From seeing to understanding: Novice sign language learners shift focus from perceptual to semantic information for newly learned signs

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Abstract

Comprehending content in a newly learned language requires interactions between perceptual, semantic, and executive processing systems. Learners whose target language differs from their own in modality (e.g. spoken language users learning to sign) provide a unique opportunity to examine the relative contributions of semantic and perceptual processing. We present data from three studies where hearing, non-signing participants with between a few hours and a few weeks of experience with American Sign Language (ASL) viewed videos of signs during fMRI scanning. Using Representational Similarity Analysis (RSA), we measure contributions of semantic-conceptual, visual perception, and cognitive control regions to processing of semantic and visual information in ASL. Across different learning paradigms, including both cross-sectional and longitudinal approaches, we find that semantic features become more decodable in semantic, visual, and cognitive control regions after learning, while visual features become less salient, especially in visual cortex.

Keywords: language learning; fMRI; semantic representation; sign language

Introduction

Comprehending content in a newly learned language is a cognitively demanding task that relies broadly on perceptual, semantic, and executive processing systems. Much research has been devoted to the mechanisms that support multiple languages in native or highly proficient bilinguals, but less is known about the relative roles of these broad neural processes across the learning trajectory.

Some research has proposed a double dissociation whereby reliance on sensory and perceptual regions decreases while involvement of semantic-conceptual regions increases with language experience. The early stages of learning may be associated with more recruitment of occipital regions during reading compared to fluent bilinguals (Lai et al., 2021), recruitment of left inferior parietal and temporal areas that increases with training (Barbeau et al., 2017), and recruitment of middle temporal areas especially for newly learned words which are semantically rich (Ferreira et al., 2015).

Language learning also requires effortful processing of new stimuli, which is associated with fronto-parietal cognitive control regions. Some evidence suggests that increases in frontal activation in novice learners correlate positively with proficiency (Wang et al., 2020), while other studies show a negative relationship between frontal activation and proficiency (Deng et al., 2008). One longitudinal study of students in a language immersion program found that frontal activation elicited by the target language was high in the first few weeks of learning but decreased one semester later. Thus, the relationship between language proficiency and cognitive control may not be linear: at the earliest stages of learning, it may be associated with engagement with the task and successful comprehension, but at later stages it may be a hallmark of more effortful processing that indicates lower proficiency.

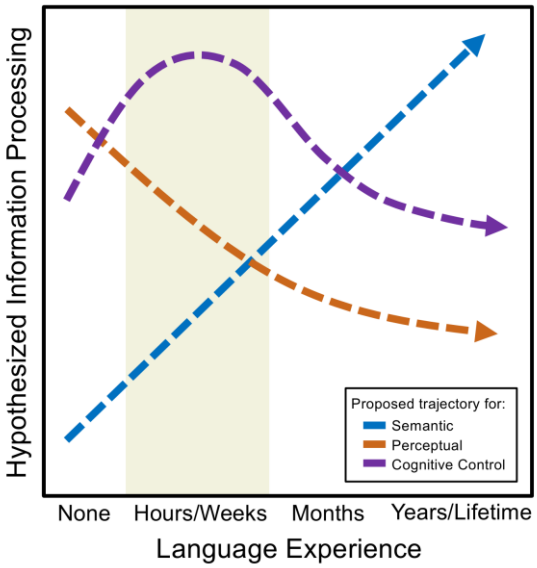

Figure 1: Hypothesized relationships between language expertise and neural processing. The interplay of semantic and visual processing in highlighted portion of the learning trajectory (hours to weeks) is comparatively understudied.

Figure 1 presents a toy diagram of how we might expect the interplay of these three neural processes (semantic comprehension, perception, and cognitive control) to shift over the course of language learning.

Signed languages (SL) provide a unique way to study the interactions of semantic and sensory processing when the modality of the language is novel to the learner (as in non-signers learning SL). Decades of work across many neuroimaging modalities have made clear that signed and spoken languages have overwhelmingly similar neural underpinnings (MacSweeney et al., 2008), although some

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work has found modality-specific effects especially in native signers (Banaszkiewicz et al., 2024; Twomey et al., 2020).

