A 3.5-minute-long reading-based fMRI localizer for the language network

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Abstract

The field of human cognitive neuroscience is increasingly acknowledging inter-individual differences in the precise locations of functional areas and the corresponding need for individual-level analyses in fMRI studies. One approach to identifying functional areas and networks within individual brains is based on robust and extensively validated 'localizer' paradigms—contrasts of conditions that aim to isolate some mental process of interest. Here, we present a new version of a localizer for the fronto-temporal language-selective network. This localizer is similar to a commonly-used localizer based on the reading of sentences and nonword sequences (Fedorenko et al., 2010) but uses speeded presentation (200ms per word/nonword). Based on a direct comparison between the standard version (450ms per word/nonword) and the speeded versions of the language localizer in 24 participants, we show that a single run of the speeded localizer (3.5 min) is highly effective at identifying the language-selective areas: indeed, it is more effective than the standard localizer given that it leads to an increased response to the critical (sentence) condition and a decreased response to the control (nonwords) condition. This localizer may therefore become the version of choice for identifying the language network in neurotypical adults or special populations (as long as they are proficient readers), especially when time is of essence.

Introduction

Neuroscientific studies of uniquely human abilities rely predominantly on non-invasive neuroimaging techniques such as functional magnetic resonance imaging (fMRI). A widespread methodological approach in fMRI studies of human brain function is to average individual activation maps for some contrast of interest in a template brain space and perform statistical analyses in each voxel across individuals to derive a group-level whole-brain statistical map. However, functional regions vary in their precise locations across individuals (Fischl et al., 2008; Frost & Goebel, 2012; Tahmasebi et al., 2012; Vázquez-Rodríguez et al., 2019; Somers et al., 2021). Correspondingly, reliance on these group-averaging approaches can lead to low sensitivity and functional resolution (Brett et al., 2002; Saxe et al., 2006; Nieto-Castañón & Fedorenko, 2012). Inter-individual variability is particularly problematic when functional regions of interest lie in proximity to functionally distinct regions, as is the case with both frontal and temporal language regions (e.g., Tomaiuolo et al., 1999; Fedorenko et al., 2012; Tahmasebi et al., 2012; Deen et al., 2015; Braga et al., 2020; Du et al., 2024; see Fedorenko & Blank, 2020, for discussion of this issue for 'Broca's area').

One increasingly popular solution that circumvents inter-individual variability in the precise locations of functional regions is the use of functional 'localizers' (Saxe et al., 2006; Nieto-Castañón & Fedorenko, 2012; Gratton & Braga, 2021). In this approach, a brain region or network that supports a mental process of interest is identified with a functional contrast in each individual brain and subsequently, the region's/network's responses to some critical condition(s) of interest are examined. Consistent use of these localizers across studies and labs (and in some cases, species; Russ et al., 2021) affords greater confidence that the 'same' region or set of regions is being studied, compared to relying on anatomical landmarks alone, and thus facilitates the accumulation of scientific knowledge.

The functional localization approach has been successful across many domains of perception and cognition including high-level visual and auditory processing, social cognition, and language (Kanwisher et al., 1997; Epstein & Kanwisher, 1998; Downing et al., 2001; Belin et al., 2002; Saxe & Kanwisher, 2003; Baker et al., 2007; Fedorenko et al., 2010, 2013; Overath et al., 2015; Fischer et al., 2016; Isik et al., 2017). In the domain of language, Fedorenko et al. (2010) developed a localizer that relies on a contrast between language processing and the processing of a perceptually similar condition that lacks linguistic structure or meaning (e.g., reading or listening to sentences vs. nonword lists, or listening to sentences vs. backwards speech or acoustically degraded sentences; Bedny et al., 2011; Scott et al., 2017; Lipkin et al., 2022; Malik-Moraleda, Ayyash et al., 2022). Such contrasts target brain areas that support computations related to accessing words and combining them into complex linguistic structures and meanings. These 'language localizers' robustly identify the left-lateralized fronto-temporal language network, which has long been implicated in language processing based on investigations of patients with aphasia (e.g., Luria, 1970; Goodglass, 1993; Bates et al., 2003; Fridriksson et al., 2018; Wilson et

al., 2023) and group-averaging neuroimaging investigations of language processing (e.g., Binder et al., 1997; Price, 2010; Friederici, 2012). Importantly, language localizers are highly generalizable, eliciting similar activations across presentation modalities, materials, and tasks (see Fedorenko et al., 2024). Moreover, the brain regions that this localizer identifies closely correspond to those that emerge from the bottom-up clustering of voxel time-courses obtained during rest (Braga et al., 2020) or while performing tasks (Du et al., 2025; Shain & Fedorenko, 2025). This correspondence highlights that the language network is a 'natural kind' in the brain: an ontologically meaningful grouping of a set of brain regions that show highly synchronized activity over time. Neuroimaging studies of language that rely on the functional localization approach have produced a number of robust and replicable findings both about i) the relationship between language and other perceptual and cognitive processes (e.g., Fedorenko et al., 2011; Deen et al., 2015; Amalric & Dehaene, 2019; Ivanova et al., 2020; Jouravlev et al., 2019; Chen et al., 2023; Shain et al., 2023), and ii) the internal organization of the language system and its computations (e.g., Blank et al., 2016; Fedorenko et al., 2020; Shain et al., 2022; Shain, Kean et al., 2024).

One practical concern that researchers often express about the use of localizers is that they take time. Time is often a precious commodity in neuroimaging research, either because the critical task is already long and/or because the population of interest may have low tolerance for the scanner environment. However, given the advantages that localizers provide—including greater sensitivity, greater functional resolution, more accurate effect size estimation, higher interpretability of the responses in the critical tasks, and the ability to meaningfully accumulate knowledge across studies, labs, and species—many researchers continue to adopt this approach. One recent effort in the field has therefore been to try to optimize localizers so that they can be as short as possible while still yielding robust individual-level responses (e.g., Dodell-Feder et al., 2011; Lee et al., 2024; Marvi, Hutchinson et al., 2025).

In this study, we develop a shorter version of a widely used reading-based language localizer (Fedorenko et al., 2010). We leverage the fact that humans can read at fast rates, especially when the need for eye movements is minimized by presenting words one at a time in the center of the screen in a rapid serial visual presentation (RSVP) paradigm (e.g., Forster, 1970; Potter et al., 1980, 1986; Potter, 2012; Mollica & Piantadosi, 2017). In these studies, participants can process linguistic information even when each word is presented for as little as ~80-200ms, as evidenced by accurate recall of the stimuli and high accuracy in answering comprehension questions about the content. Moreover, a few studies (Vagharchakian et al., 2012; Benjamin & Gaab, 2012; Christodoulou et al., 2014) have found that speeded reading, similar to reading at slower speeds, activates the language areas, but these studies have used a group-averaging approach, leaving open the question of whether speeded reading elicits sufficiently robust responses in individual participants. This is the question our study aims to address. Although this question is primarily methodological in nature, our study's design allows us to additionally ask a theoretically

interesting question about whether the increased processing difficulty due to speeded presentation affects neural responses in the language-selective network, or instead (or in addition) in the domain-general Multiple Demand network, which is sensitive to cognitive effort across diverse paradigms (e.g., Fedorenko et al., 2013; Duncan et al., 2012; Duncan, 2010; Duncan et al., 2020; Assem et al., 2020b).

Methods

Brief overview

24 adults each completed two versions of a language localizer task. In both versions, participants read sentences and lists of unconnected pronounceable nonwords presented on the screen one word/nonword at a time. The two versions differed in the presentation speed of each word/nonword. One localizer version was an extensively validated language localizer task (Fedorenko et al., 2010; Mahowald & Fedorenko, 2016; see Lipkin et al., 2022 for data from >600 participants on this version) where each word/nonword is presented for 450 ms ('standard language localizer'). The other version was a new, speeded version of the task where each word/nonword was presented for 200 ms ('speeded language localizer'). 22 of the 24 participants completed the two versions of the language localizer in the same scanning session; the remaining two—in separate sessions (1 and 463 days apart). For all participants, the speeded version was run after the standard version. Each scanning session lasted between 1 and 2 hours and included a variety of additional tasks for unrelated studies. The materials, scripts, and screen recordings for the two language localizer versions are available at https://www.evlab.mit.edu/resources-all/download-localizer-tasks (standard version) and https://github.com/el849/speeded_language_localizer/ (speeded version).

Participants

24 neurotypical adults (12 female, 12 male), aged 18 to 60 (mean: 28.04; std: 9.25), participated for payment between June 2021 and December 2022. All participants were native speakers of English, had normal or corrected-to-normal vision, and no history of neurological, developmental, or language impairments. 22 participants (~92%) were right-handed, as determined by the Edinburgh handedness inventory (Oldfield, 1971), 2 participants (~8%) were left-handed. All participants gave informed written consent in accordance with the requirements of the MIT's Committee on the Use of Humans as Experimental Subjects (COUHES).

fMRI tasks

Language network localizer tasks

Standard language localizer task

A reading task contrasted *sentences* (e.g., THE SPEECH THAT THE POLITICIAN PREPARED WAS TOO LONG FOR THE MEETING) and lists of unconnected, pronounceable *nonwords* (e.g., LAS TUPING CUSARISTS FICK PRELL PRONT CRE POME VILLPA OLP WORNETIST CHO) in a standard blocked design with a counterbalanced condition order across runs, as introduced in Fedorenko et al. (2010). Each stimulus consisted of 12 words/nonwords. Stimuli were presented in the center of the screen, one word/nonword at a time, at the rate of 450 ms per word/nonword. Each stimulus was preceded by a 100 ms blank screen and followed by a 400 ms screen showing a picture of a finger pressing a button, and a blank screen for another 100 ms, for a total trial duration of 6 s. Participants were instructed to read attentively (silently, to themselves) and to press a button on the button box whenever they saw the picture of a finger pressing a button on the screen. The button-pressing task was included to help participants remain alert. Experimental blocks lasted 18 s (with 3 trials per block) and fixation blocks lasted 14 s. Each run (consisting of 16 experimental blocks and 5 fixation blocks) lasted 358 s (5 min 58 s). Participants completed 2 runs.

Speeded language localizer task

The speeded version of the language localizer was identical to the standard version except that each word/nonword was presented for 200 ms instead of 450 ms (i.e., ~56% faster). Each stimulus was preceded by a 100 ms blank screen and followed by a 400 ms screen showing a picture of a finger pressing a button, and a blank screen for another 100 ms, for a total trial duration of 3 s. The instructions to the participants were the same as in the standard version although they were warned that the presentation would be somewhat fast, and they were told not to worry if they missed some button presses. Experimental blocks lasted 9 s (with 3 trials per block) and fixation blocks lasted 14 s. Each run (consisting of 16 experimental blocks and 5 fixation blocks) lasted 214 s (3 min 34 s). Participants completed 2 runs.

Language network localizer experimental materials

Standard language localizer materials

The materials consisted of five sets, each set comprising 48 sentences and 48 nonword sequences, for a total of 240 sentences and 240 nonword sequences. The sentences were drawn from the Brown corpus (Bird & Looper, 2004; Francis & Kucera, 1964) and were selected to include a variety of syntactic constructions and topics. The nonwords were created using the 'Wuggy' software (https://github.com/WuggyCode/wuggy; the default parameters were used) so as to respect the phonotactic constraints of English. In cases where Wuggy was unable to generate a

nonword candidate, we relied on one of the following strategies: i) broke down the word into composite words (for compound words) or morphemes, matched each composite word/morpheme to a nonword, and then reassembled those; ii) used one of the nonwords created for another word; or iii) created an English-sounding nonword ourselves. Any given participant saw one set of materials.

Speeded language localizer materials

The first 11 participants were presented with the materials from the standard version (ensuring that a different set was used). Approximately halfway through data collection, we created a new set of materials for the speeded language localizer in order to: i) generalize the findings to a new set of materials, and ii) avoid potential material overlaps between the standard and speeded localizer materials in future experiments. Hence, for the remaining 13 participants, we created five new sets each consisting of 48 sentences and 48 nonword sequences, for a total of 240 new sentences and 240 new nonword sequences. The sentences were again selected from the Brown corpus (Bird & Looper, 2004). In particular, we sampled 1,000 12 word-long sentences and then selected a set of 240 sentences that were not already included in the original set of materials, were syntactically and semantically diverse, and did not contain offensive/inappropriate content. The nonword strings were created as in the standard version.

Multiple Demand network localizer task

In addition to the language tasks, we included a non-linguistic demanding task: a spatial working memory task. The goal was two-fold. First, including a non-linguistic task allowed us to evaluate the *selectivity* of the language fROIs–defined by two versions of the localizer—for language processing (Fedorenko et al., 2011, 2024). And second, this task allowed us to examine brain responses to the conditions of the language localizer tasks in *another set of functional areas*: areas that comprise the domain-general Multiple Demand (MD) network (Duncan, 2010; Duncan et al., 2012; Fedorenko et al., 2013). This network supports executive functions like working memory and cognitive control. The spatial WM task has been previously established to robustly identify these areas at the individual-participant level (e.g., Blank et al., 2014; Mineroff, Blank et al., 2018; Shashidhara et al., 2020; Assem et al., 2020a; Malik-Moraleda, Ayyash et al., 2022). Although the areas of the MD network have been shown to not support any 'core' linguistic computations—like those related to lexical access, syntactic structure building, or semantic composition (e.g., Blank & Fedorenko, 2017; Diachek, Blank, Siegelman et al., 2020; Quillen et al., 2021; Shain, Blank et al., 2020, Shain et al., 2022)—their engagement has been reported for some cases of effortful perception and comprehension (e.g., Mattys & Wiget, 2011; MacGregor et al., 2022; Liu et al., 2022; see Discussion). We therefore wanted to evaluate the MD areas' responses to speeded comprehension, to see whether this kind of processing difficulty draws on domain-general resources.

The spatial working memory task contrasted a *hard* condition with an *easy* condition in a standard blocked design with a counterbalanced condition order across runs (e.g., Fedorenko et al., 2011, 2013; Blank et al., 2014). On each trial (duration = 8 s), participants saw a fixation cross for 500 ms, followed by a 3x4 grid within which randomly generated locations were sequentially flashed (1s per flash) two at a time for a total of eight locations (*hard* condition) or one at a time for a total of four locations (*easy* condition). Then, participants indicated their memory for these locations in a two-alternative forced-choice paradigm via a button press (the choices were presented for 1,000 ms, and participants had up to 3 s to respond). Feedback, in the form of a green checkmark (correct responses) or a red cross (incorrect responses), was provided for 250 ms, with fixation presented for the remainder of the trial. Experimental blocks lasted 32 s (with 4 trials per block) and fixation blocks lasted 16 s. Each run (consisting of 12 experimental blocks and 4 fixation blocks) lasted 448 s (7 min 28 s). Participants completed 2 runs.

