

1 **Neural representations of speech production in neocortical and cerebellar regions**

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8

9 **Abstract**

10 Speech production depends on the precise temporal integration of articulatory movements with
11 phonation. While ventral primary motor cortex is known to encode articulatory features, how
12 phonatory timing, and its coordination with articulation, is represented across cortical and
13 cerebellar circuits remains poorly understood. Using 7T functional MRI, we examined neural
14 representations during overt syllable production varying in place of articulation and voice onset
15 time. Multivariate analyses revealed reliable, syllable-specific differences in activity patterns
16 across both cortical and cerebellar speech regions. Ventral primary sensorimotor cortex
17 distinguished syllables by place of articulation, whereas dorsal sensorimotor cortex was more
18 sensitive to the timing of voice onset relative to articulation. Secondary sensorimotor speech
19 areas, including the operculum and auditory cortex, showed a hybrid representational profile,
20 integrating both articulatory and phonatory features. In the cerebellum, representational
21 geometry was dominated by the place of articulation; however, overall syllable representations
22 were most similar to those in the operculum, accounting for unique variance beyond that
23 explained by ventral sensorimotor cortex. Together, these findings reveal feature-specific
24 representational tuning across primary sensorimotor regions during speech production. The
25 selective representational alignment between operculum and cerebellum may support the
26 refinement of speech motor plans prior to execution.

27

28

Introduction

29 Speech is among the most complex motor activities humans perform, requiring the
30 coordination of approximately 100 muscles across laryngeal, respiratory and oral motor systems.
31 This coordination integrates two fundamental speech features: articulation, which shapes the
32 configuration of the vocal tract, and phonation, the generation of voiced sound. Such intricate
33 orchestration depends on a distributed neural network spanning both cortical and cerebellar
34 regions (Guenther & Hickok, 2016). Here, we aim to determine how articulatory and phonatory
35 features of speech are represented across cortical and cerebellar regions during syllable
36 production.

37 Articulatory control is primarily attributed to the ventral sensorimotor cortex (vSM), where
38 upper motor neurons project to brainstem nuclei, which in turn innervate the vocal tract via
39 various cranial nerves (Jürgens, 2002; Penfield & Boldrey, 1937). Electrophysiological and
40 imaging studies have shown that neural populations in vSM are selectively tuned to specific
41 articulators (lips, tongue, and jaw), following a somatotopic layout that recapitulates the vocal
42 tract (Bouchard et al., 2013; Carey et al., 2017). However, how speech features beyond
43 articulation, such as phonation, are represented remains unclear.

44 Phonation is the process of generating sound through the vocal folds (i.e., voicing). This
45 process involves steady exhalation and laryngeal muscle contraction to vibrate the vocal folds.
46 Cortically, laryngeal control has been mapped to two distinct regions in the vSM (Bouchard et
47 al., 2013; Eichert et al., 2020), while exhalation has been shown to recruit a specific region in the
48 dorsal sensorimotor cortex (dSM) associated with trunk movement (Brown et al., 2009; Loucks
49 et al., 2007). Notably, the dSM shows greater activation during voiced compared with whispered
50 speech, suggesting a role in phonatory control that is not limited to respiration (Correia et al.,
51 2020).

52 Beyond the primary sensorimotor cortex, clinical evidence highlights a critical role for the
53 cerebellum in speech production (Ackermann & Brendel, 2016). Cerebellar motor regions are
54 embedded in closed-loop circuits with the cerebral sensorimotor cortex. In these circuits,
55 individual cerebellar motor territories are reciprocally connected with specific, somatotopically
56 organized cortical motor areas (Kelly & Strick, 2003; Saadon-Grosman et al., 2022). This closed-
57 loop cerebellar-cortical organization predicts that cerebellar representations should closely
58 resemble those in vSM. However, recent evidence suggests that the cerebellum integrates signals

59 from multiple cortical sources (King et al., 2023). Under this integrative account, cerebellar
60 speech regions may exhibit mixed representational geometries. Specifically, these regions may
61 combine articulatory and phonatory features within their neural activity patterns.

62 In the current study, we used high-field (7T) fMRI to investigate the neural mechanisms
63 underlying speech production. Participants uttered syllables that differed in place of articulation
64 and voicing. Leveraging the high spatial resolution afforded by 7T imaging, we aimed to map
65 cortical and cerebellar regions associated with speech production. We employed Representational
66 Similarity Analysis (RSA) to determine how specific speech features are encoded in neural
67 activity patterns. Activity patterns in vSM primarily distinguished between places of articulation,
68 consistent with previous work (Bouchard et al., 2013). Representational geometries in dSM
69 differentiated between voiced and voiceless consonants, in line with the involvement of this area
70 in phonation (Correia et al., 2020). Secondary sensorimotor speech areas outside primary motor
71 cortex showed a mixture of these two representations. We then tested whether speech
72 representations in the cerebellum resemble those observed in cortical speech regions. We
73 hypothesized that cerebellar speech regions would show representational structures similar to
74 those in vSM, consistent with closed-loop cerebellar-cortical organization (Kelly & Strick, 2003;
75 Saadon-Grosman et al., 2022). Alternatively, cerebellar speech regions may encode mixed
76 representational geometries that combine ventral and dorsal sensorimotor features, reflecting the
77 convergence of cortical inputs to the cerebellum (King et al., 2023).

78

79 **Methods**

80 **Participants.** Twelve neurotypical adults were recruited for this study (6 females, 18-29 years
81 [mean \pm SD = 23.3 \pm 3.6]). All participants were right handed as estimated by the Edinburgh
82 handedness inventory (90.7 \pm 15.1; Oldfield, 1971), native-level English speakers, and had no
83 history of speech impairment or a neurological condition. All experimental procedures were
84 approved by the Research Ethics Committee at Western University. The participants signed a
85 written informed consent before participating in the study and were compensated for their
86 participation.

87 **Stimuli.** Six different consonant-vowel (CV) syllables were visually presented to the
88 participants at the center of the screen using PsychoPy (<https://www.psychopy.org/>). The

89 syllables were composed of a plosive consonant (/p/, /b/, /t/, /d/, /k/, /g/) followed by the vowel
90 /a/ (Fig. 1A). Plosives are produced by blocking the airflow in the vocal tract and then releasing
91 it, creating a burst of air. The plosive syllables in the current experiment varied along two axes:
92 place of articulation (PoA) and voice onset time (VOT). PoA refers to the location in the vocal
93 tract where the airflow is obstructed. In plosive sounds, the blockage can be formed with the lips
94 (/p/, /b/), with the tongue tip against the alveolar ridge (/t/, /d/), or with the back of the tongue
95 against the velum (/k/, /g/), corresponding to the *bilabial*, *alveolar*, and *velar* sounds,
96 respectively. VOT refers to the interval between the release of the plosive closure and the onset
97 of vocal fold vibration. In *voiceless* plosives (/p/, /t/, /k/), the vocal folds do not vibrate during
98 the release, whereas in *voiced* plosives (/b/, /d/, /g/), the vocal folds do vibrate during the release.

99 **Experimental design.** Participants underwent MRI scanning in a single session. We acquired an
100 anatomical image and 10 functional runs. Right before the MRI scan, participants were
101 familiarized with the behavioral task in a short behavioral session (2 runs, ~20 min). On each
102 trial, a syllable was presented on the screen for 2 seconds, followed by a fixation cross for 2
103 seconds (Fig. 1B). Participants were instructed to repeat the syllable out loud three times at a
104 comfortable pace during the 2s presentation period, and to remain silent during fixation to
105 prevent overlap across task phases. Each run lasted ~4 minutes and included four blocks of 48 s
106 separated by 14 s rest. Within each block all six syllables were presented, with each syllable
107 appearing twice on consecutive trials. The order of items pairs within a block was randomized,
108 resulting in a total of eight presentations of each item per run. Item and trial repetitions were
109 included to improve the contrast-to-noise ratio (CNR). A period of 10 s rest was added at the end
110 and of each functional run to allow for signal relaxation and provide a better estimate of baseline
111 activation. The entire MRI session, including the anatomical scans and setup, lasted ~60 minutes.

