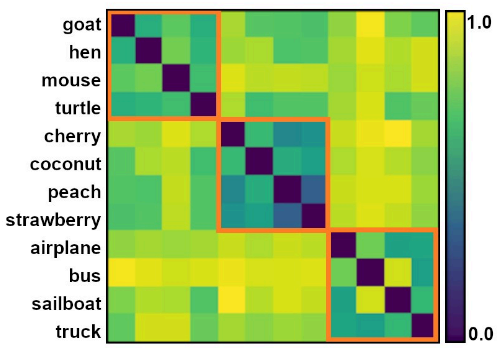

Figure 1: Word2vec semantic dissimilarity matrix. Pairwise semantic distances between each of the twelve target stimuli derived from the word2vec model are shown. The orange boxes indicate the three semantic categories (animals, fruits, and vehicles).

Multivariate Analyses

A whole-brain searchlight analysis was conducted within each participant using spherical 5mm searchlights, utilizing the PyMVPA toolbox (Hanke et al., 2009). This was repeated for the twelve item-level betas for the target stimuli set in each language (ASL, Russian, and English). In each searchlight sphere, the correlation distance between each pair of stimuli in the model was calculated to form a dissimilarity matrix (DM) for every node and its surrounding neighborhood.

Our goal was to examine whether the participants displayed unique neural activity patterns with respect to vocabulary in the language they had studied during the learning period. To this end, RSA was conducted separately for neural data recorded during presentation of stimuli in each language. Specifically, we compared the DMs at each searchlight location with a model constructed from lexical word embeddings calculated with word2vec (Mikolov et al., 2013), which represent item-level similarities between each of the twelve stimuli (shown in Figure 1). Spearman correlation between the node-level DM and the word2vec model was calculated for every node, passed through a Fisher z-transformation and compared to a null distribution calculated as the dot product of the word2vec model and a randomly permuted model and standardized over 1,000 iterations. The resulting correlations for each participant were subjected to a one-sample t-test at every node within each group. The resulting set of nodes where $p < 0.05$ (after node-level permutation correction) was further subjected to spatial cluster correction using the AFNI SurfClust function (Cox, 1996). For an FDR-corrected alpha of 0.05, only clusters with area greater than 121 mm^2 were included in further analyses.

An average DM for each cluster in the English model was then computed by averaging values at each node for all subjects within each group, then averaging across each node belonging to the cluster. Each cluster-level DM was then projected into two dimensions using multidimensional scaling (MDS), and a support vector machine (SVM) classifier with a radial basis function kernel was employed using leave-one-item-per-category-out cross-validation at each cluster to determine the degree to which the patterns of activity in that cluster reflected the categorical relationships between the items (animals vs. fruits vs. vehicles). These steps were implemented in Python using the scikit-learn package (Pedregosa et al., 2011).

In addition, for each of these clusters which had been identified as sensitive to categorical distinctions in the English stimuli with the aforementioned procedure, we also constructed an average DM of response patterns to the other two languages and repeated the same classification steps.

Results

Target Language Quiz Performance

At the end of the final training session and before the fMRI scan, participants completed a free recall quiz in which they were shown a video clip containing one of the words they had learned and asked to type the English translation into a text box. We calculated mean accuracy for the ASL group (M_{ASL} = 98.75%, SD_{ASL} = 2.01%) and the Russian group (M_{RUS} = 62.92%, SD_{RUS} = 18.89%). Due to the sizable difference in performance between the two groups, notably, the near-ceiling performance of the ASL group compared to the poor and highly variable performance of the Russian group, all subsequent analyses reported here focus exclusively on the ASL group.

Searchlight Representational Similarity Analysis

The ASL group's quiz performance immediately prior to the scan session indicated that they had achieved full mastery of the target words, so we hypothesized their fMRI data would show overlapping patterns of brain activity for a newly learned language (ASL) and a well-known language (English). Likewise, within-language semantic information (i.e., the representation of semantic categories) in ASL would also be an indication of newly learned knowledge representations.

Out of 20,484 5 mm surface searchlights probed for correlation between responses to the English stimuli and the a priori word2vec semantic model, 1,212 nodes were found to be significant after comparison with the permuted null model within subjects, and a 1-sample-test at the group level (α = .05, permutation corrected). After the cluster correction step (α = .05, FDR corrected), seven significant clusters were identified, shown in Figure 2. Correlation with the word2vec semantic model in these areas indicates the presence of semantic information about the English stimuli being represented in these areas during the trial.