23 of the 24 participants completed the MD localizer in the same scanning session as the standard language localizer; the remaining participant—in a separate session (98 days apart).

fMRI data acquisition, preprocessing and first-level analysis

fMRI data acquisition

Structural and functional data were collected on the whole-body, 3 Tesla, Siemens Trio scanner 32-channel head coil, at the Athinoula A. Martinos Imaging Center at the McGovern Institute for Brain Research at MIT. T1-weighted, Magnetization Prepared RApid Gradient Echo (MP-RAGE) structural images were collected in 176 sagittal slices with 1 mm isotropic voxels (TR = 2,530 ms, TE = 3.48 ms, TI = 1100 ms, flip = 8 degrees). Functional, blood oxygenation level dependent (BOLD) data were acquired using one of three similar sequences (denoted as sequence A, B, C). The data from the majority of participants (22 out of 24) were acquired using sequence A which we describe in this paragraph. See specifications of sequences B and C in SI Table 1 (importantly, scanning sequence is kept constant in all comparisons between the standard and the speeded versions of the localizer besides in a single participant). Sequence A was an SMS EPI sequence (with a 90 degree flip angle and using a slice acceleration factor of 2), with the following acquisition parameters: fifty-two 2 mm thick near-axial slices acquired in the interleaved order (with 10% distance factor), 2 mm × 2 mm in-plane resolution, FoV in the phase encoding (A ≫ P) direction 208 mm and matrix size 104 × 104, TR = 2,000 ms and TE = 30 ms, and partial Fourier of 7/8. The first 10 s of each run were excluded to allow for steady state magnetization.

fMRI preprocessing

fMRI data were analyzed using SPM12 (release 7487), CONN EvLab module (release 19b; https://web.conn-toolbox.org/resources/conn-extensions/evlab), and custom MATLAB scripts. Each participant's functional and structural data were converted from DICOM to NIfTI format. All functional scans were coregistered and resampled using B-spline interpolation to the first scan of the first session (Friston et al., 1995). Potential outlier scans were identified from the resulting subject-motion estimates as well as from BOLD signal indicators using default thresholds in CONN preprocessing pipeline (5 standard deviations above the mean in global BOLD signal change, or framewise displacement values above 0.9 mm; (Nieto-Castanon, 2020). Functional and structural data were independently normalized into a common space (the Montreal Neurological Institute [MNI] template; IXI549Space) using SPM12 unified segmentation and normalization procedure (Ashburner & Friston, 2005) with a reference functional image computed as the mean functional data after realignment across all timepoints omitting outlier scans. The output data were resampled to a common bounding box between MNI-space coordinates (−90, −126, −72) and (90, 90, 108), using 2 mm isotropic voxels and 4th order spline interpolation for the functional data, and 1 mm isotropic voxels and trilinear interpolation for the structural data. Last, the functional data were smoothed spatially using spatial convolution with a 4 mm FWHM Gaussian kernel.

First-level analysis

Effects were estimated using a General Linear Model (GLM) in which each experimental condition was modeled with a boxcar function convolved with the canonical hemodynamic response function (HRF) (fixation was modeled implicitly, such that all timepoints that did not correspond to one of the conditions were assumed to correspond to a fixation period). Temporal autocorrelations in the BOLD signal timeseries were accounted for by a combination of high-pass filtering with a 128 s cutoff, and whitening using an AR(0.2) model (first-order autoregressive model linearized around the coefficient a = 0.2) to approximate the observed covariance of the functional data in the context of Restricted Maximum Likelihood estimation (ReML). In addition to experimental condition effects, the GLM design included first-order temporal derivatives for each condition (included to model variability in the HRF delays), as well as nuisance regressors to control for the effect of slow linear drifts, subject-motion parameters, and potential outlier scans on the BOLD signal.

Definition of functional regions of interest (fROIs)

Language and Multiple Demand (MD) fROIs were defined using a group-constrained subject-specific (GSS) approach (Fedorenko et al., 2010) where a set of spatial masks, or parcels, is combined with each individual subject's localizer activation map, to constrain the definition of individual fROIs. The parcels delineate the expected gross locations of activations for a given contrast and are sufficiently large to encompass the variability in the locations of individual

activations. Within each parcel, we selected the top 10% most localizer-responsive voxels, based on t-values.

To define the language fROIs, we used a set of five parcels derived from a group-level probabilistic activation overlap map for the *sentences* > *nonwords* contrast in 220 independent participants. The parcels included two regions in the left inferior frontal gyrus (LIFG, LIFGorb), one in the left middle frontal gyrus (LMFG), and two in the left temporal lobe (LAntTemp and LPostTemp). Following prior work (e.g., Blank et al., 2014), to define the right-hemisphere RH fROIs, the LH parcels were transposed onto the RH, but the individual LH and RH fROIs were allowed to differ in their precise locations within the homotopic parcels. Although the mask contained six parcels, we decided to exclude the left angular gyrus (LAngG) due to accumulating evidence that LAngG differs functionally from the rest of the core temporal and frontal areas and exhibits lower functional connectivity with those core areas (for discussion, see Shain, Chen, Paunov et al., 2022). To define the MD fROIs, we used a set of 20 parcels (10 in each hemisphere) derived from a group-level probabilistic activation overlap map for the *hard* > *easy* spatial working memory contrast (Fedorenko et al., 2013) in 197 independent participants. The parcels included symmetrical regions in frontal and parietal lobes, as well as a region in the anterior cingulate cortex. All parcels are available for download from https://evlab.mit.edu/funcloc/.

Extraction of fMRI BOLD responses

We evaluated language and MD networks' responses by estimating response magnitudes to the conditions of the standard and speeded language localizers in the individually defined fROIs. For each fROI in each participant, we averaged the responses across voxels to get a single value per participant per fROI per condition (i.e., the *sentences* and *nonwords* conditions for the language localizer tasks, and the *hard* and *easy* conditions for the MD localizer task). The responses to the conditions used to localize the areas of interest (e.g., the responses to the *sentences* and *nonwords* conditions in the language fROIs) were estimated using an across-runs cross-validation procedure, where one run of the standard or speeded language localizer was used to define the fROI and the other run of the same localizer version was used to estimate the response magnitudes. The procedure was repeated for each of the two run partitions, once where the first run was used for fROI definition and the second run was used for response estimation and once where the second run was used for fROI definition and the first run was used for response estimation. Finally, the estimates were averaged to derive a single value per participant per fROI per condition.

Statistical analysis

All statistical analyses were performed in RStudio (version 2021.09.2) or Python (version 3.9.2). Linear mixed effects (LME) models were used to test for differences in BOLD response magnitudes and spatial correlations across localizer versions and conditions, while accounting for random effects from different participants and fROIs.

All LMEs reported in the paper were implemented in R using the *lmer* function from the **lme4** package (Bates et al., 2015; version 1.1-31). Fixed effects included the condition (*sentences* vs. *nonwords*) and the localizer version (standard vs. speeded). Their interaction was also included as a fixed effect where specified in order to test whether the effect of condition was different between the two localizer versions. Random intercepts were fit for participants and fROIs. Statistical significance testing was performed using the **lmerTest** package (Kuznetsova et al., 2017; version 3.1-3). Using this package, the t-statistic and associated p-values based on Satterthwaite's approximation were computed. In cases where the interaction term was included, we compared the model with and without the *condition:version* interaction. Model comparison was performed using a likelihood ratio test implemented via the *anova* function in **lme4**, which yielded a χ^2 test statistic.

For analyses involving a single dependent measure per condition (i.e. when comparing spatial correlations between activation maps across the two localizer versions), the fixed-effect included only the localizer version and random intercepts similarly included the participants and fROIs (e.g. *SpCorr LH language ~ version + (1|participant) + (1|fROI)*). Statistical significance was again computed using **lmerTest** based on the t-statistics when comparing model parameters.

For each LME reported, we provide tables containing the model formulae, fixed effects regression coefficients (β-values), t-values, p-values, and random effects coefficients (SI 2E, 3D, 3E, 3F, 4B). R-squared values were computed using the *r.squaredGLMM* function from the **MuMIn** package (version 1.47.1).

In addition to LME analyses, pairwise comparisons between two conditions were conducted using two-sided paired or one-sample t-tests, as appropriate. These tests were implemented with the scipy.stats module in Python. All tests were two-tailed and statistical significance was assessed at $\alpha = 0.05$.

Results

We compared the fMRI BOLD responses from two versions of a language localizer task (a 'standard language localizer' and a 'speeded language localizer'). The results are organized according to the following two questions: 1) Can speeded reading be used to reliably localize language-responsive areas in individual participants?, and 2) Does increased processing difficulty during speeded reading affect brain responses in the domain-general Multiple Demand brain network?

1. The speeded language localizer can reliably localize language-responsive areas in individual participants.

1.A. The activation topography is similar between the standard and speeded language localizer versions.

Twenty-four participants completed a standard language localizer task (Fedorenko et al., 2010) and a speeded localizer task. In both tasks, they silently read sentences (the *sentences* condition) and sequences of nonwords (the *nonwords* condition) (see Methods; fMRI tasks).

The activation maps for the *sentences* > *nonwords* contrast are visually highly similar between the standard and speeded language localizers (**Figure 1A**; see SI 2D for corresponding fROI surface maps in the same sample participants). To quantify this similarity, we correlated voxel-wise activation patterns (restricted to the LH language parcels; see SI 2A for whole-brain correlations) across localizer runs and versions. The correlation values were Fisher-transformed and averaged across the five LH language parcels, leading to a single value for each comparison.

First, we correlated the activation patterns across the two runs *within* each localizer version. These values characterize the stability of the activation patterns for each version and also delimit the similarity that could be obtained between the two localizer versions. The within-localizer Fisher-transformed correlations were high for both versions: 0.955 and 0.966 for the standard and speeded versions, respectively (**Figure 1B**; left bars), and did not statistically differ from each other (*speeded* > *standard*; β=0.011, t=0.226, p=0.821 via linear mixed effects (LME) modeling). Next and critically, we correlated the activation patterns between the two versions of the localizer. To match the amount of data to the within-version comparisons, we correlated activations for each run of the standard version with each run of the speeded version (four pairwise combinations, given two runs of each localizer version; **Figure 1B**; the two *within* bars). The between-localizer Fisher-transformed correlation coefficient was 0.859 (**Figure 1B**; the *between* bar: the average of the four pairwise combinations of runs between the standard and speeded versions). To statistically compare the within- vs. between-version correlations, we modeled the average within-version and between-version correlation coefficients in an LME model with a fixed effect for comparison type (within vs. between), and random intercepts for participants and parcels. The similarity of the activations *within* a given localizer version was statistically higher than between localizer versions **(Figure 1B)**, with a relatively small effect size (**Figure 1B**; *within* > *between;* β=0.102, t=2.763, p=0.006), in line with both within and between correlations being high.

In a complementary analysis, we quantified the extent of voxel overlap between functional regions of interest (fROIs) using the Dice coefficient (Dice, 1945). The results mirrored the spatial correlation analyses above. The overlap between the *sentences* > *nonwords* fROIs, defined as the top 10% of language-responsive voxels, was high for both within and between comparisons (0.754 and 0.718 for the within comparisons for the standard and speeded versions, respectively; and

0.689 for the between comparison), but slightly higher across the runs within a localizer version than between localizer versions (β=0.047, t=3.291, p=0.001) (**Figure 1C**). For fROIs of larger size (e.g., fROIs defined as the top 20% or 30% of most language-responsive voxels within the parcels), the within vs. between differences get smaller (20%: β=0.025, t=2.281, p=0.023; 30%: β=0.012, t=1.238, p=0.217), which suggests that although the peaks of the activation topographies are slightly more similar within a localizer version than between the two versions, the overall topographies are highly similar (see SI 2B for Dice coefficient comparisons across a larger range of fROI thresholds).

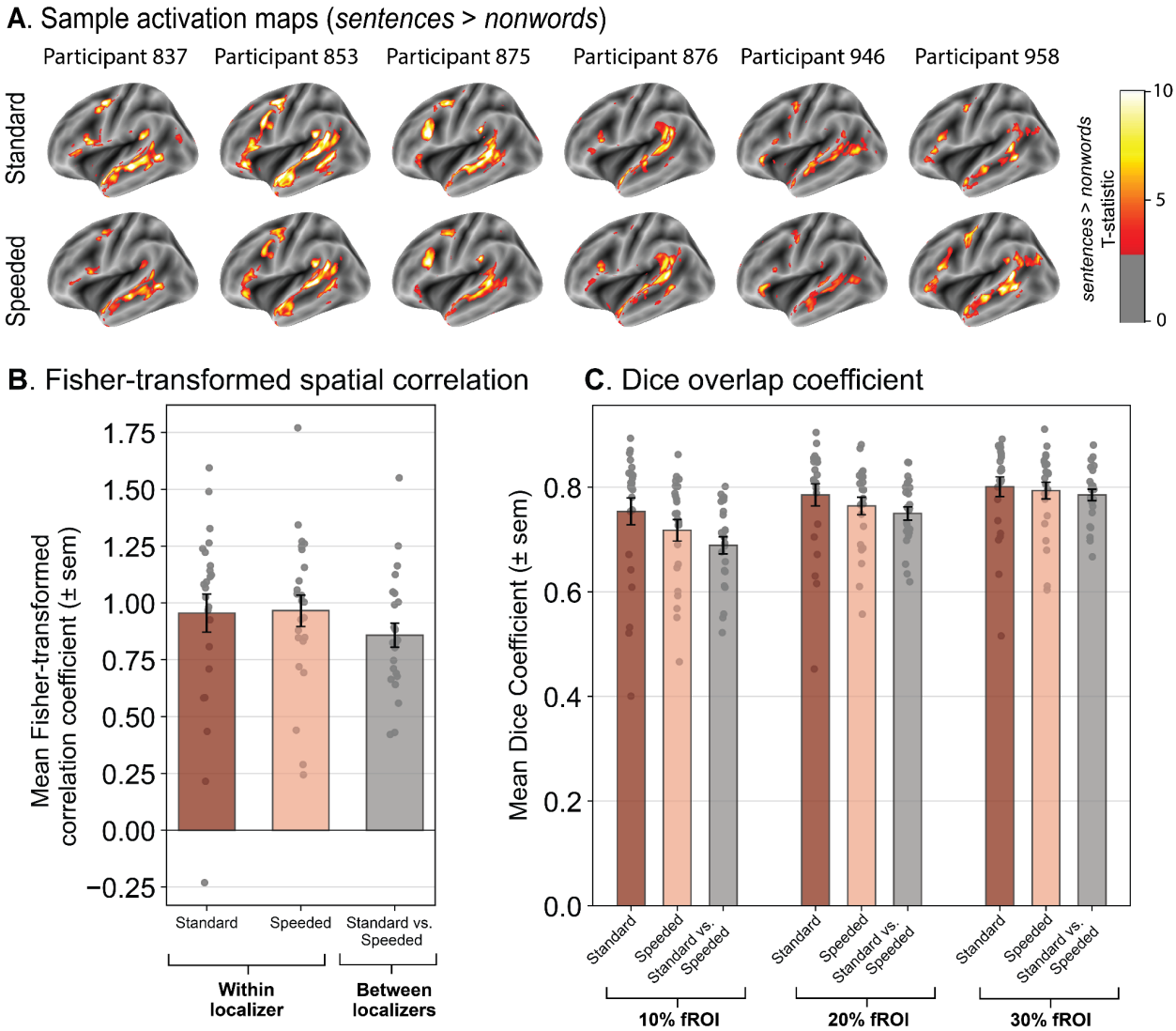

Figure 1. The activation topographies are highly similar between the standard and speeded language localizer versions.