112 **Imaging data acquisition.** Functional MRI data were acquired on a 7T Siemens Magnetom
113 scanner with a 32-channel head coil at Western University. Anatomical T1 weighted scan of each
114 participant was acquired at the beginning of the MRI session, using a magnetization-prepared
115 rapid gradient echo sequence (MP2RAGE, voxel size=0.7mm isotropic; TR=6000 ms; TE=2.27
116 ms; field of view=246×246; 224 slices). Task-based functional data were acquired using a multi-
117 band gradient-echo EPI sequence with anterior to posterior phase-encoding direction (voxel
118 size= 2.3 mm isotropic; TR=1100 ms; TE=20 ms; flip angle=30; multiband acceleration

119 factor=2; GRAPPA acceleration=3; field of view=208×208 mm; 56 slices). Each run consisted of
120 224 volumes. To correct spatial distortions caused by inhomogeneities in the magnetic field, we
121 also acquired a gradient-echo field map (voxel size=1.3 × 1.3 × 2.5 mm; field of
122 view=210×210).

123 **Preprocessing.** Functional data were preprocessed in native space for each individual separately
124 using SPM12 (fil.ion.ucl.ac.uk/spm) and custom Matlab code. Our minimal preprocessing
125 pipeline included the following steps: First, functional images were corrected for geometric
126 distortions caused by magnetic field inhomogeneity using the gradient echo field map (Hutton et
127 al., 2002). Then, functional images were realigned to the first volume of the first run to correct
128 for head motion (six parameters: translation x, y, and z, and rotation pitch, roll and yaw). Lastly,
129 the biased-corrected functional data were co-registered to the anatomical T1 image, for which the

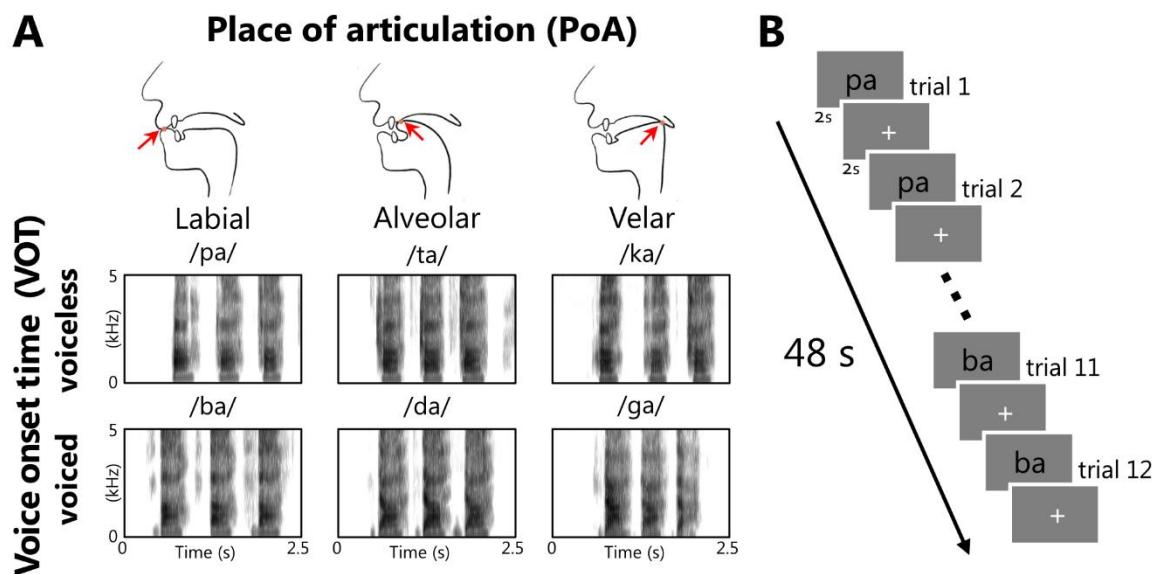


Figure 1. Syllable repetition task. **A**, Experimental stimuli. Top: Schematic illustration of the vocal tract during articulation of bilabial (/p/,/b/), alveolar (/t/,/d/), and velar (/k/,/g/) plosive consonants. Red arrow denoting the place of articulation. Bottom: Spectrograms of spoken CV syllables of one representative subject (female, 18yo) recorded during the behavioral training session. Spectrograms are grouped by voice onset time, with voiceless plosives (/pa/,/ta/,/ka/) shown in the top row and voiced plosives (/ba/,/da/,/ga/) in the bottom row. **B**, Block example. Each trial consisted of a CV syllable presented for 2 s, followed by 2 s fixation cross. Participants (N=12) were instructed to repeat the syllable three times during its presentation. Within each block, all six syllables were presented in a random order, with each syllable repeated twice on consecutive trials. Each block lasted ~48 s. Abbreviations: CV – consonant vowel; PoA – place of articulation; VOT – voice onset time.

130 (0,0,0) coordinate was moved to the anterior commissure (AC). No smoothing or normalization
131 to a group template was performed at this stage.

132 **First level general linear model.** The preprocessed functional images were analyzed with a
133 general linear model (GLM), using a separate regressor for each syllable (/p/, /b/, /t/, /d/, /k/, /g/),
134 for each run. The activation of each trial (consisting of three repetitions of the same syllable) was
135 modeled using a boxcar function of length 2 sec convolved with a two-gamma canonical
136 hemodynamic response function with a peak at 5 sec and a post-stimulus undershoot minimum at
137 11 seconds. This analysis resulted in activation images (beta maps) for each condition per run,
138 for each participant. Rest was not modeled explicitly but served as an implicit baseline.

139 **Neocortical surface reconstruction.** Reconstruction of cortical surface from the anatomical
140 image was carried out using Freesurfer (Fischl et al., 1999). In this procedure, white-gray matter
141 and pial surfaces were reconstructed for each individual. The surfaces were then inflated into a
142 sphere, and aligned to the left-right symmetric template atlas (fs_LR.32k.spec; Van Essen et al.,
143 2012) based on sulcal depth and curvature information. The functional data were projected from
144 native space to the subject's individual surface, by averaging beta values of voxels intersecting
145 the line connecting corresponding vertices of the individual white matter and pial surfaces.

146 **Cerebellar normalization.** Cerebellar isolation and segmentation into white and gray matter
147 were performed using the Spatially Unbiased Infratentorial Template (SUIT) toolbox
148 implemented in SPM12 (Diedrichsen, 2006). For each subject, the automatic segmentation was
149 carefully inspected and, when necessary, manually corrected by one of the authors (S.J.) to
150 exclude voxels originating from non-cerebellar tissue (e.g., visual cortex). Cerebellar gray and
151 white matter maps were then normalized into SUIT space using a non-linear deformation
152 algorithm (Ashburner, 2007). The activation estimates (i.e., beta weights) and residual mean-
153 square from the first level GLM were also resliced into SUIT. The functional data were further
154 resliced into MNIsymC template atlas (a symmetric version of the cerebellar only template,
155 aligned to the MNINlin2009cSym template) to enable the definition of symmetric cerebellar
156 ROIs in the left and right hemisphere. For visualization purposes, functional maps were
157 projected onto a flat representation of the cerebellum using the SUIT toolbox (Diedrichsen &
158 Zotow, 2015).

