1	A Two-Dimensional Space of Linguistic Representations
2	Shared Across Individuals
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### Abstract

Humans learn and use language in diverse ways, yet 27 all typically developing individuals acquire at least 28 one language and use it to communicate complex 29 ideas. This fundamental ability raises a key 30 Which question: dimensions of language 31 processing are shared across brains, and how are 32 these dimensions organized in the human cortex? 33 To address these questions, we collected ultra-high-34 field (7T) fMRI data while eight participants listened 35 to 200 linguistically diverse sentences. To identify 36 the main components of variance in the sentence-37 evoked brain responses, we performed data 38 decomposition and systematically tested which 39 components generalize across individuals. Only two 40 shared components emerged robustly, together 41 accounting for about 32% of the explainable 42 variance. Analysis of linguistic feature preferences 43 showed that the first component corresponds to 44 processing difficulty, and the second-to meaning 45 abstractness. Both components are spatially 46 distributed across frontal and temporal areas 47 with processing associated language but. 48 surprisingly, also extended into the ventral visual 49 cortex. These findings reveal a low-dimensional, 50 spatially structured representational basis for 51 language processing shared across humans. 52

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Keywords: language; inter-individual neural
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### Introduction

Language enables the transfer of complex ideas across 57 minds-an ability that has laid a critical foundation for 58 human culture. A set of left-lateralized frontal and 59 temporal brain areas-the "language network"-60 supports language understanding and production, 61 across modalities (spoken, written, and signed; 62 MacSweeney et al. 2002; Deniz et al. 2019; Hu et al. 63 2022) and across typologically diverse languages 64 (Malik-Moraleda, Ayyash et al. 2022). Although the 65 brain areas that support language are well-established, 66 their internal organization-what dimensions structure 67 their responses and how-remains poorly understood. 68 All frontal and temporal language areas show a similar 69 response profile: they are strongly engaged by 70

structured and meaningful language in controlled 71 paradigms (Rodd et al., 2010; Fedorenko et al., 2020) 72 and track linguistic complexity during naturalistic 73 comprehension (Shain et al. 2020; Wehbe et al. 74 2021). However, some structure may exist within this 75 network of areas that does not correspond to regional 76 boundaries (e.g., Jain et al., 2020; Regev, Casto et 77 al., 2024). In this study, we used a data-driven 78 structure-discovery approach to explain each voxel's 79 response to diverse sentences as a weighted sum of 80 a smaller number of components. Our goal is to 81 identify the organizing dimensions of language 82 representations that are shared across individuals 83 and to characterize how these dimensions are 84 distributed across the brain. 85

### Methods

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We scanned eight proficient English speakers 87 (monolinguals and multilinguals) with 7T fMRI while 88 they listened to 200 spoken sentences (2s each), 89 repeated three times in pseudorandomized order. 90 Sentence-level BOLD responses were estimated 91 using GLMsingle (Prince et al., 2022). We extracted 92 reliable voxel responses from five large anatomical 93 parcels covering the frontal and temporal cortex 94 implicated in language processing (Lipkin et al., 95 2022), and applied singular value decomposition to 96 the mean-subtracted voxel responses concatenated 97 across participants. This procedure yields the 98 "Sentence PCs", where each Sentence PC denotes 99 how much each sentence drives variance along a 100 principal dimension of voxel activity. To identify 101 Sentence PCs that generalize across individuals, we 102 used a leave-one-participant-out framework: we 103 trained ordinary least squares (OLS) models using 104 Sentence PCs derived from seven participants to 105 predict voxel responses in the held-out participant. 106 We characterized the resulting Sentence PCs using a 107 set of 12 linguistic/semantic properties-combining 108 properties from prior work (Tuckute et al. 2024) with 109 new experiments that directly probe processing 110 difficulty and abstractness of sentence meanings. 111 Finally, we visualized the Sentence PC weights on the 112 cortical surface. 113



Fig. 1. A. Overview of procedure for deriving components of sentence-evoked brain responses ("Sentence PCs"). B. Held-out participant prediction accuracy as a function of the number of Sentence PCs used. C. Correlations between Sentence PCs and linguistic features. D. Surface maps of Sentence PC weights.

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### Results

#### How many distinct components of language are shared across individuals and what characterizes

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them? To search for shared dimensions of language 117 representations. we identified the principal 118 components ("Sentence PCs") of sentence-evoked 119 brain responses (Fig. 1A) and tested their 120 generalizability across individuals. We found that 121 model performance plateaued at two Sentence PCs 122 (Fig. 1B); additional components failed to improve 123 prediction accuracy in held-out participants, indicating 124 that PCs beyond two reflect inter-individual neural 125 variability. These two PCs accounted for about 32% 126 of sentence-evoked variance. 127

Sentence PC 1 was strongly correlated with 128 measures of processing difficulty, such as reading 129 times (Boyce et al., 2020), surprisal, and frequency-130 altogether capturing a dimension that spans "Easy to 131 process" to "Hard to process" (Fig. 1C). Sentence PC 132 2 correlated most strongly with concreteness and 133 imageability (how much a sentence is tied to 134 perceptual, including visual experience), capturing a 135 dimension from "Concrete" to "Abstract" sentence 136 meanings. 137

How are the components spatially organized? To understand how the two components are distributed

across the brain and whether any systematic patterns exist across individuals, we visualized the PC weights 141 on the cortical surface, averaging across significantly 142 predicted voxels in all eight participants (Fig. 1D). 143 Both PCs were present throughout the left fronto-144 temporal language network (white demarcations), 145 with these areas showing an overall preference for 146 abstract/hard-to-process sentences. Quantifications 147 of these response profiles revealed that PC2-the 148 meaning abstractness component-was more 149 prominently present in the temporal areas compared 150 to the frontal areas (p<.05). Surprisingly, we also 151 observed robust prediction in the left ventral visual 152 cortex, typically associated with high-level vision. 153 These voxels were tuned to visualizable, "concrete" 154 sentences, potentially reflecting spontaneous visual 155 imagery or multimodal semantic processing distinct 156 from the computations implemented in the frontal and 157 temporal language areas. 158

# Conclusion

We identify two principal, cross-individual dimensions of language representations in the brain: processing difficulty and meaning abstractness. These findings lay the foundation for developing topographical models of the neural architecture of language.

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