Research on SL learners suggests that their learning trajectory follows a similar pattern to spoken language learners. As little as an hour of SL training can increase recruitment of semantically associated regions such as left angular gyrus and bilateral medial temporal areas in response to signed stimuli (Alotaibi et al., 2025), and longitudinal work by Williams and colleagues (2016) shows that engagement of visual and motor processing regions decreases over three months of training. When it comes to the role of cognitive control regions, the evidence is again mixed. While one study found frontal activation to correlate with better comprehension at 3 months (Johnson et al., 2018), another found a correlation with poorer vocabulary skills at 6 months (Williams et al., 2018).

We present evidence from three distinct studies of novice learners of American Sign Language (ASL) with experience ranging from a single hour to a few weeks. In studies 2 and 3, data are included from both studied and unstudied ASL content. We utilize the multivariate decoding method Representational Similarity Analysis (RSA; Kriegeskorte et al., 2008) to assess how novices' brains represent semantic and visual features in ASL, and present a synthesized account of how each contribute to the processing of signs at the earliest stages of learning.

Methods

We present data from three distinct studies, summarized in Table 1. All participants were fluent English speakers who reported no prior knowledge of ASL. Participants provided informed consent before participation and were compensated either with curricular extra credit points, a gift card, or a small monetary reward. All protocols were approved by the Dartmouth Committee for the Protection of Human Subjects.

Table 1: Participant demographics by study

	N	Female	Age (M)	Age (SD)
Study 1	10	6	20	1.70
Study 2	40	28	20.3	3.0
Study 3	32	20	26.7	7.86

Stimuli and Design

Stimuli for the scanner tasks were short video clips featuring a person facing the camera in front of a neutral background signing a single noun. The videos were provided by ASL-LEX, a database of lexical and phonological properties of ASL signs (Caselli et al., 2017; Sehyr et al., 2021), as well as a subset of free online quizzes published by Dr. Bill Vicars (www.lifeprint.com, used with permission).

An overview of the three learning procedures is diagrammed in Figure 2. Additional details are also provided in previous work (Hillis et al., 2022; Hillis & Kraemer, 2025) as well as on OSF (https://osf.io/fmrbs/overview?view_only=a12d051135784d8fa5ddc7edd494f0c3).

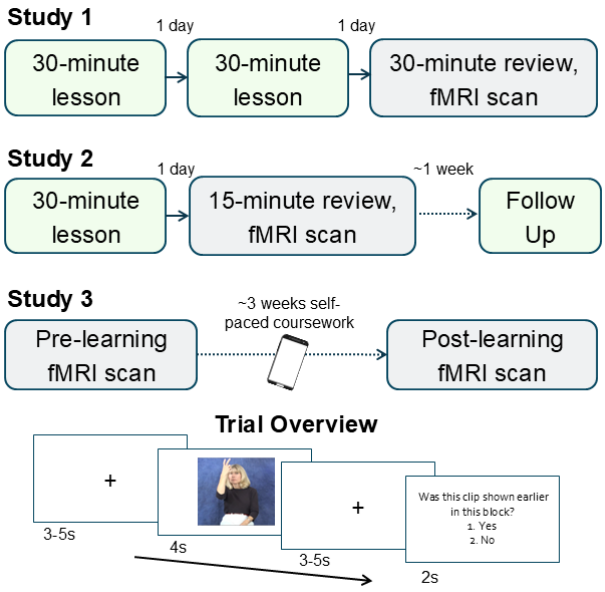

Figure 2: Procedure overview for each of the three studies. In each fMRI scan, trials consisted of single noun sign clips presented between jittered fixations, sometimes followed by a probe to check attention or sign recognition. The exact timings and contents of the probe varied by study.

Study 1. Study 1 was a pilot with ten participants who learned a set of 24 ASL nouns to ceiling over three days of training. In the scanner, they viewed single-noun video clips and answered semantic questions such as "Is this object colorful?". These participants provide a baseline of novice learners with a few days of exposure who were proficient at recognizing all studied signs.

Study 2. Study 2 employed a shorter learning paradigm (~45 minutes of training over two days). These participants were divided into two counterbalanced groups who each learned a separate list of 32 ASL nouns. This was the shortest training paradigm and the largest vocabulary list of the three studies, leading to notably more variation in recall performance in this sample. This cross-sectional design allows us to directly compare known and unknown ASL signs within participant and session.