159 **Defining functional regions of interest.** To identify brain regions activated during overt syllable
160 repetition we generated group-level activation maps across all syllable conditions (Fig. 2).
161 Individual subject data were projected into group space, spatially smoothed on the cortical
162 surface or in the volume (kernel width: 6mm), and averaged across participants. To obtain a
163 hemispheric unbiased estimate we further averaged the data across hemispheres. Functional
164 ROIs were defined by thresholding the resulting group-average map to retain the top 10% of
165 vertices in the neocortex, and top 10% of voxels in the cerebellum. For cerebellar ROIs, we
166 extracted SPM t-values, reflecting average beta maps divided by the standard deviation of the
167 residual time series at each voxel. For the neo-cortex, anatomical locations of the regions were
168 identified using the Glasser et al. (2016) atlas.

169 **Quantifying pattern reliability.** Pattern reliability was defined as the proportion of total
170 variance in fMRI activity patterns that could be explained by reliable effects, computed as the
171 sum of group-level and subject-specific variance components divided by the total variance. To
172 estimate these components, we applied variance decomposition ([https://functional-
173 fusion.readthedocs.io/](https://functional-fusion.readthedocs.io/)) to unsmoothed activity patterns in group space (cortical or cerebellar).
174 For each voxel or vertex and each run, we first subtracted the mean response across all syllables.
175 This step removes shared global activations that are not specific to individual syllables. The
176 resulting fMRI activity was decomposed into three variance components: (1) *group*: reflecting
177 patterns that are shared across subjects; (2) *subject*: capturing reliable idiosyncratic differences;
178 and (3) *noise*: representing run-by-run variability of the estimates within each person. These
179 components were estimated from the covariance matrix of activity estimates across voxels,
180 where $x_{s,i}$ denotes the pattern for subject s , in run i . The average covariance across different
181 people, $cov(x_{s,i}, x_{t,j})$, is equal to the group variance; the average covariance within a person
182 across runs, $cov(x_{s,i}, x_{s,j})$, is equal to the sum of group and subject variance; and the average total
183 average variance, $var(x_{s,i})$, is equal to all three components. Pattern reliability is then the sum of
184 the group and subject variance components divided by the total variance. Statistical significance
185 of reliability estimates was assessed using one-sample t-tests against zero.

186 To compare reliability between the cortex and the cerebellum at the subject level, we
187 conducted a linear mixed-effects model with normalized reliability as the dependent variable,
188 brain region (i.e., cortex vs. cerebellum) as a fixed effect, and subject as a random intercept. The

189 model was fitted using Restricted Maximum Likelihood (REML). Significance was assessed
190 with Wald z-tests.

191
192 **Group-level univariate analysis.** To assess whether mean activation differed systematically as a
193 function of articulatory features, we performed a repeated-measures ANOVA on percent signal
194 change values extracted from each ROI. The model included within-subject factors of Place of
195 Articulation (bilabial, alveolar, velar), and Voicing (voiced, voiceless), with subject treated as a
196 random effect. Significant main effects were followed up with post hoc comparisons, corrected
197 for multiple comparisons (FDR correction).

198 To assess the topological organization of different places of articulation, we computed
199 subject-level contrasts for each articulatory category (bilabial, alveolar, velar) against the
200 remaining syllables. Group-level effects were then estimated by performing a one-sample t-test
201 across participants at each vertex/voxel, yielding group t-statistic maps. These maps were used to
202 evaluate the spatial distribution of place-of-articulation selectivity.

203 **Multivariate pattern analysis of syllable-specific representations.** To quantify how much
204 activation patterns for each syllable differed from each other, we used the cross-validated
205 Mahalanobis distance (Nili et al., 2014), resulting in a representational dissimilarity matrix
206 (RDM). Prior to calculating the distances, beta weights were spatially prewhitened (i.e., scaling
207 each voxel's beta by the estimated noise standard deviation from the GLM). This step ensures
208 that the distance estimates reflect true pattern differences rather than noise covariance (Bosch et
209 al., 2025). To get a cross-validated estimation of the distances, we multiplied the difference
210 between the activity pattern of two syllables in one imaging run with the differences computed
211 on any other imaging run. This procedure ensures that if two patterns are only differ due to noise,
212 then the expected estimate of the distance is zero (Diedrichsen et al., 2021). For visualization
213 purposes only, the RDM values were square-root transformed and then normalized by their
214 Euclidian norm to remove overall scale differences across ROIs.

215 **Lateralization index.** To assess hemispheric asymmetry during syllable production, we
216 computed a lateralization index for each speech-related ROI. Lateralization index was defined as
217 the normalized difference between right- and left-hemisphere activity (or representational

218 distances) within each ROI. To account for potential negative values, the difference was
219 normalized by the sum of the absolute values of both hemispheres:

220

$$Lateralization\ index = \frac{R - L}{|R| + |L|}$$

221 Positive values indicate right-hemisphere dominance, while negative values indicate left-
222 hemisphere dominance. Statistical significance of the lateralization was assessed using one-
223 sample t-tests, testing whether the mean lateralization index differed from zero.

224 **Comparing representational dissimilarities.** To investigate whether the representational
225 structure of syllables differed between hemispheres we calculated the cosine similarity between
226 each subject's RDM and the leave-one-out group-average RDMs of the left and right
227 hemispheres. This resulted in four similarity measures per subject (per ROI), reflecting how well
228 each hemisphere's representational structure matched the ipsilateral and contralateral group
229 patterns. Differences between ipsilateral and contralateral similarities were assessed using a
230 paired t-test.

231 In a complementary analysis, we tested whether the superior and inferior cerebellar ROIs
232 differed in their representational structure. For each participant, we computed the cosine
233 similarity between their RDMs and the corresponding leave-one-out group-average RDMs, and
234 compared these similarities using a two-sided paired t-tests.

235 **Model comparison.** To assess the contribution of each theoretical model (PoA and VOT) in
236 explaining cortical RDMs, we first strung out the upper triangular elements of the data RDM and
237 the model RDMs into vectors. For each subject and region, we quantified the strength of each
238 feature representation by computing Pearson's correlation between the vectorized empirical
239 RDM and each model RDM. Group level significance in each region was assessed by testing
240 whether the correlation coefficients differed from zero using a one-sided one-sample t-test. To
241 evaluate the relative contribution of each model we performed a non-negative linear regression
242 for each subject, predicting the 15 inter-syllable distances from a linear combination of the two
243 models, including an intercept term to account for baseline similarity:

244

$$RDM_{region} \sim w_1 + w_2 * PoA + w_3 * VOT$$

245 For this analysis the model RDM vectors (PoA and VOT) were standardized, so that each had a
246 sum of squares equal to 1. The relative contributions of PoA and VOT were then compared using
247 a paired t-test on the regression weights w_2 and w_3 across subjects.

248 **Multidimensional scaling.** To visualize the geometric relationships of syllable representations
249 across speech-related regions, we applied classical multidimensional scaling (MDS) to the
250 vectorized RDM vectors. MDS projects the N-dimensional dissimilarity matrix into a lower
251 dimensional space, while preserving pairwise distances. To focus on the pattern of geometric
252 organization rather than overall magnitude of dissimilarities, each RDM was normalized by its
253 total quadric norm (i.e., the square root of the sum of squared Crossnobi distances) before MDS.
254 Dissimilarities were kept as squared Crossnobi distances to ensure unbiased estimates of the
255 neural pattern differences.