(A) Activation maps of the *sentences* > *nonwords* contrast in six sample participants for the standard language localizer (upper row) and the speeded language localizer (lower row). Activation maps are shown on the surface-inflated fsaverage template brain. The participant identifiers are numbers in the lab internal database and can be cross-referenced with the data tables on OSF.

(B) The correlation of the voxel-wise activation patterns for the *sentences* > *nonwords* contrast within left-hemisphere (LH) language parcels (see Methods; Definition of fROIs) within and between localizer versions. The within localizer comparisons were performed by correlating the activation patterns between the two runs of the same localizer version (dark red bar = standard version; light red bar = speeded version; the data are averaged across participant and across five LH parcels within each participant), and the between localizer comparisons were performed by correlating the four pairwise combinations of runs between the two localizers (given two runs of each localizer; gray bar) and averaging them to obtain a single value. The dots correspond to the correlation values from individual participants (*n*=24). Error bars show the standard error of the mean across participants.
(C) The Dice overlap coefficient for the *sentences* > *nonwords* contrast computed between different runs of the same localizer version or between different runs across the two localizer versions. The fROIs were defined as the top 10%, 20%, or 30% of the most language-responsive voxels in the five LH language parcels. As in panel B, the two red bars show the Dice coefficients within a localizer version (between two runs of the same localizer; the data are averaged across participants and across five LH parcels within each participant) and the gray bar shows the Dice coefficient between localizer versions (averaging across four pairwise between-run comparisons). The dots correspond to the coefficient values from individual participants (*n*=24). Error bars show the standard error of the mean across participants.

1.B. The fROIs defined by the speeded language localizer respond at least as strongly and as selectively during language processing as the fROIs defined by the standard localizer.

Having established that the activation topographies are similar across the localizer versions (**Figure 1**), we examined the magnitude of the BOLD responses for the *sentences* and *nonwords* conditions across the two versions in the fROIs defined by the standard approach of selecting top 10% of most language-responsive voxels within five broad, anatomical parcels (**Figure 2A**; see Methods; Extraction of fMRI BOLD responses). **Figure 2B** shows the average BOLD responses across the five LH language fROIs and **Figure 2C** shows the responses for each of the five fROIs individually. To statistically compare the two localizers, the BOLD responses were modeled in an LME with fixed effects for condition (*sentences* vs. *nonwords*) and localizer version (standard vs. speeded) and random intercepts for participants and fROIs.

As expected, the effect of condition (estimated in independent data) was highly significant (*sentences* > *nonwords*, β=1.897, t=23.570, p<0.0001) (**Figure 2B,C**); in contrast, the main effect of localizer version was not significant (*speeded* > *standard*, β=-0.068, t=-0.851, p=0.395). To further examine whether the standard and speeded versions differed with respect to their responses to *sentences* and *nonwords*, we used a similar LME as above but also included an interaction term between condition and localizer version. We tested for significance of the interaction using a likelihood-ratio test with a Chi Square test statistic (χ^2). Indeed, the interaction was significant (χ^2=20.653, p<0.0001), suggesting that the responses to the two conditions (*sentences* and *nonwords*) differed between localizer versions. To better understand this difference, we examined the size of the *sentences* > *nonwords* contrast and found that it was greater in the speeded localizer compared to the standard localizer (*speeded* > *standard*; β=0.723, t=7.817, p<0.0001). As can be

seen in **Figure 2B,C**, the response to the *sentences* condition was higher in the speeded localizer compared to the standard localizer (*speeded* > *standard*; β=0.293, t=2.407, p=0.017), and the response to the *nonwords* condition was lower in the speeded localizer compared to the standard localizer (*speeded* > *standard*; β=-0.430, t=-5.106, p<0.0001). Taken together, these analyses show that the fROIs defined by the speeded language localizer show a larger *sentences* > *nonwords* effect compared to the standard localizer, due to both higher responses to *sentences* and lower responses to *nonwords* in the speeded version.

Because of the increasing interest in the field of language research in non-canonical language regions (e.g., Li et al., 2024; Wang et al., 2025; Tuckute et al., 2025), we also examined responses in the so-called *extended language network*, encompassing regions on the ventral temporal surface, in the medial frontal cortex, and in the cerebellum; Wolna et al., 2025). We found that the speeded localizer successfully identifies the regions of the extended language network and produces a similar response profile to the standard localizer (**SI 3G**), demonstrating that the speeded version can be used to identify not only the core language areas but also non-canonical language-responsive areas. Following a reviewer's request, we additionally examined responses to language in the Default Mode Network (DMN), which has been implicated in semantic processing (e.g., see Fernandino & Binder, 2024; cf. Humphreys et al., 2015). Using the same individual fROI approach as in our analyses of the language areas and using the *easy* > *hard* contrast from the spatial working memory task to define the DMN regions (following Mineroff, Blank et al., 2018), we did not find substantial responses to language in the DMN regions for either localizer version (with the exception of the left anterior temporal DMN region, which overlaps with the anterior temporal language parcel) (**SI 3H**).

Next, we examined the selectivity of the language fROIs defined by both the standard and the speeded localizers for language processing relative to a non-linguistic demanding cognitive task. Prior work has established that language-responsive brain areas (as defined by standard versions of the language localizer) are highly selective for language relative to diverse non-linguistic inputs and tasks (e.g., Fedorenko et al., 2011; Ivanova et al., 2020, 2021; Chen et al., 2023; for reviews, see Fedorenko & Blank, 2020; Fedorenko et al., 2024). Here, we investigated whether the fROIs defined by the speeded language localizer exhibit a similar degree of selectivity. To do so, we collected brain responses during a spatial working memory task (see Methods; fMRI tasks) and examined BOLD response magnitudes to the *hard* and *easy* conditions in the LH language regions, defined by the standard versus speeded language localizers (**Figure 2D,E**). As expected given the high topographic overlap between the two localizer versions reported in Section 1, both sets of fROIs showed selectivity for language, with no response during the cognitively demanding spatial working memory task (standard localizer: *hard*: t=-2.376, p=0.026; *easy*: t=-0.505, p=0.618 via two-sided, one-sample t-test against zero; speeded localizer: *hard*: t=-1.803, p=0.085; *easy*: t=0.397, p=0.694). This lack of response in the language areas is in sharp contrast with the Multiple

Demand areas, which respond strongly to both conditions, and show a clear *hard* > *easy* effect (SI 3A).

Finally, in addition to the analyses reported in 1.A and 1.B above, we tested whether the BOLD response magnitudes from the fROIs defined by the standard versus speeded localizers were stable over time (across runs (SI 3B) and—for two participants who completed the localizers several times—across scanning sessions (SI 3C)). This is important to know given that BOLD response magnitudes are often used in individual-differences investigations that aim to relate neural measures to behavior (e.g., Mahowald & Fedorenko, 2016; Assem et al., 2020a; Kong et al., 2020). We found that the magnitudes were indeed highly stable within participants over time.

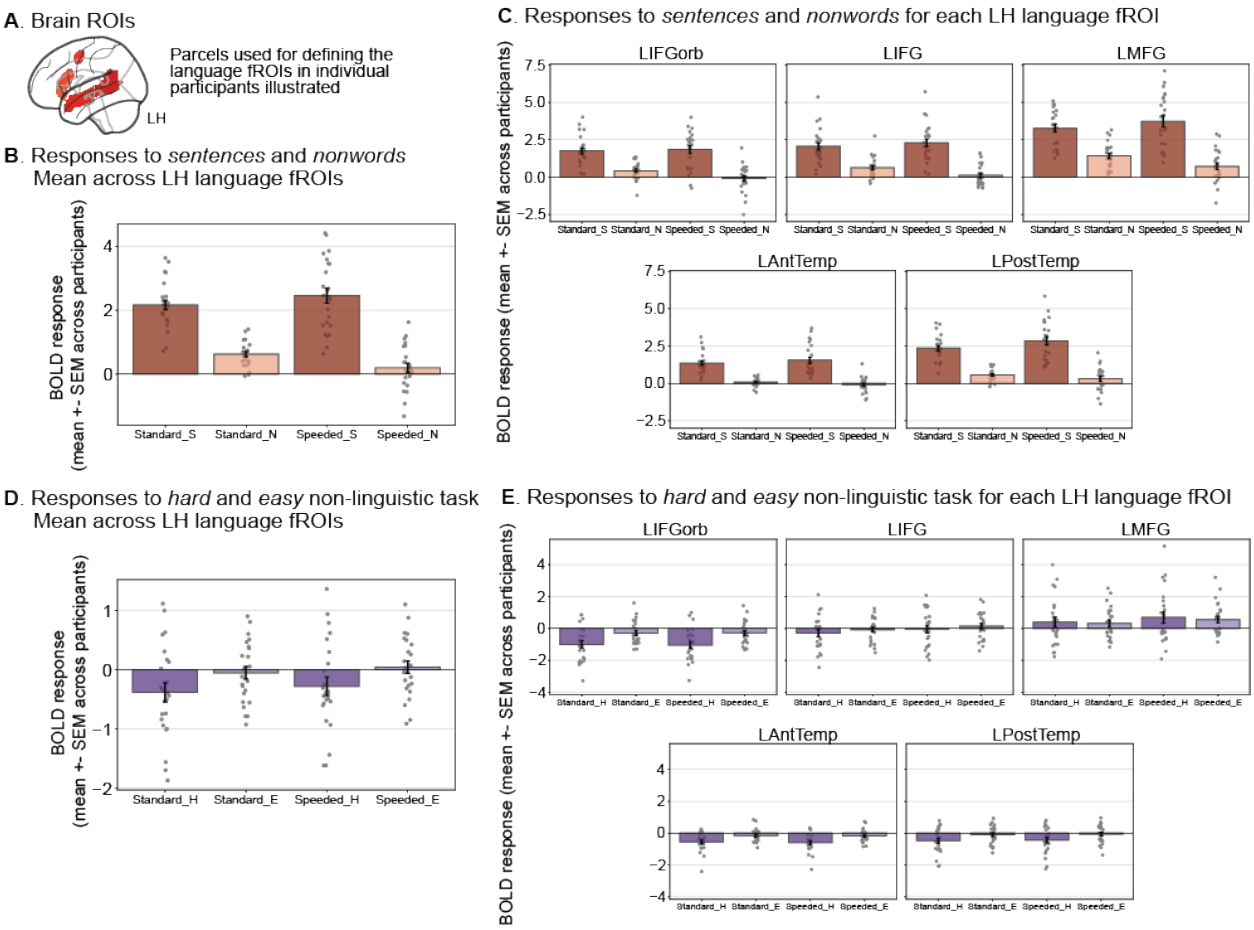

Figure 2. The speeded language localizer elicits a greater *sentences* > *nonwords* effect than the standard language localizer and the fROIs defined by the speeded localizer are similarly selective for language relative to a demanding non-linguistic task.

(A) To define language fROIs, we used a set of masks ('language parcels'; shown on the volumetric MNI152 template brain where all analyses were performed) within which most or all individuals in prior studies showed activity for the language localizer contrast in large samples (e.g., Fedorenko et al., 2010; Lipkin et al., 2022). We defined the LH language fROIs as the most language-responsive voxels (top 10%)

within the borders of these five parcels for each participant and measured the BOLD response magnitude in these fROIs in a cross-validated manner (see Methods; Definition of fROIs).
(B) Mean BOLD response to the language localizer conditions (S=*sentences*, N=*nonwords*) for the standard and speeded localizer versions averaged across the five LH language fROIs.
(C) Mean BOLD response to the localizer conditions for each LH language fROI.
(D) Mean BOLD response to a spatial working memory task consisting of two conditions, a *hard* condition (H) and an *easy* condition (E), averaged across the five LH language fROIs defined by the speeded and standard language localizers. See SI 3A for evidence that the spatial working memory task elicited a robust *hard* > *easy* response in the MD network fROIs.
(E) Mean BOLD response to the *hard* and *easy* spatial working memory task conditions for each LH language fROI.
In all panels, dots correspond to the responses of individual participants. Error bars show the standard error of the mean across participants. See SI 3E for responses in the right-hemisphere (RH) language fROIs (which also show a reliable *sentences* > *nonwords* effect, similar to the LH fROIs, although the responses are overall weaker).

2. Speeded sentence reading engages the domain-general Multiple Demand (MD) system to a greater extent than standard reading.

In addition to examining responses in the language network (Section 1.B), we investigated responses in the domain-general Multiple Demand (MD) network. This network supports computations related to goal-directed behaviors and is recruited during a broad array of cognitively demanding tasks (e.g., Duncan, 2010; Duncan et al., 2012; Fedorenko et al., 2013; Shashidhara et al., 2019; Assem et al., 2020b; Duncan et al., 2020). Of most relevance to the current investigation, the MD network appears to be engaged in some cases of effortful comprehension, including processing speech in noisy conditions or following acoustic degradation (Mattys & Wiget, 2011; MacGregor et al., 2022; Liu et al., 2022), processing accented speech (Adank & Janse, 2010; Janse & Adank, 2012; Adank et al., 2012; Banks et al., 2015), processing languages that one is not fully proficient in (Malik-Moraleda, Jouravlev et al., 2024; Wolna et al., 2024), and processing linguistic inputs that are not syntactically well-formed (Kuperberg et al., 2003; Nieuwland et al., 2012; Mollica et al., 2020; Tuckute et al., 2024b; Kauf et al., 2024). However, understanding the full range of conditions under which the MD network is recruited during language processing remains an important research goal, and is critical for deciphering the nature of the MD network's contributions to language.