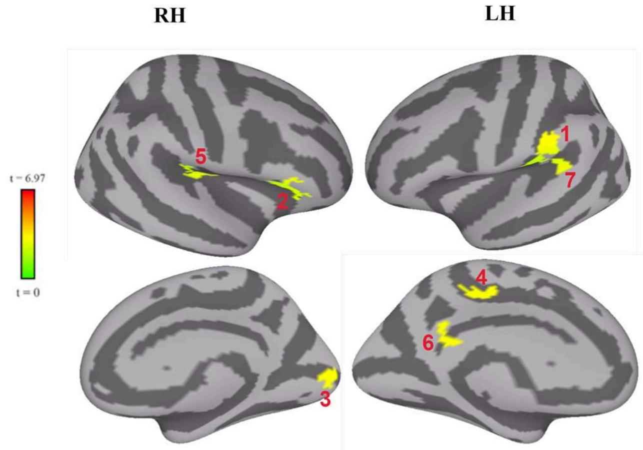

Figure 2: English RSA Results. Seven clusters (displayed on a semi-inflated cortical surface projection) were identified where the pattern of responses to the English stimuli significantly correlated with item-level dissimilarities in the word2vec model.

For the correlation between responses to the ASL stimuli and the word2vec semantic model, 1,474 nodes survived the group-level thresholding procedures after RSA (α = .05, permutation corrected), and 18 significant clusters were identified after FDR correction (α = .05, FDR corrected), shown in Figure 3.

Support Vector Machine Classification

Because all subjects were fluent English speakers with very limited training in ASL, we probed the seven clusters identified by the English model RSA for information about the object categories for all three languages. At each cluster, 1,000 iterations of SVM classification were run and the mean accuracy score was taken. On each iteration, the model was trained on nine items from the average cluster DM for five participants and tested on the held-out items in the average cluster DM of the other five participants. Mean accuracy and standard deviation for each cluster are shown in Table 1. Because data from the English trials were also used to define the clusters using RSA, English classification accuracy scores are provided primarily as a reference for the other two languages. Notably, cluster 1 was among the highest-performing clusters for both the English stimuli and ASL stimuli, for which the participants were aware of the words' semantic meaning. For the unstudied language, Russian, however, the classifier performed at chance levels in all but two clusters. The distribution of classification accuracies over 1000 iterations for cluster 1 in each language are shown in Figure 4.

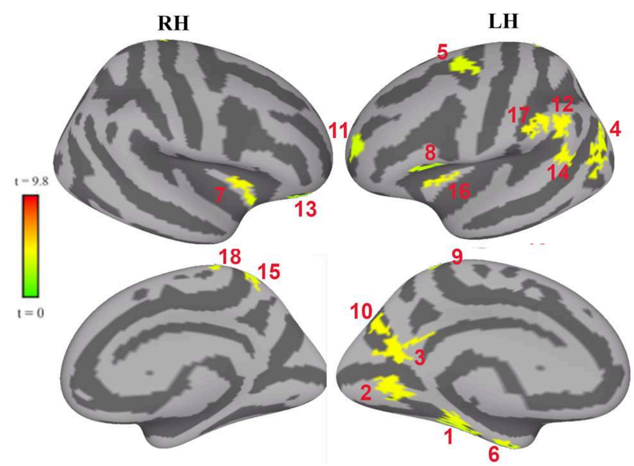

Figure 3: ASL RSA Results. Neural activity recorded during presentation of the ASL stimuli resulted in eighteen clusters (displayed on a semi-inflated cortical surface projection) that significantly correlated with item-level dissimilarities in the word2vec model.

Table 1. English RSA Cluster SVM Classification Accuracy

Cluster	M_{ENG}	SD_{ENG}	M_{ASL}	SD_{ASL}	M_{RUS}	SD_{RUS}
1. L Supramarginal Gyrus	58.58***	12.45	67.03***	14.47	28.79	9.43
2. R Ant. Lateral Fissure	60.32***	13.00	35.86***	12.59	31.08	10.46
3. R Calcarine Sulcus	54.65***	13.96	31.97*	13.00	32.54	8.93
4. L Marginal Sulcus	53.67***	13.06	41.36***	11.97	27.19	13.11
5. R Post. Lateral Fissure	51.39***	11.40	45.02***	12.67	30.39	10.64
6. L Pericallosal Sulcus	52.26***	12.37	39.04***	14.55	36.74***	12.08
7. L Planum Temporale	53.43***	12.55	42.43***	13.11	34.48*	11.37

Table 1: SVM classification accuracy in each cluster was calculated as the mean of 1,000 iterations with leave-one-item-per-category-out cross-validation. Classification results from the English trials are shown as a reference for the other two languages, where the classified data were independent from cluster selection. The highlighted rows indicate overlap with the ASL RSA results. Results from a one-tailed t-test against a distribution of permuted classification scores which exhibited chance classification (33%) in each cluster are also reported (* = p < 0.05, ** = p < 0.01, *** = p < 0.001).