256 **Cerebellum-cortex representational similarity.** To quantify the similarity between cerebellar
257 and cortical representations, we computed the cosine similarity between each subject's cerebellar
258 RDM and each cortical RDM. To assess whether these similarities exceeded what would be
259 expected under a uniform representational structure, we compared each cerebellar-cortical
260 similarity to a null model in which all pairwise syllable distances were equal. Differences
261 between cerebellar-cortical and null similarities were evaluated using a one-sided paired t-test.

262 **Leave-one-out non-negative regression.** To identify which cortical areas contribute unique,
263 non-redundant information in explaining cerebellar RDM vectors, we performed a stepwise non-
264 negative linear regression, predicting cerebellar RDMs from the cortical RDMs, by adding one
265 cortical region at each step. The model was trained using data from all but one subject and tested
266 on the left-out subject. Model performance was evaluated using cosine similarity between the
267 predicted and the observed cerebellar RDMs. To assess whether adding a cortical region
268 significantly improved prediction accuracy, we conducted one-sided paired t-test comparing the
269 performance between consecutive steps.

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Results

274 **Identifying regions responsive to syllable production**

275 We identified six neocortical regions and two cerebellar regions activated during overt syllable
276 repetition (Fig. 2), corresponding to the “minimal speech production network” described by
277 Bohland & Guenther (2006). These areas included a large region in the ventral primary motor
278 (M1) and sensorimotor (S1) cortex (vSM). A second, smaller region was identified more dorsally
279 (dSM), situated between the hand and foot representation. We also observed consistent activity in
280 medial region encompassing parts of the supplementary and pre-supplementary motor areas
281 (SMA), as well as in the frontal and parietal operculum (OP), the sylvian parietal-temporal area
282 (Spt), and the auditory belt (Aud, Fig. 2A). Within the cerebellum, we identified two distinct
283 regions associated with syllable production: a superior region in lobules V/VI (cbSUP) and an
284 inferior region in lobule VIII (cbINF) (Fig. 2B). This dual representation aligns with previous
285 fMRI findings demonstrating two somatomotor maps for tongue movement in the cerebellum
286 (Nettekoven et al., 2024; Saadon-Grosman et al., 2022).

287 To test which of the regions within this network show hemispheric asymmetry, we calculate a
288 lateralization index for each region separately (Fig. 2C). We found left hemispheric dominance in
289 the SMA ($t_{(11)} = -2.63$, $p=.023$) and vSM ($t_{(11)} = -2.97$, $p=.012$). Right hemisphere dominance was
290 observed in the operculum ($t_{(11)} = 2.90$, $p=.014$). In the cerebellum, both superior and inferior
291 regions showed significantly stronger activity in the right hemisphere (cbSUP: $p=.045$, cbINF:
292 $p=.005$).

293

294 **Pattern analysis shows encoding of different syllables**

295 We then asked whether the identified speech-related regions exhibit distinct activity patterns for
296 different syllables. Surface representations of syllable-related activity patterns showed no clear
297 spatial segregation between syllables (Fig. 3A). Instead, the maps revealed individual differences
298 in both the extent and internal organization of activity patches, consistent with previous fMRI
299 findings (Carey et al., 2017).

300 To assess whether different syllables were reliably represented despite the absence of clear
301 spatial segregation, we quantified syllable-specific reliability across runs and subjects using
302 variance decomposition (Fig. 3B). Importantly, reliability was estimated after subtracting the

303 mean activity from each voxel, ensuring the measure reflected the consistency of differences
 304 between syllables rather than overall activation levels. All ROIs showed significant positive
 305 pattern reliability (see *Methods*, all $p < 0.05$, FDR-corrected), indicating that syllable identity
 306 could be reliably decoded from these regions in individual subjects.

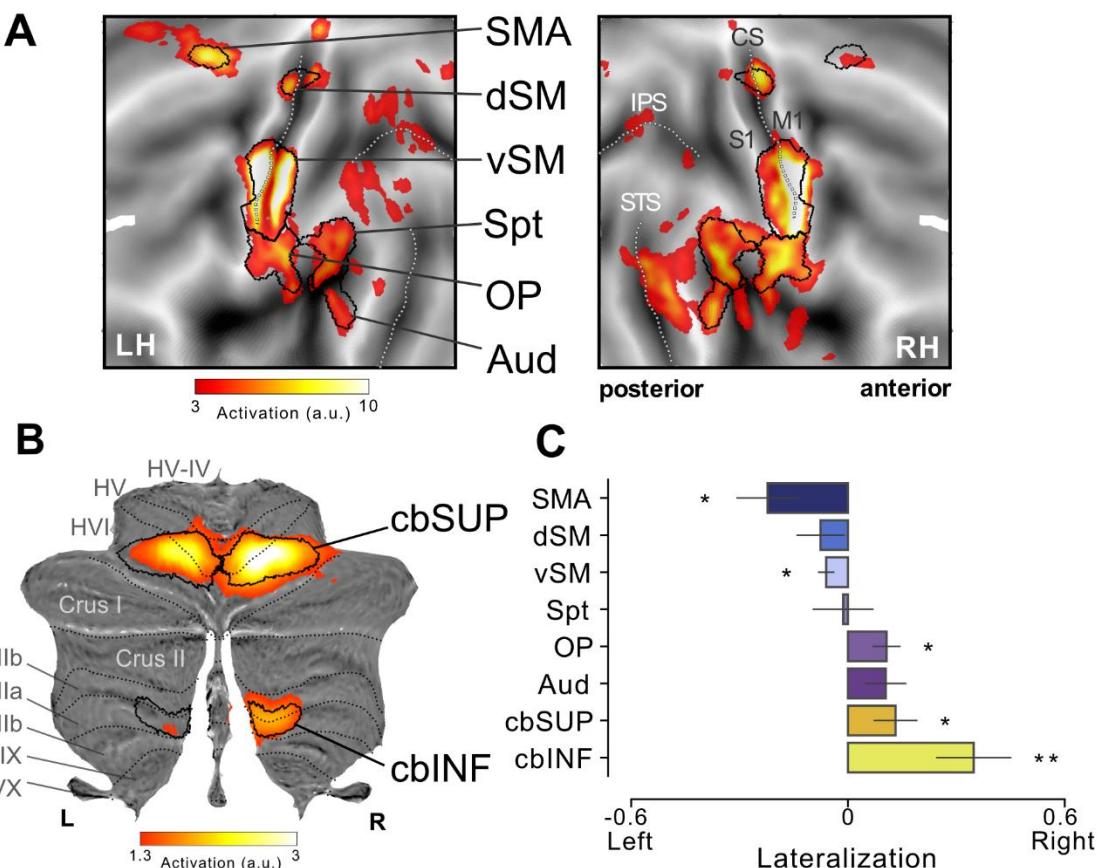


Figure 2. Average activity during overt syllable production. Group-average activation maps across all syllable types, projected onto flattened representation of the neocortex (**A**) and the cerebellum (**B**). Major neocortical sulci and cerebellar lobular boundaries are indicated by dotted lines. Boundaries of symmetrically-defined functional ROIs are outlined in black. **C**, Lateralization index of average activity. Error bar corresponds to standard error of the mean. * $p < 0.05$, ** $p < 0.01$.

Abbreviations: SMA - supplementary motor area; dSM – dorsal sensorimotor; vSM – ventral sensorimotor; OP – operculum; Spt – Sylvian parietal-temporal; Aud – Auditory cortex; CS – central sulcus; S1 – primary sensory cortex; M1 – primary motor cortex; IPS – intraparietal sulcus; STS- superior temporal sulcus; cbSUP – superior cerebellum; cbINF – inferior cerebellum.