Study 3. The final study was a longitudinal design in which participants completed a pre- and post- scan before and after a 3-week course in ASL. Twelve nouns from the course material were selected for this task. This study allows us to probe the exact same stimuli within subjects when those stimuli are unknown and known to them.

Feature Models

We constructed two *a priori* models of relationships between the items for each study: one to model semantic relationships between each stimulus, and one to model visual features of sign form, shown in Figure 3b. The dissimilarities between

each pair of stimuli estimated by each model were first z-scored and rescaled from zero to one, where zero indicates the exact same item and one indicates the maximal distance. Finally, the two models were orthogonalized to each other using linear regression. Both models were additionally controlled for sign iconicity, or the extent to which a sign's form and meaning are related. Although iconicity may not play a significant role in comprehension for fluent signers (Bosworth & Emmorey, 2010), it may impact sign recognition in novices (Lieberth & Gamble, 1991; Akers et. al., 2023).

Semantic Features from word2vec. To model semantic relationships between the stimuli, we calculated the representational distance between each pair of items using a word2vec model (Mikolov et al., 2013). Cosine dissimilarity between each pair of target items was calculated with pretrained embeddings derived from the full corpus of English Wikipedia (Yamada et al., 2020). The resulting dissimilarity matrices are used as a model of semantic relationships between the items.

Visual Sign Form Features from ASL-LEX. Features of sign form were modeled using metadata codes for individual signs provided by the ASL-LEX 2.0 database (Sehyr et al., 2021). These codes were created based on the prosodic model of sign phonology (Brentari, 1998) to describe the structural composition of signs, encompassing handshape, palm orientation, location in sign space, movement, and sign type (one- or two-handed, symmetry). We calculated sign form similarity between two signs as the number of these phonological features that each pair of signs shared.

fMRI Data Acquisition

Brain images were acquired using a 3 Tesla Siemens PRISMA fMRI scanner with a 32-channel head coil. For each participant, a single high-resolution T1-weighted anatomical scan was collected in addition to several 2D EPI sequences which varied across studies. Stimuli were presented on a projector using PsychoPy (Peirce et al., 2019).

Preprocessing and general linear model

Images from all three datasets were preprocessed with fMRIprep version 21.0.1 (Esteban et al., 2019, 2020), which is based on Nipype 1.6.1 (Gorgolewski et al., 2011). Boilerplate text generated by fMRIprep containing full details for reproducibility can be accessed on OSF (linked