Following prior work (e.g., Malik-Moraleda, Ayyash et al., 2022), we defined MD fROIs (10 in each hemisphere; **Figure 3A**) using the *hard* > *easy* contrast of the spatial working memory task described in the previous section (Section 1.B; and Methods; fMRI tasks). We then examined the responses to the *sentences* and *nonwords* conditions across the two versions of the language localizer to test whether speeded reading taxes the MD network. (For validation that the MD fROIs

behave as expected, i.e., show a reliably greater response to the hard spatial working memory condition compared to the easy one, see SI 3A.)

The BOLD response magnitudes for the *sentences* and *nonwords* conditions across both localizer versions are shown in **Figure 3B** for the average of the ten left and right hemisphere MD fROIs and **Figure 3C** for each hemisphere separately (see SI 4A for each of the twenty fROIs individually). In line with prior work (e.g., Fedorenko et al., 2013; Diachek, Blank, Siegelman et al., 2020), the MD fROIs showed a robust *nonwords* > *sentences* effect in the standard language localizer (*sentences* > *nonwords,* β=-0.275, t=-7.547, p<0.0001). In contrast, in the speeded version, reading of *nonwords* did not engage the MD network to a greater extent than reading of *sentences* (*sentences* > *nonwords*, β=-0.012, t=-0.283, p=0.777). As evident from **Figure 3C**, some participants exhibited higher MD network engagement in the *nonwords* condition, whereas others exhibited the opposite pattern. To statistically compare the responses to the two localizers, the BOLD responses were modeled in an LME with fixed effects for condition (*sentences* vs. *nonwords*) and localizer version (standard vs. speeded) and random intercepts for participants and fROIs. Using likelihood ratio tests, we confirmed a significant interaction between condition and localizer version (χ^2=18.274, p<0.0001), suggesting that the MD network was engaged differently by the two localizers. In particular, the MD network was more engaged in the *sentences* condition during the speeded localizer compared to the standard localizer (*speeded* > *standard*, β=0.200, t=4.584, p<0.0001), whereas the responses to the *nonwords* condition did not reliably differ between the two versions (*speeded* > *standard*, β=-0.064, t=-1.519, p=0.129). In summary, speeded sentence reading was more effortful than slower-paced reading, and under the speeded-reading conditions, no *nonwords* > *sentences* effect was observed.

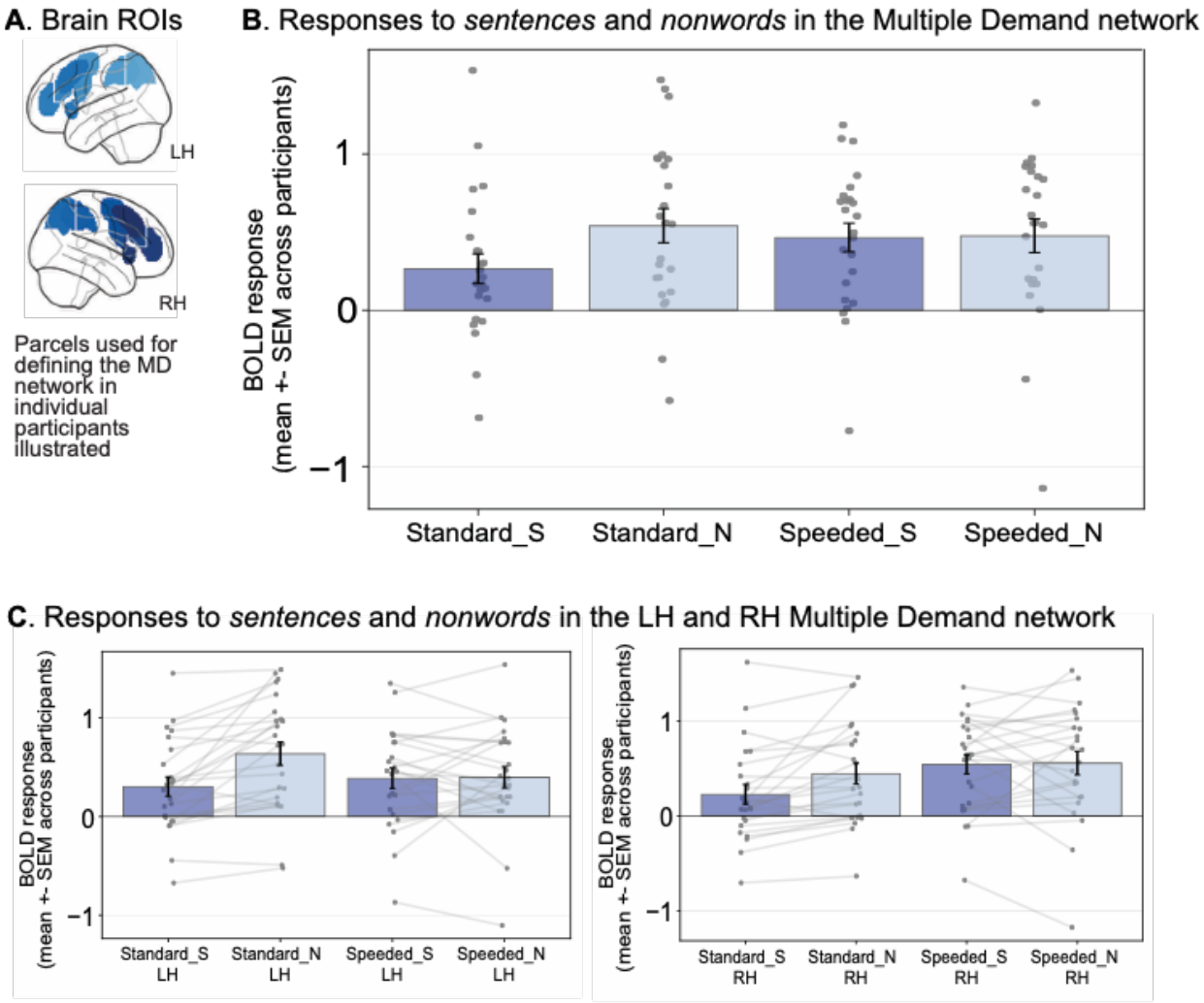

Figure 3. The Multiple Demand (MD) network is more engaged in speeded sentence reading compared to standard sentence reading.
(A) To define MD fROIs, we used a set of masks ('MD parcels'; shown on the volumetric MNI152 template brain) within which most or all individuals in prior studies showed activity for the MD *hard* > *easy* spatial working memory contrast in large samples (e.g., Diachek, Blank, Siegelman et al., 2020). We defined the LH and RH MD fROIs as the most working-memory-responsive voxels (top 10%) within the borders of the twenty parcels for each participant, and measured the BOLD response magnitude in these fROIs in a cross-validated manner (see Methods; Definition of fROIs).
(B) Mean BOLD response to the language localizer conditions (S=*sentences*, N=*nonwords*) for the standard and speeded localizer versions averaged across the twenty LH/RH MD fROIs (see SI 4A for individual fROIs).
(C) Mean BOLD response to the language localizer conditions (S=*sentences*, N=*nonwords*) for the standard and speeded localizer versions averaged across the LH and RH MD fROIs. Light gray lines connect the responses to the two conditions for a given participant and localizer version.
In all panels, dots correspond to the responses of individual participants. Error bars show the standard error of the mean across participants.

Discussion

In cognitive neuroscience, there is a growing recognition of inter-individual differences in the precise functional topographies, especially in the association cortex (e.g., Frost & Goebel, 2012; Tahmasebi et al., 2012; Braga et al., 2020; Gratton & Braga, 2021; DiNicola et al., 2023; Du et al., 2024). We here show that a standard localizer for the language network (Fedorenko et al., 2010) can be halved in time by using speeded reading, and that the speeded-reading-based contrast is even more robust than the one based on standard-paced reading. In the remainder of the Discussion, we elaborate on these findings and their implications.

1. Robustness and generalizability of the language localizer.

The standard language localizer (Fedorenko et al., 2010) investigated in our study has been widely used over the past decade (e.g., Fedorenko et al., 2010; Mahowald & Fedorenko, 2016; Braga et al., 2020; Lipkin et al., 2022; Du et al., 2024). The localizer contrasts the reading of well-formed sentences versus sequences of nonwords. The brain areas identified by this contrast have been shown to be robust across different linguistic materials (e.g., Fedorenko et al., 2010)—an effect we replicate here—and tasks (e.g., Diachek, Blank, Siegelman et al., 2020; Gao et al., 2025). Moreover, this contrast generalizes well to the auditory and audio-visual presentation modalities (e.g., Fedorenko et al., 2010; Scott et al., 2017; Olson et al., 2023) and works well across typologically diverse languages (Richardson et al., 2020; Malik-Moraleda et al., 2022; Terhune-Cotter et al., 2023) and for diverse populations, including children (Hiersche et al., 2024; Ozernov-Palchik, O'Brien et al., in press), older healthy adults (Billot, Jhingan et al., 2025), and individuals with stroke aphasia (Billot, 2023; Clercq et al., 2024; Billot et al., in prep). In the current study, we show that the reading version of the localizer is robust to presentation speed, in line with past behavioral work showing the ability to understand language at fast speeds when presented word-by-word in a rapid serial visual presentation (RSVP) paradigm (e.g., Forster, 1970; Potter et al., 1980, 1986; Potter, 2012; Mollica & Piantadosi, 2017), and in line with prior group-averaging fMRI studies (Vagharchakian et al., 2012; Benjamin & Gaab, 2012). In the speeded version that we evaluated, each word was presented for 200 ms (compared to 450 ms in the standard localizer, i.e., ~56% faster), and we demonstrate that language areas in individual participants can be reliably localized using this version.

2. The speeded language localizer shows at least as strong selectivity for language relative to the control condition and a non-linguistic demanding task.

In the current work, we first established that the voxel-level activation topographies were highly similar between the standard and speeded language localizers, and then demonstrated that the response magnitudes in fROIs defined by each localizer version were also similar both in their responses to language and a control condition, and in their selectivity for language relative to a non-linguistic working memory task (e.g., Duncan, 2010; Fedorenko et al., 2013). Moreover, the speeded localizer is actually more effective than the standard version given that it better differentiates the critical language condition and the control condition. Specifically, the speeded

localizer elicited a stronger response to the *sentences* condition, possibly due to an increase in attentional demands or processing difficulty (but see next discussion section), and a weaker response to the control condition (*nonwords*). The reduced response to nonwords may be due to the increased challenge of reading nonwords quickly which in turn might reduce the accessibility of information about their phonotactic properties (e.g., Regev et al., 2024). Thus, the speeded localizer produced a response profile with at least as strong responses to language as the standard localizer. Additionally, the areas identified by the speeded localizer were selective for language relative to a non-linguistic spatial working memory task, similar to the profile of the areas identified using the standard localizer (see Fedorenko & Blank, 2020 and Fedorenko et al., 2024 for reviews).

We also found that the size of the *sentences* > *nonwords* contrast was stable across runs for the speeded localizer version, similar to the standard version, which suggests that the speeded localizer can also be used in studies that relate neural markers to behavior or genetics to study individual differences (e.g., Mahowald & Fedorenko, 2016; Assem et al., 2020a; Kong et al., 2020).

3. Contributions of the Multiple Demand (MD) network to language comprehension.

The Multiple Demand (MD) network is broadly implicated in cognitively demanding tasks and goal-directed action, showing strong responses to diverse executive function tasks (Duncan & Owen, 2000; Duncan, 2010; Duncan et al., 2012; Fedorenko et al., 2013; Shashidhara et al., 2019b; Assem et al., 2020b; Duncan et al., 2020) as well as during some domains of reasoning, like arithmetic reasoning (e.g., Monti et al., 2009; Fedorenko et al., 2013; Amalric & Dehaene, 2019) and understanding computer code (e.g., Ivanova et al., 2020; Liu et al., 2020). Further, language paradigms where comprehension/production is accompanied by extraneous task demands—e.g., performing meta-linguistic judgments or answering comprehension questions—have been shown to engage frontal and parietal areas whose topography is consistent with that of the MD network (e.g., Cutting et al., 2006; Christodoulou et al., 2014). Similar studies that have included an MD network localizer confirm that these task effects occur in the MD areas (e.g., Diachek, Blank, Siegelman et al., 2020; Gao et al., 2025). However, during naturalistic comprehension of even syntactically complex stimuli, the MD network is not engaged, at least when linguistic stimuli are presented auditorily, and the costs of language processing are localized to the language-selective system (Diachek, Blank, Siegelman et al., 2020; Quillen et al., 2021; Wehbe et al., 2021; Shain et al., 2022; see review, see Fedorenko & Shain, 2021). Unlike passive listening to language, passive sentence reading, even at typical speeds, sometimes elicits a slightly above-baseline response (e.g., Gao et al., 2025). We see such a response here for our standard version as well. This effect may have to do with the fact that unlike listening, reading is a later-acquired skill and may be associated with some amount of cognitive effort even for proficient readers.

In contrast to the costs associated with *linguistic* demands specifically (e.g., processing unexpected elements or building non-local inter-word dependencies; Shain, Blank et al., 2020; Shain et al.,

2022), some cases of effortful comprehension, even without external task demands, appear to engage the MD network. Such cases include listening to speech in noisy conditions (Mattys & Wiget, 2011; MacGregor et al., 2022; Liu et al., 2022), processing accented speech (Adank & Janse, 2010; Janse & Adank, 2012; Adank et al., 2012; Banks et al., 2015), processing sentences in a language that one is not fully proficient in (Malik-Moraleda, Jouravlev et al., 2024; Wolna et al., 2024), and processing linguistic inputs that are not syntactically well-formed (Kuperberg et al., 2003; Nieuwland et al., 2012; Mollica et al., 2020; Tuckute et al., 2024b; Kauf et al., 2024). A possible generalization about these cases is that they all involve difficulty extracting a syntactically parsable word sequence from perceptual linguistic inputs.

Here, we present another case where passive language comprehension engages the MD network: speeded reading (for earlier evidence, see Vagharchakian et al., 2012, although the evidence is indirect as no independent MD localizer is included). The MD regions' response during the *sentences* condition was ~43% higher in the speeded version compared to the standard version (cf. a much smaller difference observed in the language regions: a ~16% increase for the speeded version). Interestingly, in some previously reported cases, the linguistic condition that engages the MD network to a greater extent elicits a *lower* response in the language areas. For example, Malik-Moraleda, Jouravlev et al. (2024) show that comprehension of languages in which participants have low proficiency engages the MD network more strongly than higher-proficiency languages, but elicits a *lower* response in the language network. In contrast, the speeded sentence reading condition elicited a higher response compared to the normal-speed reading condition in both the MD network and the language network. This pattern may be taken to suggest that the generalization above—that the MD network gets engaged when it is difficult to extract a syntactically parsable word sequence from perceptual inputs—is not correct: this kind of difficulty should systematically lead to lower responses in the language network given that partially comprehensible stimuli should not be able to engage linguistic computations to the full extent (see Malik-Moraleda, Jouravlev et al., 2024 and Ozernov-Palchik, O'Brien et al., in press, for discussion). Thus, the precise contributions of the MD network during different kinds of effortful linguistic processing remain to be determined.