307 We then decomposed pattern reliability into two components: group variance, reflecting
308 structure shared across individuals, and subject-specific variance, capturing reliable but
309 idiosyncratic patterns. In vSM, the group component was highly significant (left: $t_{(11)}=6.79$,
310 $p_{(FDR)}=.0001$; right: $t_{(11)}=5.93$, $p_{(FDR)}=.0001$), accounting for 35.93% ($\pm 5.19\%$) of the individual
311 pattern reliability. Thus, despite the apparent lack of common organization on visual inspection
312 (Fig. 3A), vSM exhibits a systematic topology shared across subjects. To illustrate this, we
313 plotted group contrasts for each place of articulation (bilabial, alveolar, velar) against the
314 remaining syllables. The resulting map (Fig. 3C) shows more dorsal activation for bilabials, and
315 more ventral activity for velars, with alveolar syllables preferentially engaging voxels in
316 between, consistent with previous findings (Bouchard et al., 2013; Carey et al., 2017; Correia et
317 al., 2020; Eichert et al., 2020).

318 Lastly, we tested whether syllable-specific information differed across hemispheres (Fig.
319 3D). Significant left lateralization was observed in both SMA and vSM, with stronger
320 information in the left hemisphere compared to the right (SMA: $t_{(11)}=-2.97$, $p=.012$; vSM: $t_{(11)}=-$
321 4.15, $p=.001$). The dSM showed a non-significant trend toward left lateralization ($t_{(11)}=-1.66$,
322 $p=.12$). In contrast, the inferior cerebellum exhibited a significant right lateralization, with higher
323 information encoded in the right cerebellar hemisphere ($t_{(11)}=2.55$, $p=.026$). The operculum,
324 auditory cortex, Spt, and superior cerebellum showed no hemispheric differences in the strength
325 of syllable-specific information (all $p > .1$).
326

327 **Representational geometry in cortical speech regions**

328 Having established reliable syllable-specific information, we next examined its organization
329 across regions using representational similarity analysis (Kriegeskorte & Diedrichsen, 2019). For
330 each ROI, cross-validated Mahalanobis distances between activation patterns for different
331 syllables were computed, yielding a representational dissimilarity matrix (RDM) per region (Fig.
332 4A). As no significant hemispheric differences were found (see *Methods*, all $p > 0.1$), data from
333 left and right hemispheres were averaged to produce a single representational estimate per ROI.
334 To complement this multivariate approach, we also quantified mean activation responses for each
335 syllable within each ROI (Fig. 4B).

336 We then examined how syllables are represented within each region by comparing the data
337 RDM to two models—place of articulation (PoA) or voice onset time (VOT) (Fig. 4C). First, we

338 assessed whether each feature was reflected in the regional representational geometry by
 339 correlating the data RDM with each model RDM separately (Fig. 4D). This analysis revealed a
 340 strong correspondence with the PoA model in the vSM (mean $r=0.67$, $p=1.57\times 10^{-7}$), the
 341 operculum (mean $r=0.29$, $p=.001$), and to a lesser degree in the auditory cortex (mean $r=0.18$,

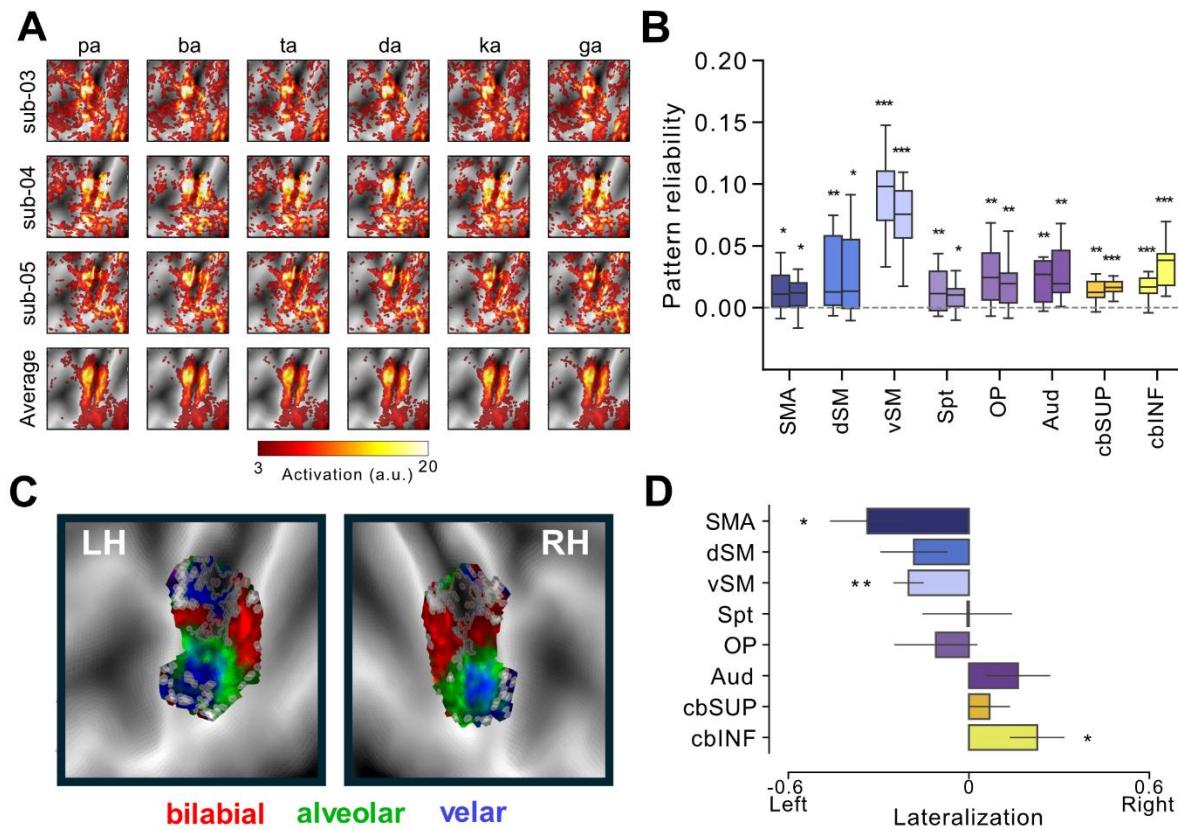


Figure 3. Evoked activity patterns during the production of different syllables. **A**, Activation maps in the left vSM are shown on a flattened neocortical surface. Each row displays activity patterns from an individual participant, with the bottom row showing the group-average across all subjects (N=12). **B**, Reliability of activity patterns for single syllables in speech ROIs. Pattern reliability reflects the variance explained by shared variance across subjects and task conditions within each subject, across runs. Within each ROI, reliability for the left hemisphere (left boxplot) and right hemisphere (right boxplot) are presented. **C**, Group t-maps in left and right vSM showing articulator-selective contrasts for bilabial (red), alveolar (green), and velar (blue). **D**, Lateralization index calculated as the normalized difference between right and left average Mahalanobis distances, in each ROI. Error bars indicate standard error of the mean. * $p<.05$, ** $p<.01$, *** $p<.001$.
 Abbreviations: SMA- supplementary motor area; dSM – dorsal sensorimotor; vSM – ventral sensorimotor; OP – operculum; Spt – Sylvian parietal-temporal; Aud – Auditory cortex; cbSUP – superior cerebellum; cbINF – inferior cerebellum; LH – left hemisphere; RH – right hemisphere.