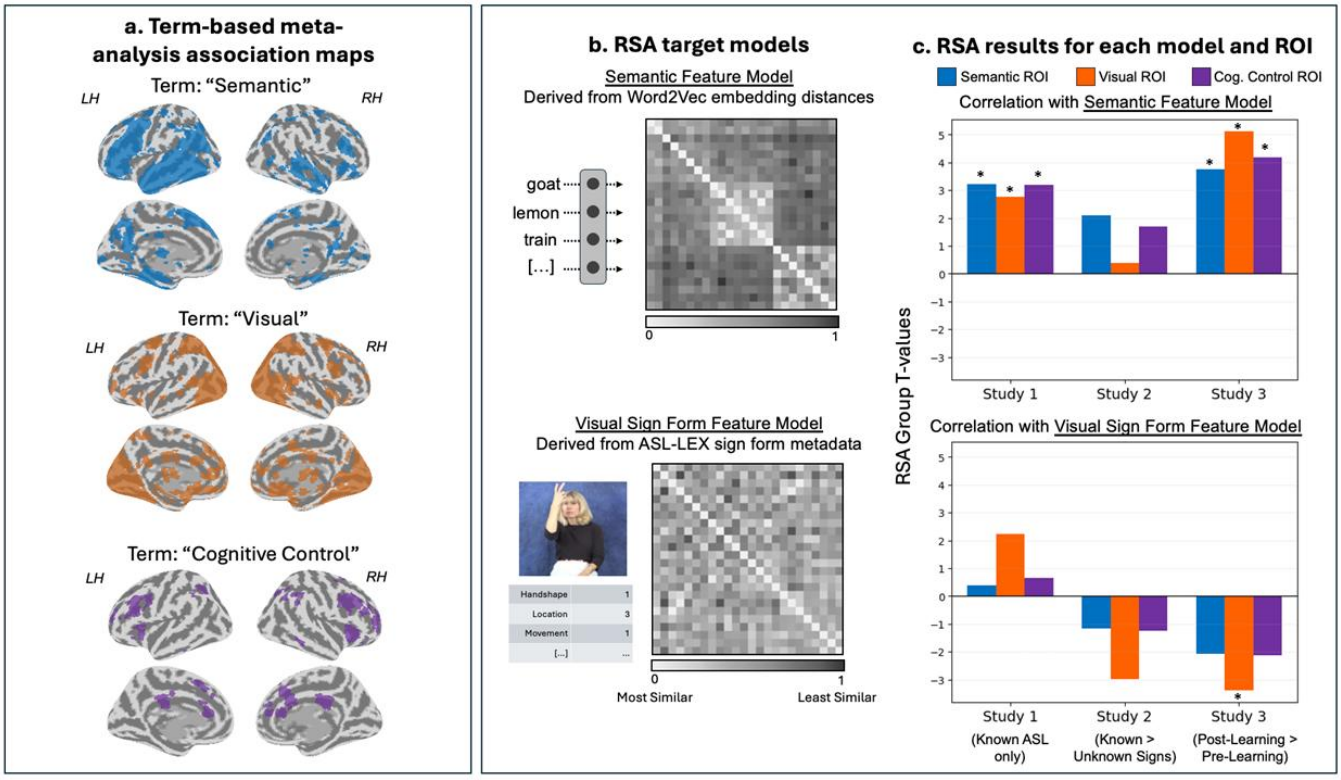

Figure 3: RSA results for each ROI and target model. (a.) Binary masks for each term-based ROI. Selected voxels are those which were associated with the term at an FDR q<0.01 level. (b.) *A priori* target models used for RSA. Semantic features were derived from word2vec similarity embedding space, while visual feature similarity was calculated based on sign form data provided by ASL-LEX. (c.) Group-level T-statistics for each RSA. Scores for each study, target model, and ROI are shown. Study 1 scores are presented as one-sample T-values for known ASL signs, while for the studies which included an unknown condition, the difference between neural alignment to the model for known > unknown signs is shown. Comparisons where this difference met a strict FDR q < 0.05 threshold are marked with asterisks.

under 'Stimuli and Design'). In summary, preprocessing included skull stripping, slice-time correction, smoothing, registration and normalization. fMRIprep also estimates the time course of confounds such as head motion.

Beta estimation. After preprocessing, a univariate regression model using the GLM was then calculated at the trial level, such that beta-value estimates for each stimulus and their temporal derivatives were generated separately for each run using Nilearn's firstlevelmodel tool (RRID: SCR_001362). Additional regressors of no interest were also included in the model: the time course of six motion parameters (translation and rotation in the X, Y, and Z dimensions) generated by fMRIprep, and spike regressors for any timepoints with framewise displacement greater than three standard deviations above the mean. Finally, for stimuli which appeared in more than one run, beta estimates were additionally combined across runs with an item-level fixed effects model, yielding a single contrast estimate for each sign clip.

Meta-Analysis regions of interest

We leveraged meta-analysis results from the NeuroSynth term association database (Yarkoni et al., 2011) to estimate a map of brain regions associated with semantic, visual, and executive functions. This tool provides coordinates of reported activation indexed by key terms which appear in the abstract for a large dataset of neuroimaging literature. The association maps for each term are coordinates that are more likely than chance to appear in a publication using that term (FDR corrected at the 0.01 level). Binary masks of voxels associated with the terms "semantic", "visual", and "cognitive control" are shown in Figure 3a. Each of these maps was treated as a region of interest (ROI) in the present analyses.

Representational Similarity Analysis (RSA)

In each region defined by the term association maps, we constructed neural dissimilarity matrices (DMs) for each subject of the pairwise distances between each stimulus in that region. Unsurprisingly given the broad and interconnected nature of these three processing domains, there is substantial overlap between the meta-analysis ROIs. To additionally compare the representations of the ASL stimuli in a set of discrete, functionally defined regions, we constructed one DM for each subject at each network in the Yeo 7-Network parcellation (Yeo et al., 2011). In both cases, after computing the neural dissimilarities between stimuli in each subject and region, we used RSA to assess the correlation between these neural DMs and *a priori* models in each ROI. Spearman correlation between the neural DM and each feature model was passed through a Fisher z-transformation and compared to a null distribution calculated as the dot product of the true model and a randomly permuted model standardized over 1,000 iterations. The resulting correlations were subjected to a one-sample t-test at each ROI to identify brain regions where the neural correlation with the model was greater than zero, in other words, areas where BOLD activity patterns reflected the hypothesized relationships between the items.