Finally, given the MD network's stronger response during the speeded sentence reading condition but a similarly strong response during the nonword reading condition, the speeded localizer does not elicit a *nonwords* > *sentences* effect in the MD regions, in contrast to the standard language localizer (Fedorenko et al., 2013; Diachek, Blank, Siegelman et al., 2020). A practical implication is that it is not possible to use the *nonwords* > *sentences* contrast in the speeded version to localize the MD network (in addition to the language network) as is sometimes done (e.g., Shain, Blank et al., 2020). Whether the time saved by the speeded language localizer version is worth this trade-off of not being able to functionally define the MD regions using the same localizer will depend on the researcher's goals.

4. Other efforts in cognitive neuroscience to develop efficient localizers.

Functional localizers increase the sensitivity, functional resolution, and interpretability of research in cognitive neuroscience, but they take up precious time during the study. As a result, there is growing interest in making localizers more efficient. Two approaches have been taken to create more efficient localizers: i) reducing the number and/or the duration of experimental blocks , or ii) trying to optimize the critical stimuli so as to increase the size of the *critical* > *control* effect. Our approach falls into the first category: by increasing the speed of (visually) presenting linguistic materials (by ~56%), we shortened experimental blocks from 18 s (3 6-second trials) to 9 s (3 3-second trials). (Note that although we retained the original 14 s fixation blocks for maximum comparability with the standard version, the fixation blocks could likely be shortened to 9 s, which would shave off another 30 s from the run's duration.) Lee et al. (2024) also took the first approach, but instead of changing the presentation speed, they iteratively removed blocks and examined the consequences on brain responses. They showed that for a standard auditory language localizer based on the contrast of *intact speech* > *degraded speech* (as introduced in Scott et al., 2017) reducing the two-run protocol from ~12 minutes (16 intact and 16 degraded blocks) to ~6 minutes at 50% (16 blocks total) and even ~3.5 minutes at 25% (8 blocks total) suffice for localizing the language regions.

The approach of stimulus optimization was used by Dodell-Feder et al. (2011), who analyzed responses to individual stimuli in a standard Theory of Mind (ToM) network localizer (Saxe & Kanwisher, 2003). Using a large dataset of a few hundred participants, they identified a) a subset of the critical-condition items (false belief stories) that elicit the highest response in the ToM brain areas, and b) a subset of the control-condition items (false photograph stories) that elicit the lowest response in the ToM areas. These subsets were used to create a highly efficient ToM localizer (see Chen, Kamps et al., 2024 for a related approach). Other studies have attempted to select stimuli that would be especially exciting for particular individuals based on their interests. For example, Olson, D'Mello et al. (2023) used language materials on topics of interest to different individuals with autism and found stronger responses in the language areas with those custom-selected stimuli. Finally, with the advent of neural networks that are predictive of brain responses (e.g., Yamins et al., 2014; Schrimpf et al., 2021, Tuckute et al., 2024a), it is now possible to create or select stimuli that elicit maximal responses in the target region/network (Bashivan et al., 2019; Xiao & Kreiman, 2020; Ratan Murty et al., 2021; Gu et al., 2023; Tuckute et al., 2024b). To our knowledge, these advances have not yet been leveraged in the creation of efficient localizers, but they certainly can and should be.

In addition to increasing the efficiency of a given localizer, another recent effort is to combine several localizers into a single experiment. For example, Marvi, Hutchinson et al. (2025) propose a multimodal localizer with simultaneous presentation of visual stimuli, such as faces, bodies, and scenes, which can be processed relatively bottom-up/automatically (e.g., Bugatus et al., 2017; Mur et al., 2025), and auditory stimuli, such as meaningless speech, sentences, and even short passages,

which engage high-level ToM areas. This multimodal localizer is shown to elicit brain responses comparable to administering all the different contrasts in independent tasks.

Increasing localizer efficiency in all these ways is valuable given the increasing popularity of precision imaging approaches in cognitive neuroscience (Gordon et al., 2017; Naselaris et al., 2021; Gratton & Braga, 2021; Allen et al., 2022).

5. Limitations.

A limitation of the speeded localizer is that it is dependent on the reading level of participants and the ability to read under speeded conditions. We took inspiration from prior behavioral evidence of successful linguistic processing under RSVP at presentation rates that are even faster than the 200ms/word used here (e.g., Forster, 1970; Potter et al., 1980, 1986; Potter, 2012; Mollica & Piantadosi, 2017). But of course, in those earlier studies, and in our study, the participants are proficient adult readers. The speeded localizer may be less suitable for children, older adults, and other populations that may have difficulties with reading at fast rates (e.g., Christodoulou et al., 2014).

A limitation of the current study design is that the standard language localizer was always presented prior to the speeded version (typically separated by other, unrelated tasks), so differences, or lack thereof, between the two versions could be confounded by task order. Although the experimental materials were always different between the versions, repeating a similar task within a session can modulate BOLD responses through practice with the task, practice-related changes in strategy, or reduced attention later in the session. However, these kinds of confounds should lead to lower BOLD responses later in the session (e.g., Landau et al., 2004; Grill-Spector et al., 2006). However, we observe that the response to the critical sentence condition in the speeded version is *higher* than the responses to sentences in the standard version despite being administered later in the session. It is quite likely that doing the reading in an RSVP paradigm at a slower rate makes it easier to perform it at a faster rate later, so performing the speeded version first may lead to an even stronger response to the sentence condition, but this possibility remains to be evaluated.

6. Conclusions.

We hope that researchers working with populations who are proficient readers would benefit from this version of the language localizer, and that creating more efficient localizers, like this one, would lead to an even more widespread adoption of functional localization as a way to build a cumulative research enterprise where findings can be more straightforwardly compared across studies and labs.

Data and code availability

The scripts for running the speeded language localizer as well as the associated analyses can be found here: https://github.com/el849/speeded_language_localizer/. The data can be found on OSF: https://osf.io/2vskh/.

Author contributions

Conceptualization: G.T., E.F. Data curation: G.T., E.J.L., A.S. Investigation: G.T., E.J.L., A.S. Formal analysis: G.T., E.J.L. Visualization: G.T., E.J.L., Writing-original draft: G.T., E.J.L., E.F., Writing-review and editing: G.T., E.J.L., A.S., E.F.

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Ethics

All participants gave informed written consent in accordance with the requirements of the MIT's Committee on the Use of Humans as Experimental Subjects (COUHES).

Declaration of competing interests

The authors have no competing interests to declare.

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Supplementary Information

Overview

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SI 1: Details on fMRI acquisition sequences

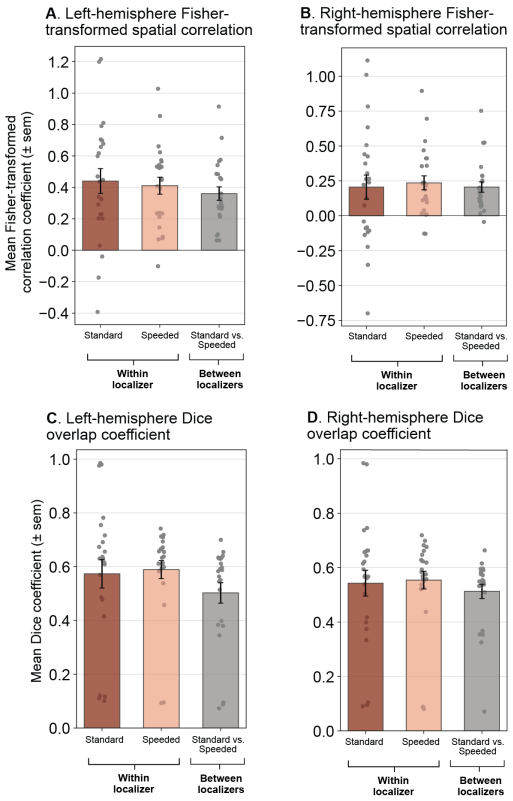
	A	B	C
Number Participants	22*	2*	1
Sequence			
Type	SMS-EPI	EPI with GRAPPA	EPI with GRAPPA
Flip Angle	90	90	90
Acceleration Factor	2	2	2
Acquisition Parameters			
Number Slices	52	33	31
Slice Thickness	2mm	4mm	4mm
In-plane Resolution	2mm x 2mm	2.1mm x 2.1mm	2.1mm x 2.1mm
FoV	208mm	200mm	200mm
FoV Matrix Size	104 x 104	96 x 96	96 x 96
TR	2000ms	2000ms	2000ms
TE	30ms	30ms	30ms

SI Table 1. **Functional MRI acquisition sequences.**

* One participant had the standard language localizer acquired using sequence B, and the speeded language localizer acquired using sequence A. For all remaining participants, the acquisition sequence was kept constant in all comparisons between the standard and the speeded versions of the language localizer. For acquisition of the Multiple Demand (MD) localizer task, all participants besides one, completed the MD localizer task in the same session as the language localizer tasks. The remaining participant completed the two language localizer tasks using sequence B, while the MD task was acquired using sequence A in a later session.

SI 2: Information related to Results Section 1.A

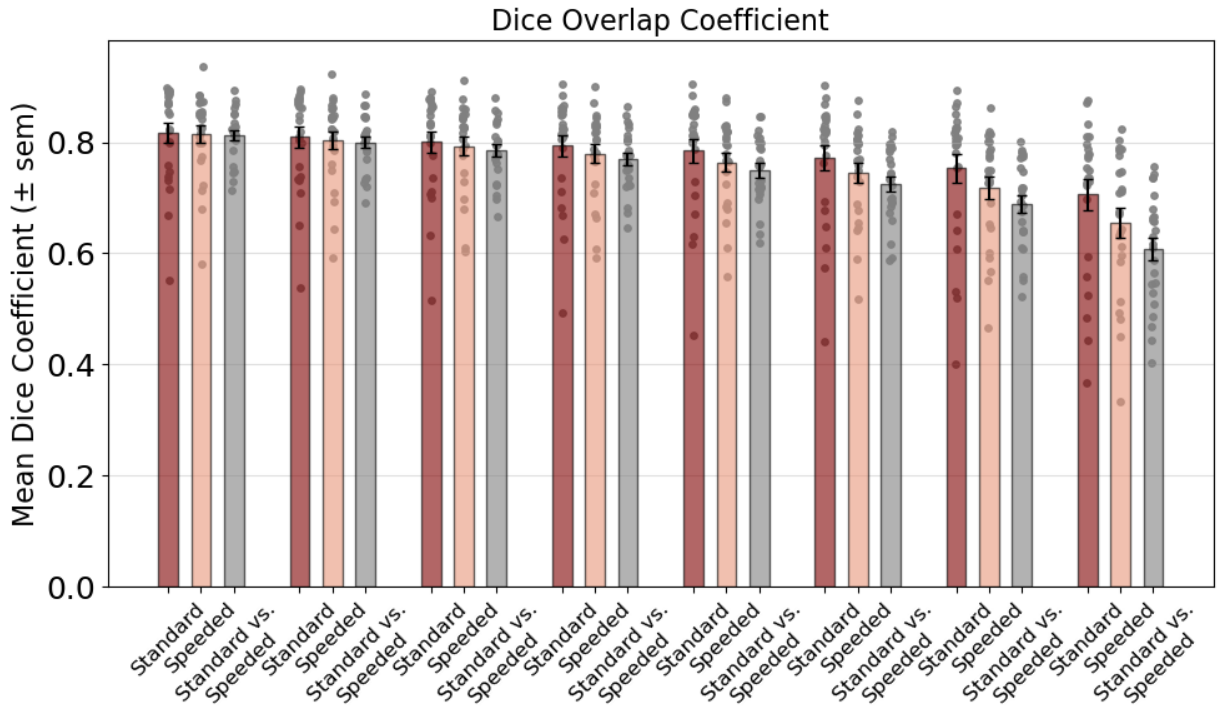
SI 2A: Whole-brain spatial correlation (supplementing language parcel correlations in Figure 1B and Figure 1C)



SI Figure 2A: Correlation of whole-brain voxel-wise activation patterns and overlap coefficient within and between language localizer versions (for the left and right hemispheres separately).
(A-B) We quantified the correlation of the voxel-wise activation patterns for the *sentences* > *nonwords* contrast within the whole left hemisphere (**panel A**) and right hemisphere (**panel B**) within localizer versions (between the two runs of the same localizer; red bars) and between localizer versions (for a total of four such pairwise combinations, given two runs of each localizer version; gray bar). In both panels, the bars show the average Fisher-transformed correlation coefficient across participants and individual points show the correlation values from individual participants (*n*=24). Error bars show the standard error of the mean across participants.
(C-D) For an additional metric of the similarity of voxel-wise activation patterns for the *sentences* > *nonwords* contrast between the standard and speeded localizers, we computed the Dice coefficient overlap within the whole left hemisphere (**panel C**) and right hemisphere (**panel D**) within localizer versions (between the two runs of the same localizer; red bars) and between localizer versions (for a total of four such pairwise combinations, given two runs of each localizer version; gray bar). The Dice coefficient was computed as: $2 * |Standard \cap Speeded| / (|Standard| + |Speeded|)$ for each hemisphere, where $|Standard \cap Speeded|$ denotes the number of voxels that were in the top 10% responsive voxels for both the standard and speeded localizer versions, $|Standard|$ denotes the number of voxels in the top *10%* for the standard localizer version, and $|Speeded|$ denotes the number of voxels in the top 10% for the speeded localizer version (Note: $|Standard| = |Speeded|$ because the same parcels were used for both localizer

versions). This computation provides a value between 0 and 1, where 0 indicates that the two localizer versions identified completely non-overlapping regions, and 1 indicates that the two localizer versions identified completely overlapping regions. In both panels, the bars show the average Dice coefficient across participants and individual points show the overlap values from individual participants (*n*=24). Error bars show the standard error of the mean across participants.