342 p=.018), indicating sensitivity to articulatory structure in those regions. Consistent with these
343 representational effects, univariate analysis of mean activity showed significant main effects of
344 PoA in vSM and auditory cortex (Table 1). Post-hoc comparisons revealed distinct response
345 profiles across regions: in the vSM and operculum, alveolar syllables elicited the highest
346 activation, whereas in the auditory cortex, bilabial syllables evoked the lowest activation, and
347 velar syllables the strongest responses (Fig. 4B).

348 In contrast to PoA representations, significant correlations with VOT were observed in SMA
349 (mean $r=0.155$, $p=.023$) and Spt (mean $r=0.157$, $p=.023$). The dSM did not show significant
350 correlations with either model, though it was positively correlated with VOT (mean $r = 0.15$,
351 $p=.129$). Univariate analyses revealed a significant main effect of VOT in Spt, SMA and dSM,
352 with post-hoc tests showing higher mean activation for voiceless compared to voiced consonants
353 (Table 1, Fig. 4B). Notably, the operculum showed a significant univariate effect for VOT
354 alongside PoA sensitivity in the representational analysis, suggesting an integrated representation
355 of both articulatory place and temporal voicing information in this region. In the auditory cortex,
356 voiced consonants elicited higher activity than voiceless consonants, although this effect did not
357 reach significance.

358 Next, we evaluated the unique contribution of each feature in explaining the regional RDMs
359 (Fig. 4E). To do this, we used non-negative linear regression to simultaneously fit each cortical
360 RDM with both model RDMs, allowing the two features to compete for shared variance. We then
361 compared the resulting beta weights within each region. vSM showed a significantly stronger
362 weight for PoA compared to VOT ($t_{(11)}=4.85$, $p=.0005$). The operculum also exhibited a stronger
363 weight to PoA over VOT, albeit to a lesser extent ($t_{(11)}=2.28$, $p=.043$). Other cortical regions
364 showed no significant difference between PoA and VOT weights (all $p>.1$), though the auditory
365 cortex, SMA and dSM showed trends toward VOT dominance.

366 Multidimensional scaling (MDS; Fig. 4F) summarizes these findings by visualizing the
367 organizational structure of cortical regions in two dimensions: The first dimension contrasts vSM
368 and auditory cortex along the PoA-VOT axis, while the second dimension separates vSM,
369 operculum, and auditory cortex from Spt, SMA and dSM, reflecting a broader distinction
370 between areas sensitive to articulatory versus temporal features.

371

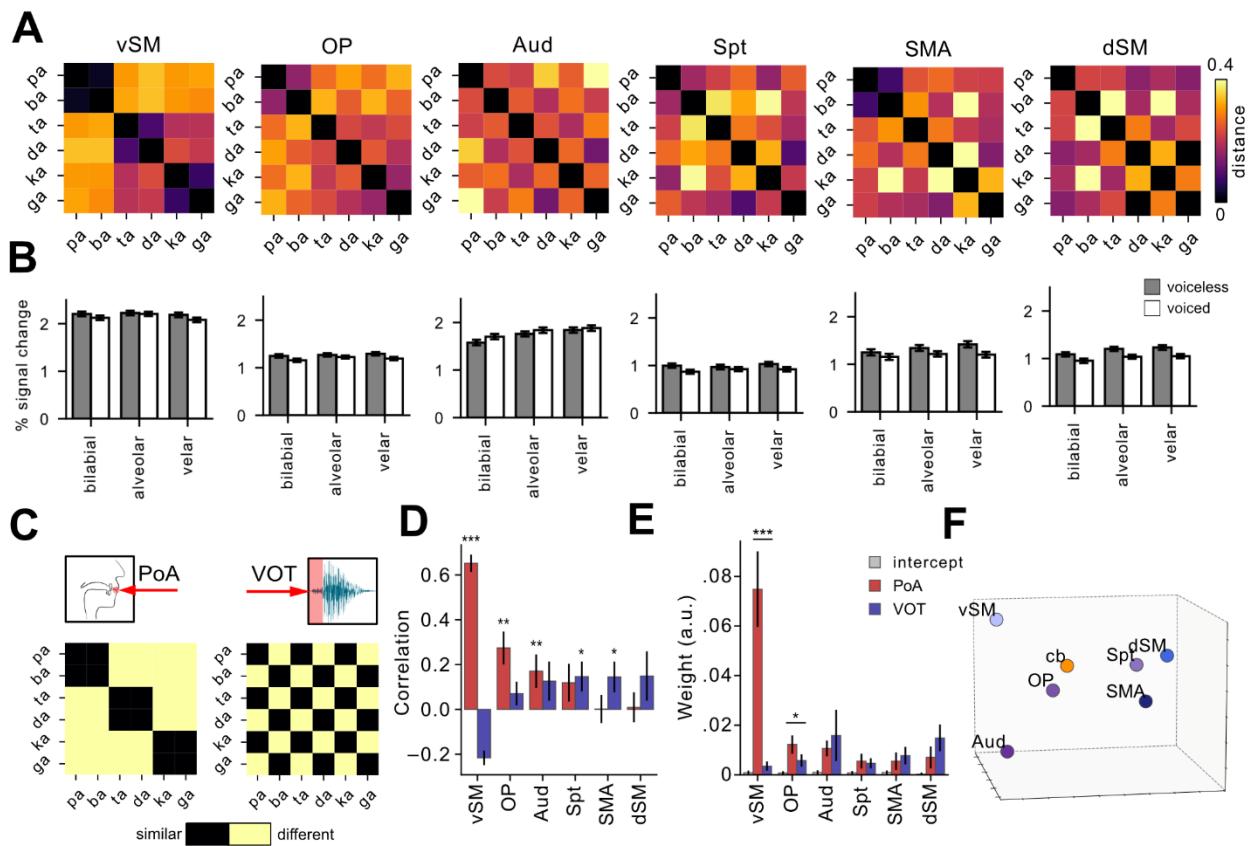


Figure 4. Representational geometry of syllables within the neocortex. **A**, RDMs between activity patterns evoked by different syllables, averaged across hemispheres and subjects within each region. **B**, Percent signal change (mean \pm SEM) for each region depicted in A, grouped by POA, with voiced (white) and voiceless (gray) consonants shown separately. **C**, Distance structure for the PoA (left) and VOT (right) models. Black indicated no difference between syllables; yellow indicates large differences. **D**, Pearson's correlation coefficient (mean \pm SEM) between each regional RDM and the feature models. PoA correlations are shown in red and VOT correlations in blue. **E**, Comparison of syllable model fits across speech related ROIs. Bars show mean weight ($w \pm SEM$) across participants for intercept (gray), PoA (red), and VOT (blue). **F**, Multidimensional scaling of differences between ROIs in three-dimensional space. * $p < .05$, ** $p < .01$, *** $p < .001$.

Abbreviations: RDM – representational dissimilarity matrix; vSM – ventral sensorimotor; OP – operculum; Aud – Auditory cortex; Spt – Sylvian parietal-temporal; SMA- supplementary motor area; dSM – dorsal sensorimotor; cb – cerebellum; PoA – place of articulation; VOT – voice onset time.

Table 1. Repeated-measures ANOVA results for place of articulation (PoA) and voicing (VOT) effects on average activity in each region.