Results

RSA in meta-analysis ROIs

RSA results for each study and meta-analysis ROI are reported in Table 2, and group level statistics are displayed in Figure 3c. For Study 1, where participants only saw known ASL signs in their single scan session, the result of a group-level test against zero was used to measure correlation with each of the feature models and is plotted for each ROI. For Studies 2 and 3, RSA results are presented as the difference between the known and unknown conditions. For Study 2, this condition was a set of signs that they had never seen during training, presented during the same scan as their known sign stimuli. For Study 3, the unknown condition was collected prior to the ASL course, allowing the comparison of the exact same signs within subject, before and after learning. For each study, we first subtracted individual subject RSA correlation values for the unknown condition from the known condition to calculate a delta Z score. These

Table 2: RSA results for each feature model and term-based ROI

		Semantic Feature Model (word2vec)			Visual Sign Form Features (ASL-LEX)		
	ROI	R (Z)	T	FDR q	R (Z)	T	FDR q
Study 1	Semantic	1.09	3.22	0.016*	0.08	0.38	0.711
	Visual	0.93	2.76	0.022*	0.08	2.22	0.160
	Cog. Control	1.05	3.20	0.016*	0.13	0.64	0.711
Study 2	Semantic	0.38	1.59	0.298	-0.18	-0.77	0.504
	Visual	0.09	0.40	0.862	-0.41	-1.70	0.298
	Cog. Control	0.29	1.13	0.502	-0.17	-0.76	0.504
Study 3	Semantic	0.59	2.26	0.030*	-0.31	-1.26	0.216
	Visual	0.78	3.02	0.029*	-0.63	-2.19	0.035*
	Cog. Control	0.61	2.63	0.0393*	-0.31	-1.35	0.185

subject-level scores were then submitted to a group-level t-test to determine if they significantly differed from zero (in other words, whether there was a difference between neural responses to known and unknown. Thus, for Studies 2 and 3, positive T-values can be interpreted as greater neural alignment to the model when participants understood the ASL content, and negative values indicate that neural alignment was greater when participants did *not* understand. Comparisons are summarized in Table 2.

Despite differences in task, condition, length of training and behavioral accuracy across the three paradigms, a similar pattern of results emerges. Correlation to the semantic (word2vec) features was generally greater for known versus unknown signs, and in Study 3 this amounted to a correlation significantly greater than zero in all three ROIs (FDR-corrected $p < 0.05$). Correlation to visual sign form (ASL-LEX) features was generally greater for unknown signs, especially in the "visual" ROI, and was significantly less for known versus unknown in Study 3. Cognitive control regions also showed greater alignment to semantic features for known versus unknown signs, suggesting that effortful processing accompanies successful decoding of semantic meaning at this early stage of learning. For Study 2, in which participants were given the least training, there was no significant correlation to either model. In Study 1, which had no "unknown" condition to compare to, a one sample t-test against zero is instead reported. Correlation to the semantic model was significantly positive (greater than zero) in all three ROIs, indicating that the semantic features were significantly correlated with neural activity in each region.

Whole Brain Yeo Network RSA

To further investigate the brain regions that support semantic and visual feature processing during sign language comprehension, we additionally ran an RSA in each of the 7 networks in the Yeo parcellation atlas (Yeo et. al, 2011). Considering the entire brain helps avoid any assumptions inherent to the term-based meta-analysis maps. Correlation of each network's neural DM to the target DMs was computed for each study following the same permutation test procedure as the meta-analysis ROIs.

Figure 4a. shows the RSA results for each of the seven ROIs. As before, Study 1 results are presented as a group-level T-test for each ROI indicating where correlation to the target model differed from zero. For studies 2 and 3, the delta between the known and unknown ASL conditions is plotted instead. The heatmap of ROI scores across the brain is shown for studies 1 and 3 in figure 4b and figure 4c respectively. These heatmaps provide context for the whole brain patterns underlying the meta-analysis ROI results – notably, that the dissociation between known and unknown words is not restricted to the meta-analysis ROIs, although in many cases the strongest associations overlap with one or more of the term ROIs.