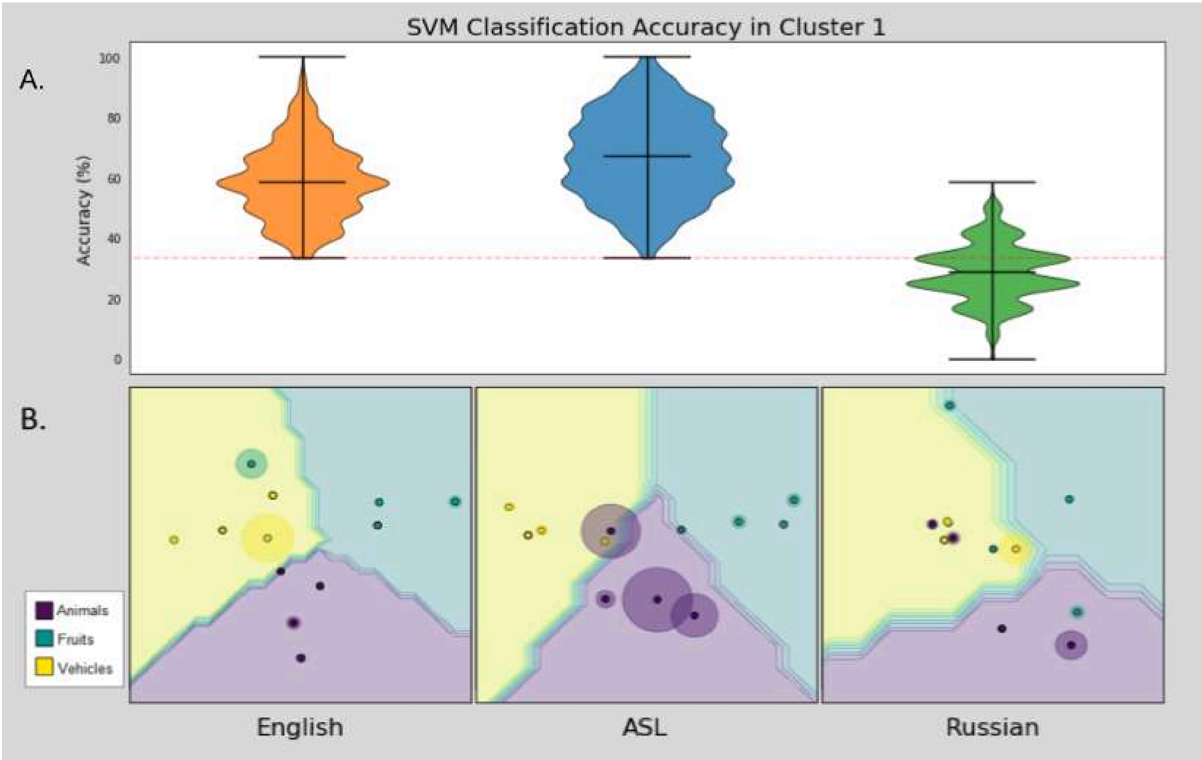

Figure 4: SVM Classification Results

(A) Violin plots show SVM classification accuracies over 1,000 iterations in Cluster 1 for each of the three languages (English, ASL, and Russian). The horizontal lines indicate the maximum, mean, and minimum for each language condition and the curves represent frequency of the result in the distribution. Chance accuracy (33%) is indicated by the dashed line.

(B) An example MDS-SVM plot for each cluster. The Cluster 1 average DM for each language was projected into two dimensions using MDS, and an SVM model was fitted to classify the items into the three semantic categories. Decision boundaries are plotted to demonstrate the separability of the item categories

Mean classification accuracy and standard deviation for all three languages in the significant clusters identified by the RSA of the ASL trials is shown in Table 2. The same iterative half-sample and leave-one-item-per-category out cross-validation procedure as before was performed in each cluster.

Discussion

The results of the present study indicate that shared semantic representations can be observed across language modalities (sign and speech), even for novice learners. Thus, decoding across languages and within a newly-learned language can provide a stable neural indicator of learning, even following relatively brief training. This finding is consistent with studies which have found common category-based coding between items presented as pictures and text (Shinkareva et al., 2011), or presented to fluent bilinguals in languages of different modality (Evans et al., 2019). The cluster with the greatest extent of category classification in both English and ASL for the ASL group was located in the left supramarginal gyrus (SMG), an area which has previously been associated with word recognition (Stockel et al., 2009) and phonological processing (Sliwinska et al., 2012). In particular, Alfred et al. (2020) found that cross-modal decoding (between words and pictures) in the left SMG was predicted by individual differences in preference for attending to verbal labels over pictorial representations.