Region	Factor	F(df1,df2) ^a	p-value	Post-hoc comparison	Post-hoc p-value ^b
vSM	PoA	F(2,22) = 6.50	.0060	Alveolar > Velar	.020
	VOT	F(1,11) = 4.73	.052		
	PoA × VOT	F(2,22) = 1.00	.383		
OP	PoA	F(2,22) = 1.96	.165		
	VOT	F(1,11) = 8.72	.013	Voiceless > Voiced	.013
	PoA × VOT	F(2,22) = 0.66	.528		
Aud	PoA	F(2,22) = 24.86	< .001	Bilabial < Alveolar	.001
	VOT	F(1,11) = 1.92	.193	Bilabial < Velar	<.001
	PoA × VOT	F(2,22) = 0.44	.650		
Spt	PoA	F(2,22) = 1.11	.348		
	VOT	F(1,11) = 9.75	.0097	Voiceless > Voiced	.0097
	PoA × VOT	F(2,22) = 0.75	.485		
SMA	PoA	F(2,22) = 4.91	.017	Bilabial > Velar	.011
	VOT	F(1,11) = 12.32	.0049	Voiceless > Voiced	.0049
	PoA × VOT	F(2,22) = 1.55	.235		
dSM	PoA	F(2,22) = 6.36	.0066	Bilabial > Velar	.025
	VOT	F(1,11) = 17.29	.0016	Voiceless > Voiced	.0016
	PoA × VOT	F(2,22) = 0.19	.832		
cb	PoA	F(2,22) = 10.35	< .001	Bilabial < Alveolar	.000367
	VOT	F(1,11) = 3.73	.079	Bilabial < Velar	.020
	PoA × VOT	F(2,22) = 0.89	.423		

^aF values are reported with numerator and denominator degrees of freedom.

^bPost hoc p values are FDR-corrected.

372

373 **Representational geometry in the cerebellum**

374 We next investigated syllable representations within the cerebellum. Initially, we compared the
 375 superior and inferior cerebellar speech regions and found no significant differences between
 376 them (p>0.3; Fig. 5A). This aligns with previous studies reporting dual representations of body
 377 parts in sensorimotor cerebellar regions, without clear differences in tuning or representational

378 patterns (Nettekoven et al., 2024; Wiestler et al., 2011). Accordingly, we averaged the RDMs
379 across these two cerebellar regions to obtain a more reliable, consolidated measure of syllable
380 organization within the cerebellum (Fig. 5B). Mean activations for each condition were also
381 averaged across these regions to complement the representational analysis with univariate
382 measures (Fig. 5C).

383 To characterize the geometrical structure of cerebellar syllable representations, we tested
384 their relationships with the feature models. Pearson's correlation revealed a significant
385 correlation between cerebellar RDMs and the PoA model (mean $r=0.34$, $p=.002$), but not with
386 the VOT model (mean $r=-0.008$, $p=.537$) (Fig. 5D). Univariate analysis supported these findings,
387 showing a main effect of PoA, with lower activation for bilabial sounds (Table 1). Finally, non-
388 negative linear regression demonstrated a significantly stronger weight for PoA compared to
389 VOT ($t_{(11)}=2.55$, $p=.026$) (Fig. 5E).

390 The arrangement of representations in speech regions (Fig. 4B) suggests that the
391 representational structure in cerebellar speech areas closely resembles that of the operculum. To
392 quantify these relationships, we calculated cosine similarity between the cerebellum and each
393 cortical region. Because cerebellar syllable-related activity patterns were more variable across
394 subjects than cortical patterns (linear mixed-effects model: $\beta=-0.012$, $SE=0.006$, $z=-2.27$,
395 $p=.023$), subsequent analyses were performed at the individual-subject level to capture subject-
396 specific relationships between the cortex and the cerebellum. Within each subject, the cerebellar
397 RDM was significantly more similar to the operculum ($t_{(11)}=2.206$, $p=.025$) than to a reference
398 model predicting uniform dissimilarities (Fig. 5F). Cerebellar RDMs also showed some
399 similarity to vSM, though this did not reach statistical significance ($p=.059$). Similarities to other
400 regions were not significant, indicating a selective engagement of the cerebellum with the
401 operculum and vSM during speech production.

402 Can the cerebellar representation be best described as a mixture of several cortical regions,
403 or is a single region suffice? To address this, we estimated weights that best predicted cerebellar
404 RDMs based on cortical RDMs, using a leave-one-out cross-validation approach incrementally
405 adding ROIs to the model based on their similarity. We found that adding the operculum to a
406 model already including vSM significantly improved prediction of cerebellar RDMs ($t_{(11)}=2.65$,
407 $p=.002$), indicating that the operculum contributes unique information over and above vSM. In
408 contrast, adding vSM to a model that already included the operculum did not significantly

409 improve model fit ($p=0.1$), suggesting that the operculum could account for most of the syllable
 410 representation in the cerebellum (Fig. 5F).
 411

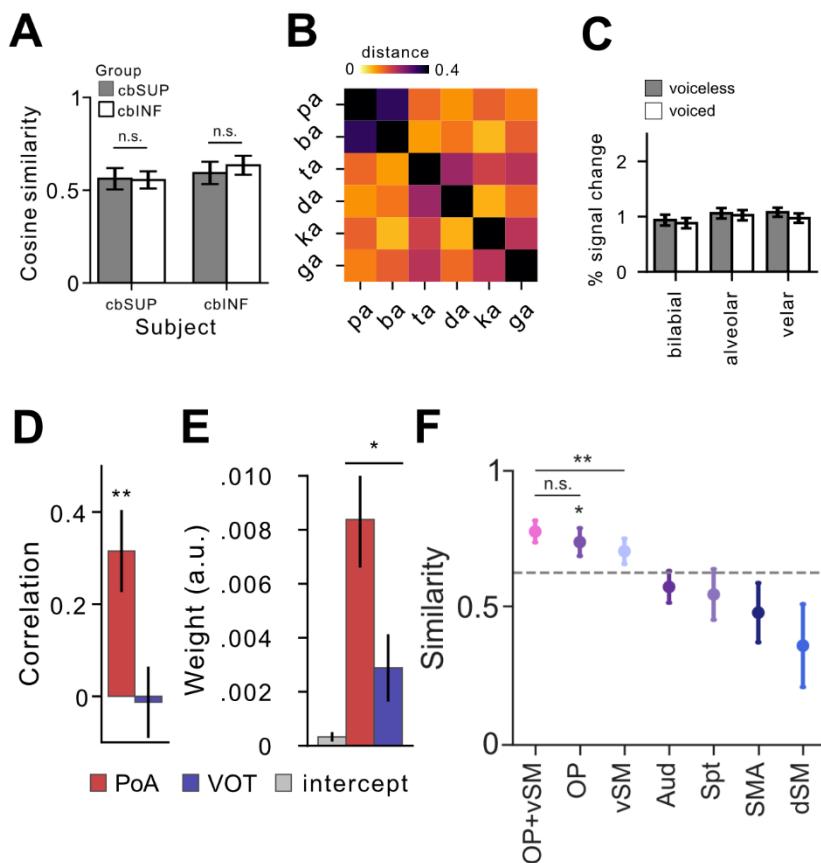


Figure 5. Representational geometry of syllables within the cerebellum. **A**, Cosine similarities between cerebellar ROIs. Plotted are the cosine similarities of each participant's cbSUP (left) and cbINF (right) RDMs compared to the leave-one-out group RDMs of cbSUP (gray) and cbINF (white). **B**, RDMs between activity patterns evoked by different syllables, averaged across cbSUP and cbINF. **C**, Percent signal change (mean \pm SEM), grouped by POA, with voiced (white) and voiceless (gray) consonants shown separately. **D**, Pearson's correlation coefficient (mean \pm SEM) between cerebellar RDM and the feature models. **E**, Size of model weights ($w \pm \text{SEM}$) across participants for intercept (gray), PoA (red), and VOT (blue) in the combined model. **F**, Cosine similarity between the cerebellum and neocortex. Similarities were calculated between observed and predicted cerebellar RDMs using cross validated stepwise non-negative regression. The dashed gray line represents the similarity of cerebellar RDMs to a null reference, averaged across participants. * $p < .05$, ** $p < .01$, *** $p < .001$. Abbreviations: RDM – representational dissimilarity matrix; cbINF- inferior cerebellum; cbSUP- superior cerebellum; PoA – place of articulation; VOT – voice onset time; vSM – ventral sensorimotor; OP – operculum; Aud – Auditory cortex; Spt – Sylvian parietal-temporal; SMA- supplementary motor area; dSM – dorsal sensorimotor.