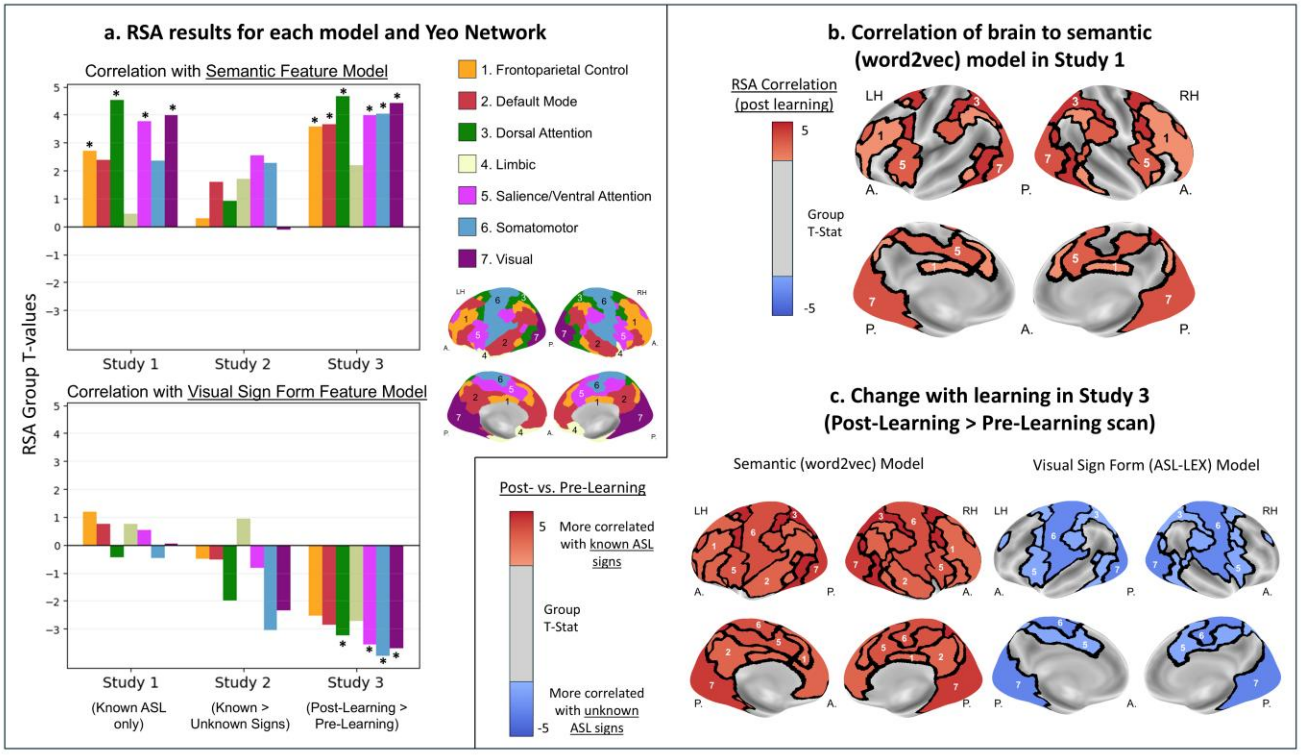

Figure 4: RSA results for each of the seven Yeo networks. (a.) Bars represent group T-stats from each RSA. Asterisks indicate FDR $q<0.05$. (b.) Heatmap of correlation between neural data and semantic (word2vec) model for Study 1. Networks that were correlated at the FDR $q<0.05$ level are shown on the semi-inflated FSAverage6 surface. (c.) Heatmap of delta (Post-learning>Pre-learning) T-values from Study 3 for significant networks for each feature model.