SI 2B: Dice overlap coefficient between the standard and speeded language localizer versions

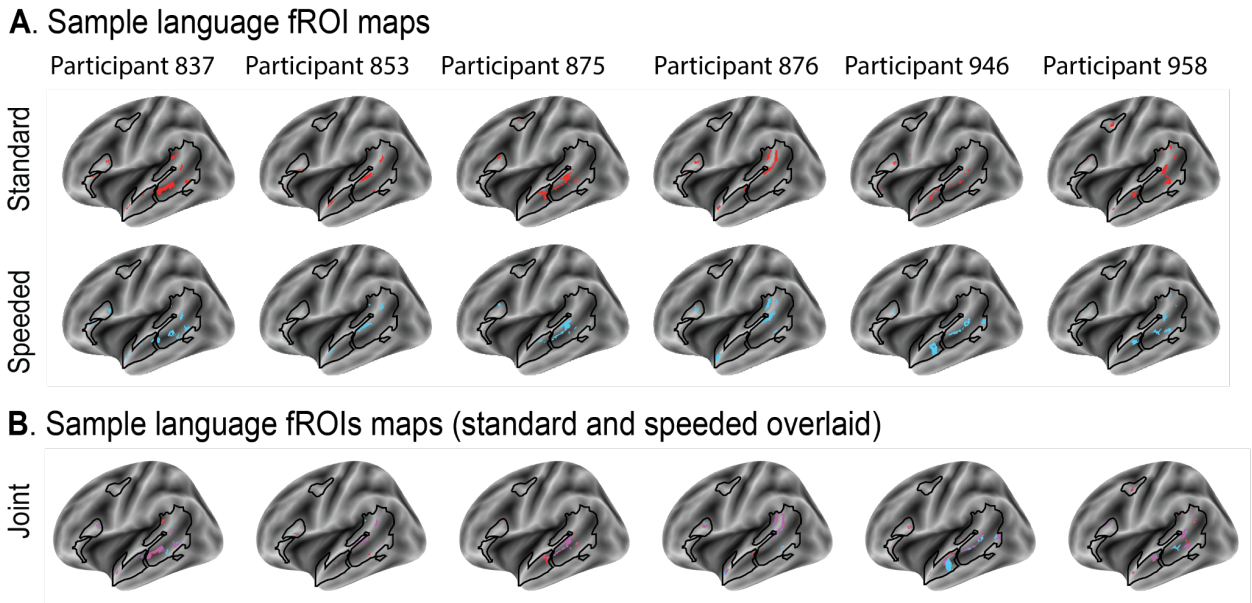


SI Figure 2B. Dice coefficient overlap values across a range of fROI definition thresholds.
We quantified the Dice coefficient overlap at a range of fROI definition thresholds. For each participant, the top *n*% most responsive voxels to the *sentences* > *nonwords* contrast in each of the LH language parcels were selected in both the standard and speeded localizer versions. *n* denotes the percentage threshold for fROI inclusion, and we show results for *n* = [5, 10, 15, 20, 25, 30, 35, 40]. The bars above show the average Dice coefficient across the five LH language fROIs.
Note that in some participants (in particular for larger values of *n*), not all top *n*% voxels displayed a positive *sentences* > *nonwords* t-statistic. In this case, the voxels with negative t-statistic (i.e., opposite selectivity) were excluded from the Dice coefficient analyses. See the number of included voxels across the range of *n* in SI Table 2C.

Firstlevel	Constant	Threshold (top n%)	LH_IFGorb Mean	LH_IFGorb StDev	LH_IFG Mean	LH_IFG StDev	LH_MFG Mean	LH_MFG StDev	LH_AntTemp Mean	LH_AntTemp StDev	LH_PostTemp Mean	LH_PostTemp StDev
Standard	S-N	40	145.167	9.412	276.958	67.322	181.875	14.069	651.000	0.000	1179.000	0.000
		35	128.750	4.484	243.708	57.326	160.083	9.390	570.000	0.000	1032.000	0.000
		30	111.333	1.857	209.792	47.352	138.042	4.695	488.000	0.000	885.000	0.000
		25	93.708	3.470	175.875	37.635	116.000	0.000	407.000	0.000	737.000	0.000
		20	75.500	7.348	141.958	28.440	93.000	0.000	326.000	0.000	590.000	0.000
		15	56.000	0.000	107.833	20.412	70.000	0.000	244.000	0.000	443.000	0.000
		10	37.000	0.000	72.375	12.860	47.000	0.000	163.000	0.000	295.000	0.000
		5	19.000	0.000	36.917	5.307	24.000	0.000	82.000	0.000	148.000	0.000
	ODD_S-N	40	143.750	9.918	273.125	65.409	181.125	11.066	651.000	0.000	1179.000	0.000
		35	129.292	5.137	242.958	54.865	160.792	4.303	570.000	0.000	1032.000	0.000
		30	112.208	6.359	210.708	45.028	139.000	0.000	488.000	0.000	885.000	0.000
		25	93.000	0.000	178.083	36.710	116.000	0.000	407.000	0.000	737.000	0.000
		20	74.000	0.000	143.042	29.190	93.000	0.000	326.000	0.000	590.000	0.000
		15	56.000	0.000	107.583	21.637	70.000	0.000	244.000	0.000	443.000	0.000
		10	37.000	0.000	72.125	14.085	47.000	0.000	163.000	0.000	295.000	0.000
		5	19.000	0.000	36.667	6.532	24.000	0.000	82.000	0.000	148.000	0.000
	EVEN_S-N	40	137.292	25.752	268.500	70.902	174.958	33.146	651.000	0.000	1163.458	47.110
		35	122.417	19.525	237.667	58.238	154.125	26.713	570.000	0.000	1030.417	5.563
		30	106.292	13.343	206.833	46.400	133.042	20.230	488.000	0.000	885.000	0.000
		25	90.542	7.763	174.917	35.466	111.958	13.757	407.000	0.000	737.000	0.000
		20	73.750	3.926	141.792	25.307	90.875	7.321	326.000	0.000	590.000	0.000
		15	57.250	5.712	107.875	15.470	69.708	1.429	244.000	0.000	443.000	0.000
		10	37.000	0.000	73.542	7.144	47.000	0.000	163.000	0.000	295.000	0.000
		5	19.000	0.000	38.000	0.000	24.000	0.000	82.000	0.000	148.000	0.000
Speeded	S-N	40	148.000	0.000	294.625	8.272	185.000	0.000	651.000	0.000	1179.000	0.000
		35	130.000	0.000	260.000	0.000	162.000	0.000	570.000	0.000	1032.000	0.000
		30	111.000	0.000	223.000	0.000	139.000	0.000	488.000	0.000	885.000	0.000
		25	93.000	0.000	186.000	0.000	116.000	0.000	407.000	0.000	737.000	0.000
		20	74.000	0.000	149.000	0.000	93.000	0.000	326.000	0.000	590.000	0.000
		15	56.000	0.000	112.000	0.000	70.000	0.000	244.042	0.204	443.000	0.000
		10	37.000	0.000	75.000	0.000	47.000	0.000	163.000	0.000	295.000	0.000
		5	19.000	0.000	38.000	0.000	24.000	0.000	82.000	0.000	148.000	0.000
	ODD_S-N	40	148.000	0.000	286.708	38.150	185.000	0.000	651.000	0.000	1179.000	0.000
		35	130.000	0.000	252.792	28.915	162.000	0.000	570.000	0.000	1032.000	0.000
		30	111.000	0.000	218.750	20.821	139.000	0.000	488.000	0.000	885.000	0.000
		25	93.000	0.000	183.292	13.268	116.000	0.000	407.000	0.000	737.000	0.000
		20	74.000	0.000	147.833	5.715	93.000	0.000	326.000	0.000	590.000	0.000
		15	56.000	0.000	112.000	0.000	70.000	0.000	244.000	0.000	443.000	0.000
		10	37.000	0.000	75.000	0.000	47.000	0.000	163.000	0.000	295.000	0.000
		5	19.000	0.000	38.000	0.000	24.000	0.000	82.000	0.000	148.000	0.000
	EVEN_S-N	40	141.417	24.702	289.875	25.197	185.000	0.000	646.625	21.433	1168.333	52.256
		35	124.917	20.231	255.958	15.482	162.000	0.000	569.000	4.899	1027.458	22.250
		30	107.500	15.916	221.500	7.348	139.000	0.000	488.000	0.000	885.000	0.000
		25	90.500	12.247	186.000	0.000	116.000	0.000	407.000	0.000	737.000	0.000
		20	72.292	8.369	149.000	0.000	93.000	0.000	326.000	0.000	590.000	0.000
		15	55.042	4.695	112.000	0.000	70.000	0.000	244.000	0.000	443.000	0.000
		10	36.833	0.816	75.000	0.000	47.000	0.000	163.000	0.000	295.000	0.000
		5	19.000	0.000	38.000	0.000	24.000	0.000	82.000	0.000	148.000	0.000

SI Table 2C. Number of included voxels across fROI definition thresholds for Dice overlap analyses. Mean and standard deviation for the number of voxels across participants in each left-hemisphere language fROI that were included in the fROIs for the Dice coefficient overlap analyses (i.e., voxels with a positive t-value corresponding to the *sentences* > *nonwords* contrast). For the Dice analyses, voxels that demonstrate the opposite selectivity (negative t-values) were excluded. The total number of voxels in the parcels were: LH_IFGorb: 370; LH_IFG: 743, LH_MFG: 462, LH_AntTemp: 1627, LH_PostTemp: 2948, and if no participants displayed negative t-values for the *sentences* > *nonwords* contrast the number of voxels included in the Dice analyses would always correspond to a given percentage threshold (*n*). As evidenced from the table, in most cases all *n* % voxels show positive t-values, but occasionally some voxels are excluded (in particular, for larger *n*).

SI 2D: Sample participant fROI Maps



SI Figure 2D. fROI maps for the standard and speeded language localizers.
(A) Binary maps of the language fROIs in six sample participants for the standard language localizer (upper row in red) and the speeded language localizer (lower row in blue). fROIs were defined by selecting the top 10% most responsive voxels to the *sentences* > *nonwords* contrast (see Methods; Definition of fROIs). Maps are shown on the surface-inflated fsaverage template brain. The participant identifiers are numbers in the lab internal database and can be cross-referenced with the data tables on OSF.
(B) Overlay of the language fROI maps from **(A)**. The fROI defined using the standard language localizer is shown in red, the fROI defined using the speeded language localizer is shown in blue. Regions that are overlapping in the two localizers are shown in purple.

SI 2E: Statistics tables for Results Section 1.A

In the tables below, "SpCorr" denotes the Fisher-transformed spatial correlation coefficient. "within_between" denotes whether a spatial correlation coefficient was computed within localizer or between localizer versions. "participant" denotes each of the *n*=24 participants. "fROI" denotes each of the LH or RH regions of interest (five fROIs in each hemisphere).

SpCorr LH language ~ version + (1|participant) + (1|fROI)

Spcorr comparison of (within) standard and (within) speeded localizers, $r^2 = 0.4024$

	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	0.955	0.078	22.310	12.221	0.000
VersionSpeeded	0.011	0.047	211.788	0.226	0.821

SpCorr LH language ~ within_between + (1|participant) + (1|fROI)

Spcorr within localizer vs. between localizer versions, $r^2 = 0.432$

	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	0.859	0.074	24.566	11.601	0.000
Conditionwithin	0.102	0.037	331.871	2.763	0.006

SpCorr language (LH wholebrain) ~ within_between + (1|participant)

Spcorr within localizer vs. between localizer versions (left-hemisphere wholebrain), $r^2 = 0.5399$

	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	0.360	0.059	45.810	6.076	0.000
Conditionwithin	0.065	0.050	48.000	1.315	0.195

SpCorr language (RH wholebrain) ~ within_between + (1|participant)

Spcorr within localizer vs. between localizer versions (right-hemisphere wholebrain), $r^2 = 0.4235$

	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	0.206	0.060	53.012	3.406	0.001
Conditionwithin	0.015	0.056	48.000	0.265	0.792

Dice coefficient ~ within_between + (1|participant) + (1|fROI)

Dice within localizer vs. between localizer versions (top 10%), $r^2 = 0.344$

	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	0.689	0.028	13.617	24.527	0.000
Conditionwithin	0.047	0.014	331.866	3.291	0.001

Dice within localizer vs. between localizer versions (top 20%), $r^2 = 0.3726$

	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	0.750	0.023	13.771	32.806	0.000
Conditionwithin	0.025	0.011	331.882	2.281	0.023

Dice within localizer vs. between localizer versions (top 30%), $r^2 = 0.361$

	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	0.785	0.019	15.668	40.276	0.000
Conditionwithin	0.012	0.010	331.870	1.238	0.217

Dice coefficient (LH wholebrain) ~ within_between + (1|participant) + (1|fROI)

Dice within localizer vs. between localizer versions (left-hemisphere wholebrain top 10%), $r^2 = 0.0518$

	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	0.502	0.042	71.944	12.078	0.000
Conditionwithin	0.079	0.050	48.000	1.565	0.124

Dice within localizer vs. between localizer versions (left-hemisphere wholebrain top 20%), $r^2 = 0.3757$

	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	0.953	0.020	56.158	46.970	0.000
Conditionwithin	-0.003	0.020	48.000	-0.130	0.897

Dice within localizer vs. between localizer versions (left-hemisphere wholebrain top 30%), $r^2 = 0.2216$

	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	0.969	0.003	65.909	370.615	0.000
Conditionwithin	-0.002	0.003	48.000	-0.878	0.384

Dice coefficient (RH wholebrain) ~ within_between + (1|participant) + (1|fROI)

Dice within localizer vs. between localizer versions (right-hemisphere wholebrain top 10%), $r^2 = 0.1371$

	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	0.513	0.036	69.680	14.337	0.000
Conditionwithin	0.036	0.041	48.000	0.875	0.386

Dice within localizer vs. between localizer versions (right-hemisphere wholebrain top 20%), $r^2 = 0.2916$