412

Discussion

413 This study characterized the neural representations of speech during overt syllables
414 production using multivariate analysis and 7T fMRI. We demonstrate that the patterns associated
415 with each syllable showed reliable differences in both cortical and cerebellar speech related
416 regions. These regions exhibited differential tuning along the PoA-VOT axis: While vSM was
417 primarily tuned to place of articulation, dSM, SMA, and Spt were more sensitive to voice onset
418 time. The operculum and auditory cortex demonstrated a hybrid profile, with sensitivity to both
419 features. Furthermore, we found that in the cerebellum, syllables are better represented by their
420 place of articulation rather than voice onset timing. Surprisingly, cerebellar representations
421 aligned most closely with the operculum rather than primary sensorimotor cortex, suggesting that
422 speech control relies on cerebellar-cortical circuits beyond primary motor cortex.

423 In this study, we found a functional contrast between vSM and dSM in their tuning to speech
424 features. The tuning of the vSM for different places of articulation supports its established role in
425 the motoric sculpting of the vocal tract (Bouchard et al., 2013). Therefore, vSM may function as
426 a motor map with topographical regularities across individuals. The dSM, in contrast, showed
427 greater sensitivity to voice onset time compared to place of articulation (Fig. 4E). Although this
428 effect did not reach statistical significance ($p=.146$), the pattern is consistent with a functional
429 role of the dSM in phonation (Correia et al., 2020). Unlike the somatotopic maps of articulators
430 in vSM, the neural patterns for voice onset time may be more idiosyncratic, potentially reflecting
431 individual-specific strategies for timing respiration and articulation.

432 Traditionally, the dSM has been associated with trunk movements during respiration (Brown
433 et al., 2009; Loucks et al., 2007). Here, by varying the temporal onset of phonation relative to
434 articulation, we demonstrate that dSM activity reflects the precise temporal gating of airflow
435 during speech production. Recently, the role of the dSM has been extended beyond a simple
436 representation of the trunk. For example, Correia et al., (2020) demonstrated that voiced speech
437 recruits the dSM more heavily than whispered speech, even when controlling for lung volume,
438 suggesting a specific involvement in phonatory control. While we did not directly monitor
439 breathing patterns in the current study, our finding that the dSM is tuned to voice onset time,
440 supports the notion that this region is involved in the synchronization of respiration and laryngeal
441 tension. Future studies utilizing simultaneous fMRI and respiratory tracking are needed to
442 distinguish the dSM's role in global respiration vs. its role in syllable-specific temporal gating.

443 Contrary to our predictions, cerebellar representations did not exclusively resemble those in
444 vSM, nor did they reflect a mixture of ventral and dorsal sensorimotor representations. Instead,
445 cerebellar representational structure aligned most closely with that of the operculum (Fig. 5F).
446 BOLD signals in the cerebellum predominantly reflect afferent input rather than local output
447 computations (Caesar et al., 2003; Thomsen et al., 2004, 2009). Therefore, the close alignment
448 between opercular and cerebellar representational geometry observed in our data likely reflects
449 information transmitted from the operculum to the cerebellum. Notably, the cerebellum also
450 interacts with the neocortex cortex by sending outputs back to it. However, such efferent
451 interactions are not directly captured by cerebellar BOLD measurements.

452 According to the DIVA model, opercular-cerebellar interactions support the generation and
453 refinement of feedforward speech motor commands (Guenther, 2006). Within this framework,
454 the frontal operculum is hypothesized to encode speech-motor plans, while the cerebellum
455 contributes to the tuning of these plans. If this account is correct, both regions should be active
456 during speech execution, but only the operculum should show activation during speech
457 preparation. Alternatively, if the cerebellum forms a closed-loop circuit with the operculum,
458 preparatory activation should be observed in both regions.

459 Clinical evidence further implicates the cerebellum in speech planning. Apraxia of speech
460 and dysarthria are dissociable speech disorders, with apraxia reflecting impaired motor planning,
461 and dysarthria reflecting deficits in motor execution (Ziegler et al., 2012). While dysarthria is
462 classically associated with direct cerebellar damage, highlighting the cerebellum's established
463 role in speech execution (Ackermann, 2008), recent findings in left-hemisphere stroke patients
464 reveal a link between reduced cerebellar gray matter and greater apraxia severity (Gibson et al.,
465 2025). Notably, gray matter volume in right cerebellar lobules V/VI, identified here as the
466 superior cerebellar speech region, best predicted apraxia severity. In contrast, dysarthria severity
467 showed weaker associations with cerebellar gray matter, underscoring the specificity of this
468 relationship to speech planning deficits. Together with its representational alignment to the
469 operculum, these clinical findings strengthen the interpretation that the cerebellum also
470 contributes to speech planning rather than solely to motor execution.

471 Speech production relies on interactions between the motor and auditory systems, enabling
472 the coordination of articulatory commands with their auditory consequences (Guenther, 2006;
473 Hickok et al., 2011). Our results show that speech production evokes robust and reliable

474 activations in the auditory cortex, primarily located along the medial and lateral Heschl's gyrus
475 (Fig. 2A). Previous studies have shown that this region responds more strongly to speech than
476 non-speech sounds, and encodes acoustic-phonetic features during speech perception (Binder et
477 al., 2000; Mesgarani et al., 2014). Our data extend these findings by demonstrating that the
478 auditory cortex represents phonatory features not only during speech perception, but also during
479 speech production. Because external auditory feedback was largely masked by scanner noise in
480 the current study, these representations are unlikely to arise solely from the airborne auditory
481 feedback. Instead, our results could indicate that the auditory representations are caused by
482 internally generated predictions derived from an efference copy of the articulatory command
483 (Houde et al., 2002). However, these representations may also reflect auditory input transmitted
484 through bone-conductance (v. Békésy, 1949).

485 In the current study we used a limited set of syllables, focusing exclusively on plosive
486 consonants combined with a low-back vowel (i.e. /a/). While this choice provided strong control
487 over articulatory and temporal dimensions of speech, it limits the extent to which our results can
488 be generalized to other phonemic categories, different manners of articulation, or to more
489 complex, naturalistic, speech. Both vowel identity and manner of articulation evoke distinct
490 activity patterns within the vSM (Bouchard et al., 2013; Bouchard & Chang, 2014). Importantly,
491 because vowel identity shapes consonant articulation via coarticulation, restricting syllables to a
492 single vowel may limit the range of consonant-related representational structure captured here.

493 In summary, this study reveals feature-specific representational tuning of articulatory and
494 phonatory features within primary sensorimotor areas, with ventral sensorimotor cortex encoding
495 place of articulation and dorsal regions showing sensitivity to voice onset timing. Secondary
496 speech areas, such as the operculum and auditory cortex, exhibited a hybrid representational
497 profile, reflecting heightened sensitivity to the phonetic differences. Surprisingly, cerebellar
498 representations aligned most closely with those of the operculum, suggesting an opercular-
499 cerebellar circuit involved in speech motor planning prior to execution. It remains to be seen
500 which specific computations are performed within the cerebellum and how they influence
501 neocortical speech area.

502

503

504

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509

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