Discussion

Examining newly learned representations of signed language in learners with primarily spoken language experience can provide a unique lens into the dynamics of semantic and visual feature processing during language learning. Across three studies, we found that learning increases alignment of neural data to a semantic model for known (versus unknown) ASL signs, while visual sign form features were more decodable from unknown signs than known ones. Particularly for Studies 1 and 3, this pattern held across all three studied ROIs (semantic, visual, and cognitive control regions), although the shift in alignment to visual features was especially pronounced in the "visual" ROI. This result is consistent with previous findings that activation of perceptual regions may decrease with language proficiency (Lai et al., 2021; Williams et al., 2016). It is striking that the shift from reliance on visual features to semantic decoding is detectable in these subjects, some of whom received as little as one and a half hours of training. In Study 3, who received the most training, neural activity was not only correlated with the semantic feature model after learning, but simultaneously less correlated with the visual sign form feature model. This compliments previous analyses of these data which identify alignment with the semantic model after learning (Hillis et. al, 2022), as well as other findings that sensory-perceptual features of words might become less salient with increasing proficiency (Lai et al., 2021). For Study 2, despite previous evidence suggesting alignment of neural data to semantic features on the individual level might predict learning (Hillis & Kraemer, 2025), there was no significant correlation to the semantic feature model in the group average. This could have resulted from the lower training time (45 minutes) and increased vocabulary size compared to the other studies, which reduced overall comprehension of the stimuli, suggesting that successful learning (not merely exposure) is necessary to observe this shift.

These findings highlight that not only do functional changes as a result of learning occur rapidly (with just a few hours to weeks of learning), but that they involve many distributed areas of the brain. Given the complex and multifaceted nature of language comprehension, it is neither surprising that there is overlap in the term-based ROI maps, nor that the three studied ROIs followed somewhat similar patterns of decoding (as opposed to the visual ROI responding exclusively to visual features, and the semantic ROI exclusively to semantic features). In fact, the whole brain network analysis would suggest that the pattern of neural responses shifts in this direction across most of the brain. However, the consistency with which the cognitive control network tracks semantic information for known items lends weight to the theory that in the early stages of learning, fronto-parietal cognitive control areas support successful comprehension through effortful processing.

In general, several fronto-parietal regions (notably the left inferior frontal gyrus, or IFG) have been widely reported to play a role in sign acquisition, but its relationship with proficiency is unclear, with some studies finding that its activation increases with proficiency (Newman-Norlund et al., 2006) while others report a decrease that tracks with proficiency (Johnson et al., 2018; Williams et al., 2018; for additional evidence from spoken languages, see Deng et al., 2008; Stein et al., 2009). One feature that differentiates the study conducted by Newman-Norlund and colleagues (2006) is the length of training. While the majority of studies examine intermediate learners with several months or years of exposure to the target language, this study was conducted longitudinally over a two-week period. This is a closer analogue of the present studies. Thus, as diagrammed in Figure 1, we hypothesize that at the earliest stages of learning, frontal control regions may support the difficult task of identifying recently learned vocabulary, but further along the learning trajectory a reduction in need for effortful frontal control becomes a hallmark of successful learning.

Some work supports a role for frontal control areas in sign processing for native signers as well. For example, Emmorey and colleagues (2011) reported that for native signers, viewing linguistically structured but meaningless pseudosigns activated left IFG and superior temporal cortex more than familiar ASL signs, possibly reflecting effortful lexical search. This result would make sense if fronto-parietal involvement was a hallmark of task difficulty, which is also theoretically high at the earliest stages of learning.

As novices begin to acquire sign language skills, dynamic cognitive processes support their ability to watch and understand signed content. At the early stages explored in this set of studies (hours to weeks of exposure), we demonstrate that both semantic and visual features can be decoded with multivariate pattern analysis techniques like RSA, and that their signatures are spread across a diverse network of interconnected brain regions. Specifically, we found that although regions that have been associated with visual processing are somewhat more sensitive to visual features than either semantic or cognitive control regions, which show more attunement to semantic features for known signs, both semantic information and visual information are represented across widespread networks of the brain. Within these broad patterns, we find support for the idea that semantic features increase in importance as learners acquire a new language, and lower-level sensory features may decrease in importance. Future research may explore later stages in language acquisition to investigate whether if, as sign recognition becomes automatized over months or years, the role of visual features continues to decrease. Further research may also be necessary to characterize the relationship of cognitive control and proficiency. Although cognitive control regions appear to be sensitive to semantic features of known signs in the present study, previous findings that follow learners over longer periods of time have found evidence that they might be associated with poorer learning outcomes after a certain point. Taken together, these studies provide novel insight into the often-understudied earliest stages of the learning trajectory and demonstrate that the relative contributions of semantic and visual features to sign recognition shift rapidly after brief training.

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