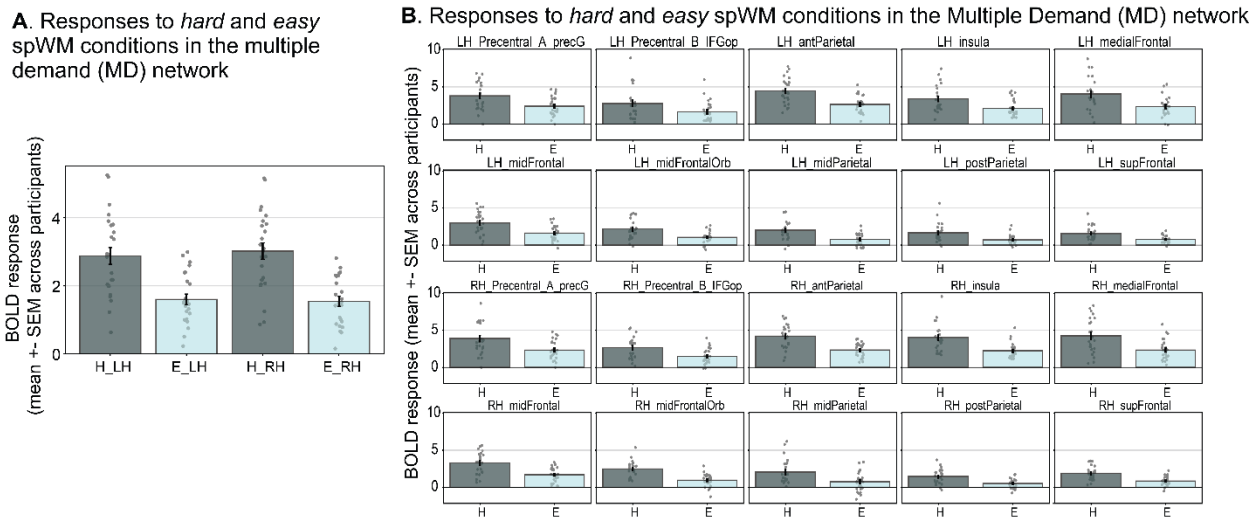
	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	0.944	0.025	61.579	38.090	0.000
Conditionwithin	-0.008	0.026	48.000	-0.312	0.756

Dice within localizer vs. between localizer versions (right-hemisphere wholebrain top 30%), $r^2 = 0.0911$

	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	0.966	0.003	70.960	335.496	0.000
Conditionwithin	-0.002	0.003	48.000	-0.688	0.495

SI 3: Information related to Results Section 1.B

SI 3A: Validation of *hard* > *easy* contrast from the MD localizer



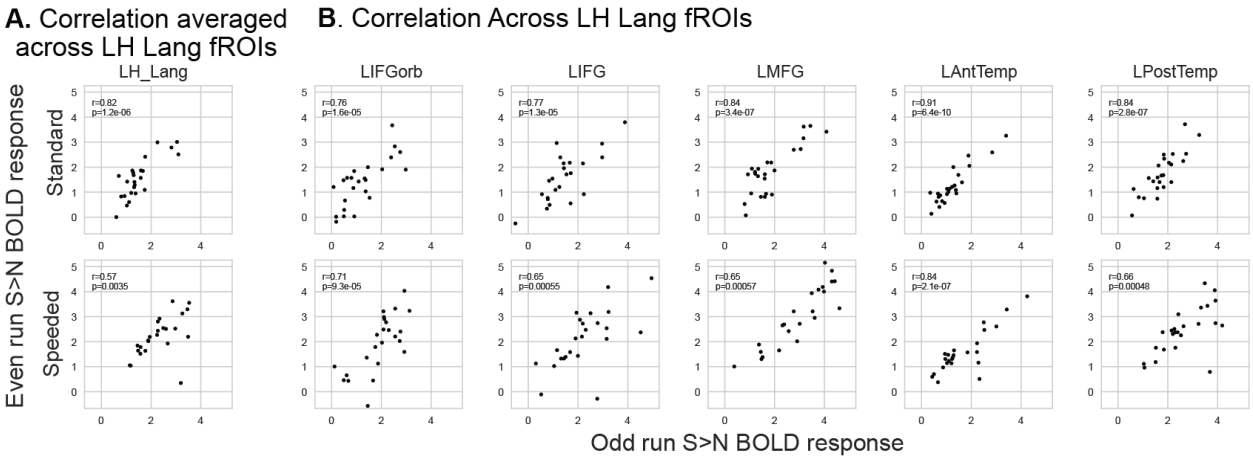
SI Figure 3A. Responses to the hard and easy spatial working memory (spWM) conditions in the MD localizer task.

(A) Mean response to the MD localizer conditions (H=*hard*, E=*easy*) averaged across ten Multiple Demand (MD) fROIs in each hemisphere. Dots show the mean response across fROIs of each individual participant. Error bars show the standard error of the mean across participants. **(B)** Mean response to the MD localizer conditions for each MD fROI. Dots show the mean response in the particular fROI of each individual participant. Error bars show the standard error of the mean across participants.

SI 3B: *Sentences* > *nonwords* BOLD response magnitudes are highly correlated across runs for both the standard and speeded language localizer versions

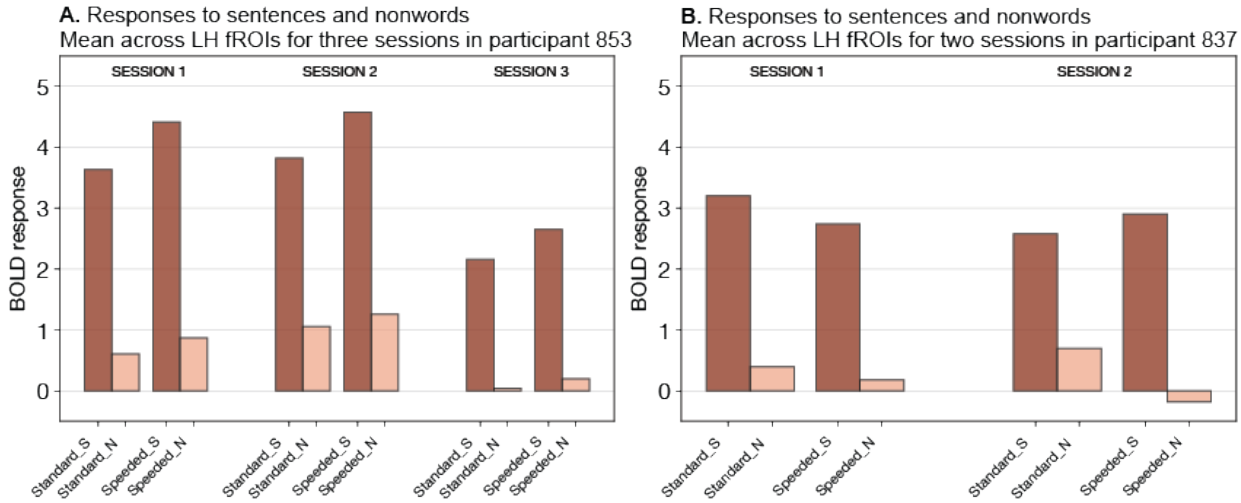
To investigate how stable the *sentences* and *nonwords* BOLD responses were across individual scanning runs, we quantified the average BOLD response magnitudes of the *sentences* > *nonwords* contrast for each LH language fROI for the odd and even run of each localizer version separately. Note that independent data were used to localize the fROI (i.e., data from the odd run were used to define the fROI, and responses were extracted from the even run, and vice versa).

The correlation between the average *sentence* > *nonwords* magnitude across LH language fROIs was greater in the standard language localizer than the speeded language localizer (**SI Figure 3B, panel A**). The correlation of the *sentences* > *nonwords* magnitude between odd and even runs across the five language fROIs was r = 0.82 (p<0.0001) for the standard language localizer, and r = 0.57 (p=0.0035) for the speeded language localizer. (Note that without the one outlier participant–bottom right in **SI Figure 3B, panel A**–the correlation was r = 0.83 for the speeded language localizer, p<0.0001).
The odd-even correlation values for individual fROIs were similarly high (**SI Figure 3B, panel B**): The average correlation across the five language fROIs was 0.823 (SD across fROIs: 0.062; five ps<0.001) for the standard language localizer, and 0.704 (SD: 0.083; five ps<0.001) for the speeded language localizer.



SI Figure 3B. Correlation of *sentences* > *nonwords* BOLD magnitudes within LH language fROIs obtained from odd and even runs.
(A) Correlation between *sentences* > *nonwords* BOLD magnitudes (averaged across the five LH language ROIs) of odd (x-axis) and even (y-axis) runs of the standard language localizer (upper row) and speeded language localizer (bottom row). Dots represent the *sentences* > *nonwords* BOLD response for each individual participant (*n*=24).
(B) Same as in panel A, just for each individual language fROI.

SI 3C: Consistency of localizers within participants *across* sessions



SI Figure 3C: Responses to the *sentences* and *nonwords* conditions in the standard and speeded language localizer for two participants across sessions.
Two participants in our dataset completed the two language localizers in different sessions (i.e., different days): One participant completed three sessions (the three sessions were 5 and 7 days apart, **panel A**), another participant completed two sessions (the two sessions were 99 days apart, **panel B**).
The mean responses to the language localizer conditions (S=*sentences*, N=*nonwords*) for each of the standard and speeded versions of the localizer task averaged across the five LH language fROIs are shown.

SI 3D: Statistics tables for Results Section 1.B (responses to language)

In the tables below, "BOLD response" denotes the BOLD response magnitude for the given condition (*sentences, nonwords,* or *sentences* > *nonwords;* note that "language" denotes both *sentences* and *nonwords* responses). "condition" denotes the *sentences* and *nonwords* conditions in the LMEs where they are modeled together. "version" denotes the language localizer version, either standard or speeded. "participant" denotes each of the *n*=24 participants. "fROI" denotes each of the five LH fROIs.

(i) *BOLD response language ~ condition + version + (1|participant) + (1|fROI)*

Standard vs Speeded Without Interaction (LHLang), $r^2 = 0.6515$

	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	0.442	0.270	7.587	1.636	0.142
ConditionS	1.897	0.080	451.954	23.570	0.000
VersionSpeeded	-0.068	0.080	451.954	-0.851	0.395

(ii) *BOLD response language ~ condition + version + condition:version + (1|participant) + (1|fROI)*

Standard vs Speeded With Interaction (LHLang), $r^2 = 0.6671$

	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	0.623	0.273	7.895	2.282	0.052
ConditionS	1.535	0.111	451.955	13.801	0.000
VersionSpeeded	-0.430	0.111	451.955	-3.866	0.000
ConditionS:VersionSpeeded	0.723	0.157	451.955	4.597	0.000

(iii) *BOLD response sentences>nonwords ~ version + (1|participant) + (1|fROI)*

Standard vs Speeded S-N (LHLang), $r^2 = 0.5214$

	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	1.535	0.204	10.980	7.521	0.000
VersionSpeeded	0.723	0.093	211.888	7.817	0.000

(iv) *BOLD response sentences ~ version + (1|participant) + (1|fROI)*

Standard vs Speeded S (LHLang), $r^2 = 0.546$

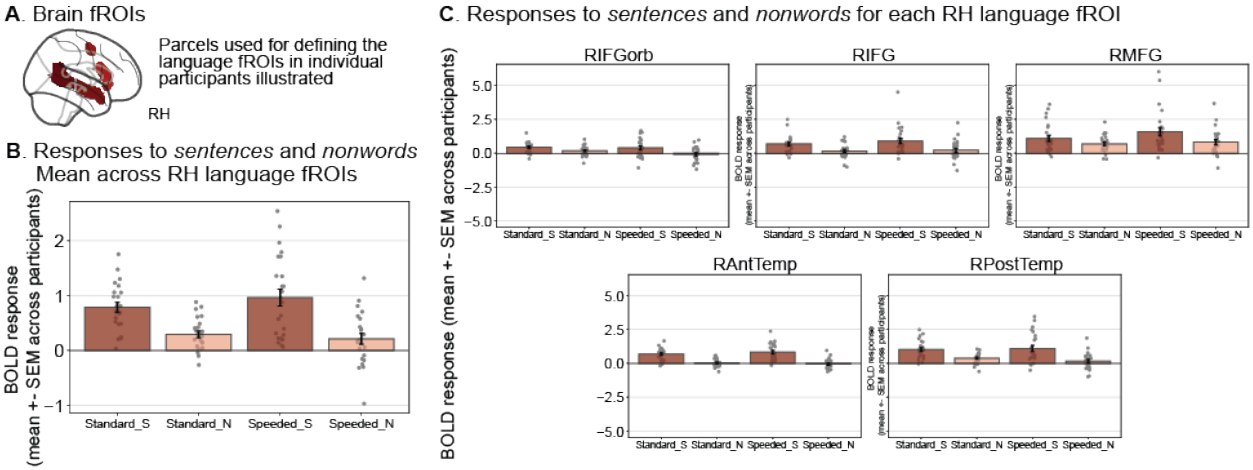
	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	2.158	0.361	7.700	5.978	0.000
VersionSpeeded	0.293	0.122	211.940	2.407	0.017

(v) *BOLD response nonwords ~ version + (1|participant) + (1|fROI)*

Standard vs Speeded N (LHLang), $r^2 = 0.3951$

	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	0.623	0.182	7.397	3.418	0.010
VersionSpeeded	-0.430	0.084	211.884	-5.106	0.000

SI 3E: Language BOLD responses for right hemisphere fROIs



SI Figure 3E: Responses to the language localizer conditions (*sentences* and *nonwords*) for the standard and speeded language localizers in right hemisphere (RH) language fROIs.

(A) We defined the RH language fROIs as the most language-responsive voxels (top 10%) within the borders of the five anatomical parcels (see Methods; Extraction of fMRI BOLD responses) for each

participant, and measured the BOLD response magnitude in these fROIs in a cross-validated manner (see Methods; Definition of fROIs).
(B) Mean BOLD response to the language localizer conditions (S=*sentences*, N=*nonwords*) for both the standard and speeded localizer versions averaged across the five RH language fROIs.
(C) Mean BOLD response to the localizer conditions for each RH language fROI. In both panels, dots show the mean response of each individual participant. Error bars show the standard error of the mean across participants.

The statistics tables accompanying SI Figure 3E are found below.