Even beyond the category-level information used for cross-language decoding, these results provide evidence that patterns of brain activity reflecting item-level semantic information can be observed in novice learners of a new language. Significant clusters within areas with well-documented roles in language processing including the planum temporale (Shapleske et al., 1999) and left angular gyrus (Seghier, 2013) were found to represent the semantic structure of the word2vec model for the ASL stimuli condition, despite a short training period of three 30-

Table 2. ASL RSA Cluster SVM Classification Accuracy

Cluster	M_{ENG}	SD_{ENG}	M_{ASL}	SD_{ASL}	M_{RUS}	SD_{RUS}
1. L. Lateral Fusiform Sulcus	53.52***	14.79	57.64***	10.24	33.69	11.61
2. L. Medial Lingual	37.74***	10.25	58.02***	15.16	37.32***	10.51
3. L. Parietal Occipital Sulcus	51.80***	11.79	51.08***	15.49	32.17	11.22
4. L. Inf. Angular Gyrus	43.55***	11.40	63.27***	13.79	44.01***	13.66
5. L. Sup. Precentral Gyrus	43.36***	12.88	47.85***	13.09	24.33	9.40
6. L. Parahippocampal Gyrus	37.02***	11.22	55.70***	11.42	36.95***	10.48
7. R. Circular Insular Sulcus	51.45***	13.05	34.66***	11.49	28.46	11.32
8. L. Ant. Lateral Fissure	44.44***	13.66	48.93***	11.49	32.01	11.31
9. L. Precuneus	32.30**	11.28	29.18***	12.05	31.18	11.65
10. L. Parietal Occipital Sulcus	36.78***	10.67	41.47***	9.83	35.83***	9.57
11. L. Frontal Middle Sulcus	32.48	13.47	44.34***	11.29	47.50***	13.11
12. L. Planum Temporale	42.33***	14.32	48.32***	13.58	35.94***	12.65
13. R. Orbital H-shaped Gyrus	31.70	12.44	43.89***	16.36	39.49***	14.29
14. L. Sup. Lateral Gyrus	40.57***	12.24	51.76***	14.78	26.76	10.64
15. R. Precuneus	33.92*	10.75	31.71	11.66	35.61***	10.36
16. L. Circular Insular Sulcus	46.48***	12.51	62.24***	10.37	30.53	8.74
17. L. Supramarginal Gyrus	55.53***	14.62	61.50***	13.15	29.88	9.13
18. R. Paracentral Sulcus	35.62***	9.03	36.26***	10.70	30.93	13.08

Table 2: SVM classification accuracy in each cluster from the ASL RSA was calculated as the mean of 1,000 iterations with leave-one-item-per-category-out cross-validation. On each iteration, the model was trained on the average of 5 participants and tested on the average of the held-out five. Classification results from the ASL trials (the same trials which were used to define the clusters in RSA) are shown as a reference for the other two languages, where the classified data were independent from cluster selection. Results from a one-tailed t-test against a distribution of permuted classification scores which exhibited chance classification (33%) in each cluster are also reported. The highlighted rows indicate areas of overlap with the English trial RSA results.

minute sessions. Importantly, similarly robust evidence of semantic representation in relevant areas was not observed for the unstudied language, Russian. Furthermore, a significant cluster in the left visual motion processing area MT was found in the ASL RSA but not the English RSA. This is consistent with the findings of Evans et al. (2019), who found V5/MT to be selective for sign but not speech. Research in fluent signers has suggested that age of sign language acquisition modulates recruitment of V5/MT for sign processing (Bavelier et al., 2001; Neville et al. 1998). Another direction for future study could be to investigate whether left MT activity correlates with proficiency in the earlier stages of learning as well.

Another study by Zinszer et al. (2012) concluded that similarity between neural activity patterns evoked by participants' first and second languages correlated with proficiency in the second language. While the present study examined responses to a specific set of target words for which the participants had been trained to ceiling, an important future direction could apply this approach as an individual differences measure to predict language proficiency as measured by more traditional learning assessments such as quiz scores.

The present study demonstrated that through multivariate pattern analysis methods, it is possible to detect overlapping neural representations of semantic concepts evoked by homologous words in two different languages even in novices with very brief exposure to a new language. Although the sample size of 10 participants is a limitation of this preliminary study, this finding provides a proof of concept for the study of overlapping semantic representation in novice language learners. We found evidence of shared representations evoked by languages of different modalities, such as sign and speech, and we found evidence of newly learned semantic representations in the second language. Future research may also consider using this and similar multivariate neuroimaging approaches not only to detect but to quantify the extent of learning in individual learners, and to correlate neural response patterns with other indicators of real-world knowledge.

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