(i) *BOLD response RH language ~ condition + version + (1|participant) + (1|fROI)*

Standard vs Speeded Without Interaction (RHLang), $r^2 = 0.32751$

	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	0.228	0.146	8.359	1.555	0.157
ConditionS	0.623	0.065	451.888	9.617	0.000
VersionSpeeded	0.047	0.065	451.888	0.732	0.465

(ii) *BOLD response RH language ~ condition + version + condition:version + (1|participant) + (1|fROI)*

Standard vs Speeded With Interaction (RHLang), $r^2 = 0.3332$

	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	0.291	0.150	9.180	1.942	0.083
ConditionS	0.496	0.091	451.889	5.438	0.000
VersionSpeeded	-0.079	0.091	451.889	-0.872	0.384
ConditionS:VersionSpeeded	0.254	0.129	451.889	1.968	0.050

(iii) *BOLD response RH sentences>nonwords delta ~ version + (1|participant) + (1|fROI)*

Standard vs Speeded S-N (RHLang), $r^2 = 0.3587$

	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	0.496	0.105	17.126	4.717	0.000
VersionSpeeded	0.254	0.067	211.758	3.776	0.000

(iv) *BOLD response RH sentences ~ version + (1|participant) + (1|fROI)*

Standard vs Speeded S (RHLang), $r^2 = 0.2493$

	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	0.787	0.168	9.317	4.678	0.001
VersionSpeeded	0.174	0.106	211.768	1.651	0.100

(v) *BOLD response RH nonwords ~ version + (1|participant) + (1|fROI)*

Standard vs Speeded N (RHLang), $r^2 = 0.2648$

	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	0.291	0.134	7.002	2.175	0.066
VersionSpeeded	-0.079	0.071	211.842	-1.118	0.265

SI 3F: Statistics tables for Results Section 1.B (responses to working memory task)

In the tables below, "BOLD response" denotes the BOLD response magnitude for the given condition (*hard, easy*). "version" denotes the language localizer version, either standard or speeded. "participant" denotes each of the *n*=24 participants. "fROI" denotes each of the five LH fROIs.

i) *BOLD response hard ~ version + (1|participant) + (1|fROI)*

Standard vs Speeded H (LHLang), $r^2 = 0.549$

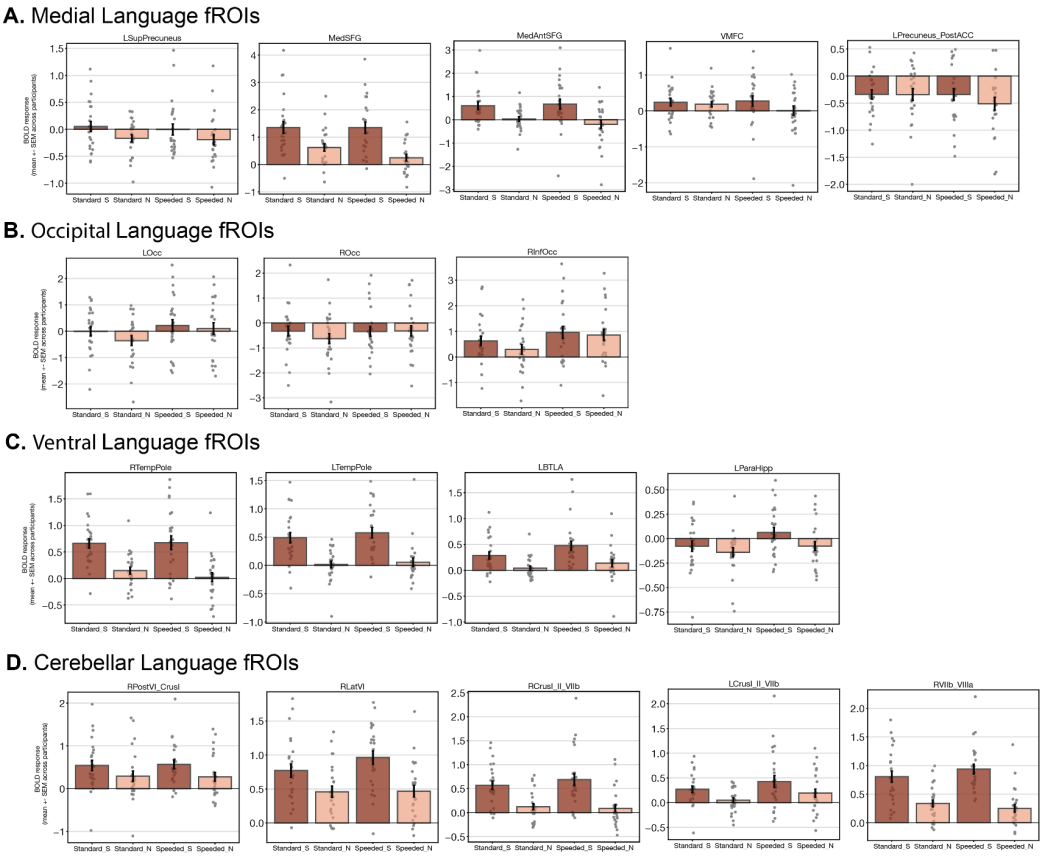
	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	-0.383	0.284	9.648	-1.347	0.209
VersionSpeeded	0.101	0.104	211.929	0.973	0.332

ii) *BOLD response easy ~ version + (1|participant) + (1|fROI)*

Standard vs Speeded E (LHLang), $r^2 = 0.4984$

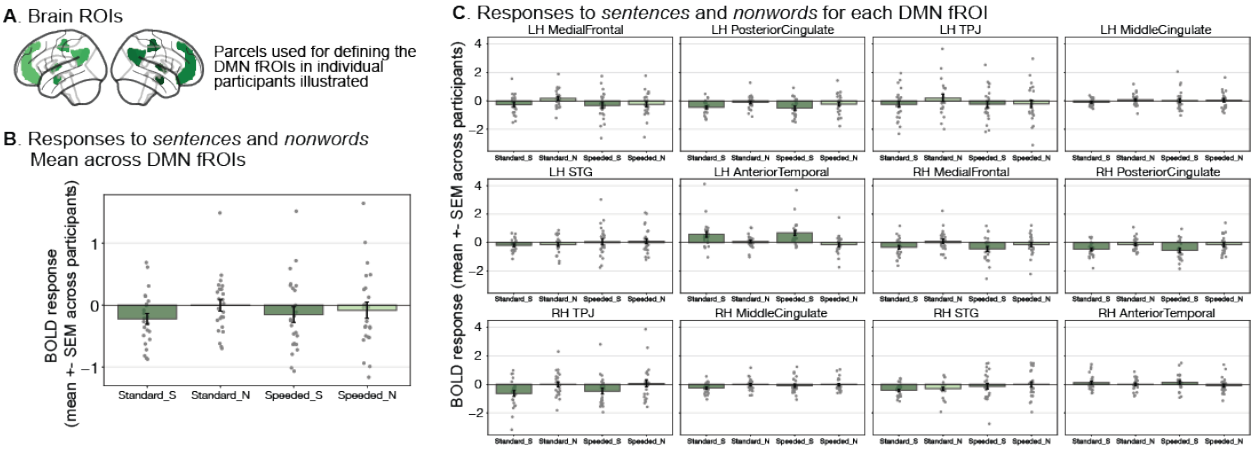
	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	-0.054	0.156	13.538	-0.343	0.737
VersionSpeeded	0.096	0.070	211.891	1.361	0.175

SI 3G: Language responses in extended language network fROIs



SI Figure 3G. **Responses to the standard and speeded localizer tasks in the extended language network.** Mean BOLD response to the language localizer conditions (S=sentences, N=nonwords) for each of the standard and speeded versions of the localizer task for each fROI in the **(A)** Medial, **(B)** Occipital, **(C)** Ventral, and **(D)** Cerebellar regions of the extended language network as described by Wolna et al. (2025). Dots show the mean response across fROIs of each individual participant. Error bars show the standard error of the mean across participants.

SI 3H: Language responses in DMN fROIs



(A) To define the DMN fROIs, we used a set of 12 parcels (6 in each hemisphere) derived from a group-level probabilistic activation overlap map for the *easy* > *hard* spatial working memory contrast (Fedorenko et al., 2013) in 197 independent participants. The *easy* > *hard* contrast has been shown to robustly activate DMN regions, in line with prior work using similar tasks and contrasts (Leech et al., 2011; Mineroff, Blank et al., 2018). The parcels included symmetrical regions in the posterior cingulate cortex, four medial frontal regions, the precuneus, and temporoparietal junction. We used the *easy* > *hard* spatial working memory (WM) contrast to identify the top 10% most responsive voxels within these parcels, and extracted responses to sentences and nonwords conditions within these fROIs for both the standard and speeded language localizer versions. We measured the BOLD response magnitude to the language localizer conditions in these fROIs in a cross-validated manner (see Methods; Definition of fROIs).

(B) Mean BOLD response to the language localizer conditions (S=sentences, N=nonwords) for both the standard and speeded localizer versions averaged across the DMN fROIs. On average, the DMN parcels demonstrated a *nonwords* > *sentences* effect (*sentences* > *nonwords*, β=-0.218, t=-3.913, p<0.0001).

(C) Mean BOLD response to the localizer conditions for each DMN fROIs. In both panels, dots show the mean response of each individual participant. Error bars show the standard error of the mean across participants. With the exception of the left anterior-temporal region, all DMN regions demonstrated a *nonwords* > *sentences* response. Notably, this left anterior-temporal region lies within the left anterior-temporal region of the language parcel, and hence the positive *sentences* > *nonwords* response is likely explained by language-selective voxels in this region.

BOLD response standard language ~ condition + (1|participant) + (1|fROI)

S-N Standard (DMN), R-Squared = 0.4035

	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	-0.005	0.100	34.967	-0.047	0.963
ConditionS	-0.218	0.045	540.891	-4.858	0.000

BOLD response speeded language ~ condition + (1|participant) + (1|fROI)

S-N Speeded (DMN), R-Squared = 0.4904

	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	-0.084	0.134	32.106	-0.624	0.537
ConditionS	-0.071	0.052	540.921	-1.372	0.170

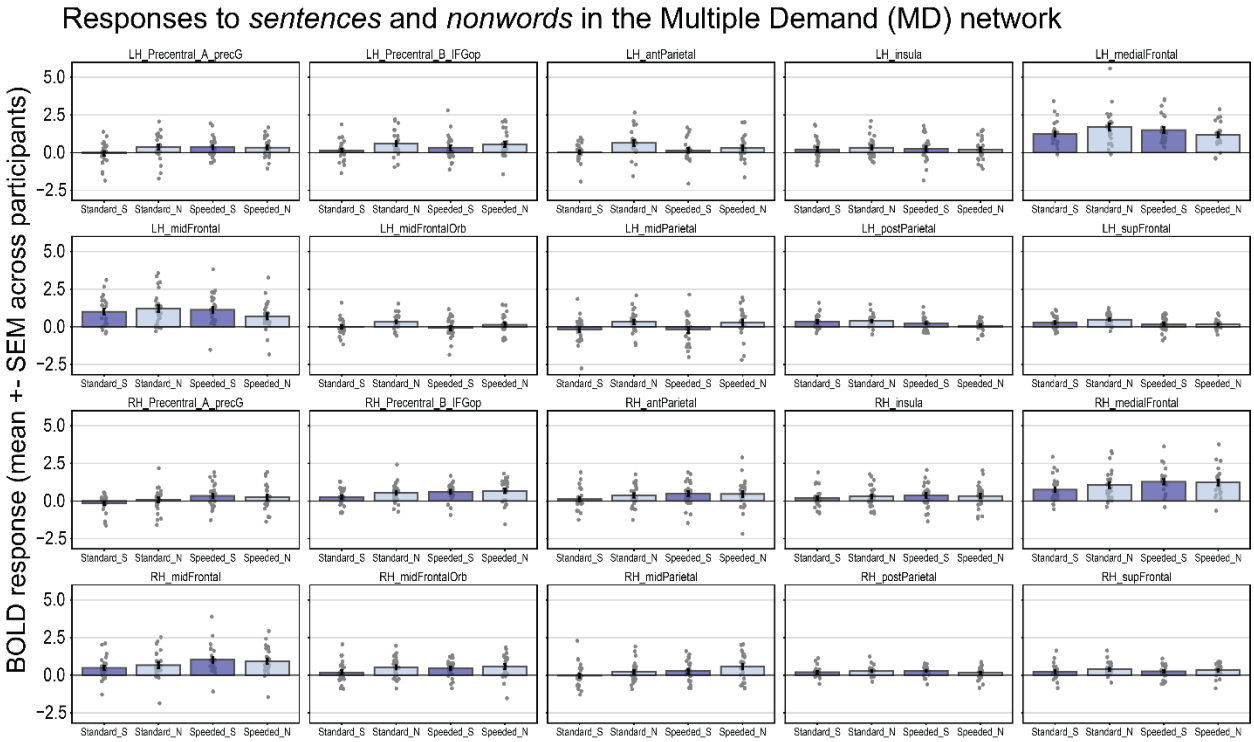
BOLD response language ~ condition + version + condition:version + (1|participant) + (1|fROI)

Standard vs. Speeded With Interaction (DMN), R-Squared = 0.2778

	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	-0.005	0.098	41.296	-0.048	0.962
ConditionS	-0.218	0.056	1116.905	-3.913	0.000
VersionSpeeded	-0.079	0.056	1116.905	-1.415	0.157
ConditionS:VersionSpeeded	0.147	0.079	1116.905	1.867	0.062

SI 4: Information related to Results Section 2 (Multiple Demand network)

SI 4A: MD responses to the language localizer versions across fROIs



SI Figure 4A. Responses to the standard and speeded localizer tasks in the Multiple Demand Region across all 10 left and right hemispheric MD fROIs. Mean BOLD response to the language localizer conditions (S=*sentences,* N=*nonwords*) for each of the standard and speeded versions of the localizer task for each Multiple Demand (MD) fROI in the left and right hemispheres. Dots show the mean response

across fROIs of each individual participant. Error bars show the standard error of the mean across participants.

SI 4B: Statistics tables for Results Section 2

In the tables below, "BOLD response" denotes the BOLD response magnitude for the given condition (*sentences, nonwords*; note that "language" denotes both *sentences* and *nonwords* responses). "condition" denotes the *sentences* and *nonwords* conditions in the LMEs where they are modeled together. "version" denotes the language localizer version, either standard or speeded. "participant" denotes each of the *n*=24 participants. "fROI" denotes each of the twenty LH/RH MD fROIs.

BOLD response standard language ~ condition + (1|participant) + (1|fROI)

S-N Standard (MD), $r^2 = 0.5257$

	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	0.541	0.125	42.783	4.325	0.000
ConditionS	-0.275	0.036	916.956	-7.547	0.000

BOLD response speeded language ~ condition + (1|participant) + (1|fROI)

S-N Speeded (MD), $r^2 = 0.44$

	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	0.477	0.123	42.998	3.864	0.000
ConditionS	-0.012	0.041	916.942	-0.283	0.777

BOLD response language ~ condition + version + condition:version + (1|participant) + (1|fROI)

Standard vs. Speeded With Interaction (MD), $r^2 = 0.3504$

	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	0.541	0.108	45.171	5.002	0.000
ConditionS	-0.275	0.044	1876.956	-6.328	0.000
VersionSpeeded	-0.064	0.044	1876.956	-1.470	0.142
ConditionS:VersionSpeeded	0.264	0.062	1876.956	4.285	0.000

BOLD response sentences ~ version + (1|participant) + (1|fROI)

Standard vs. Speeded S (MD), $r^2 = 0.3263$

	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	0.266	0.104	36.377	2.549	0.015
VersionSpeeded	0.200	0.044	916.907	4.584	0.000

BOLD response nonwords ~ version + (1|participant) + (1|fROI)

Standard vs. Speeded N (MD), $r^2 = 0.4024$

	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	0.541	0.117	42.660	4.634	0.000
VersionSpeeded	-0.064	0.042	916.932	-1.519	0.129