Report: August 2022 to June 2023

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June 2023

1 Introduction

This document lists all the experiments performed over the period of August 2022 to June 2023. The tasks were categorised into Experiment design and coding (Section 2), EEG data processing (Section 3), MRI data processing (Section 4), Condition-wise EEG data differences (Section 5) EEG-to-speech experiments (Section 6) and Classification experiments (Section 7)

2 Experiment design and coding

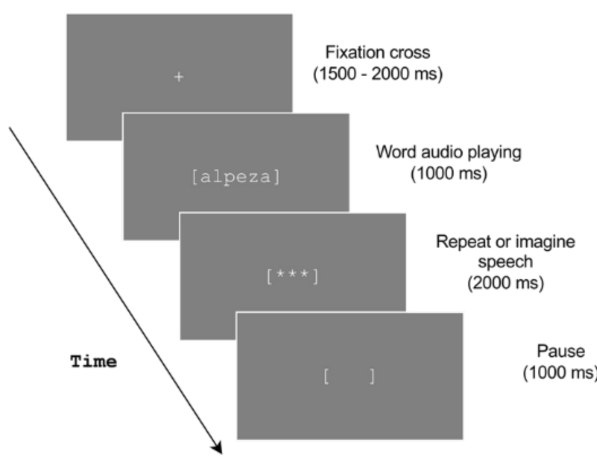


Figure 1: Flowchart of experiment

A new speech experiment was designed using the psychopy toolbox. The task involved listening to a pseudoword followed by repeating the word covertly or aloud.

The experiment was designed with variable fixation cross duration, ability to pause and resume at any point during the trial, participant friendly user interface (e.g image based cues to repeat aloud and to repeat covertly) and randomised ordering of conditions and stimuli.

3 MRI data processing

3.1 Conversion dicom to nifti

Initially, the dicom to niftii conversions were performed with a Matlab function called dicom2nifti. There were issues with performing it iteratively for all the nested folders.

Instead, a python package and function called 'dicom2nifti.convert_directory' was way more straightforward and had a better success rate, i.e. it converted some folders that the Matlab function could not convert.

3.2 Choosing good T1 and electrode scan images

Once all the nifti files were obtained, it became accessible by softwares such as SPM and FSL.

There were multiple fMRI images for each patient. We needed to choose one T1 image (an image of the brain without electrodes) and an electrode image (the image that only contains the outline of the brain and the embedded deep electrodes). One T1 and one electrode image was chosen by visual inspection by looking for the clearest images.

3.3 Reorientation and normalisation of images

As the T1 and electrode images were taken separately and at different times, the images were not oriented in the same way. Some FSL commands were used to reorient the images. The T1 images were used as a reference and the electrode image was reoriented to the T1 images.

After the reorientation, the images were normalised to the MNI system. This put both images in a standard normalised coordinate system.

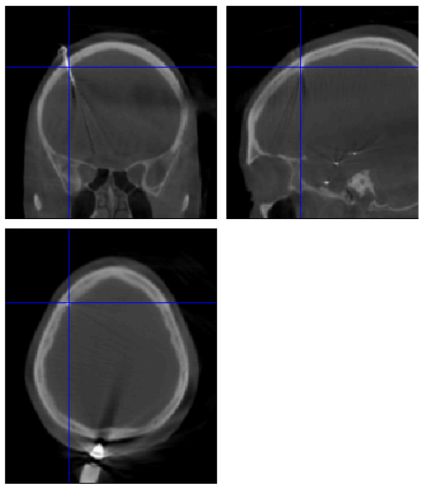
The images were then merged so that the brain areas and the electrodes can be seen superimposed on each other. This merged image was not used eventually. The MNI normalised reoriented electrode images were used for the next steps.

3.4 Electrode identification and positioning

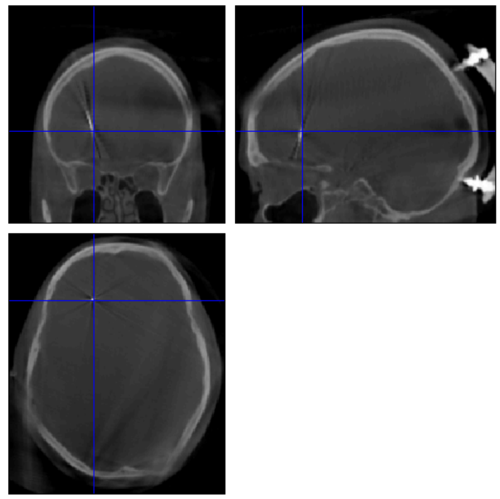
For each patient, we looked at the normalised electrode images in SPM. In parallel, we looked at the report of the patient which contained the names and the graphical representation of each deep electrode.

Using the electrode information and the help of the 3 axes representation in SPM, the [x,y,z] position of the extremities of each electrode were noted.

We looked for the start and the end of the electrode by visual inspection and moving the cursor gradually. Figure 2 shows the cursor at the start and end of one electrode.



(a) Start of electrode



(b) End of Electrode

Figure 2

Once the start and end positions were available, we needed the positions for each of the contact points of each electrode. This was obtained by getting the number of contact points for each electrode from the report and dividing the line joining the start point to the end point into as many sections as the number of contacts.

4 Data Preparation

4.1 Aligning EEG with audio

Detailed account of this can be found in David Murcia's report.

In brief, the alignment task involved getting the starting point of the trial using the 'Experiment Start' markers in both the EEG and the audio signals.

4.2 filtering

The filtering and preprocessing was done as per the methods listed by [**?**].

4.3 Extracting epochs of EEG data

The epochs chosen were the 1500ms corresponding to the read aloud/covertly section in the VCV task and the 2000ms corresponding to the name picture aloud/covertly section in the picture naming task.

4.4 Creating a matrix of EEG data

A matrix of the EEG data was created with the selected epochs (time) on one axis and the chosen electrodes on the other axis.

4.5 One hot encoding of categories

For the VCV task, each stimulus was labelled with the vowel present in the word. This information was then translated into a one hot encoded format, thereby having 5 columns, one for each vowel.

Similarly, a one hot encoded vector was made for the picture naming task with 6 columns. i.e., 6 picture categories.

5 EEG-to-speech experiments

EEG to speech experiments were performed using several algorithms. For all the experiments, high gamma features of the EEG signal were mapped with the spectral features of the audio signal. a Griffin Lim algorithm or a vocoder was used to reconstruct audio signal from output spectral features.

Firstly we tried to replicate the experiment from Christian Herff which was based on a Dutch word data set. Secondly, sincnet algorithm was used and thirdly a system used to generate speech from EMG signals was used to do the same from EEG to speech signals.Neither of the above experiments generated audible speech results.

6 Condition-wise EEG data differences

High gamma features were extracted for the two conditions (read aloud/covertly). A significant difference was found between the high gamma feature values for both the conditions (See Figure 3).

7 Experiment design and coding

8 Classification experiments

8.1 MNIST

The MNIST experiment for handwritten digit recognition was used for classifying vowels in the VCV task and picture categories in the picture naming

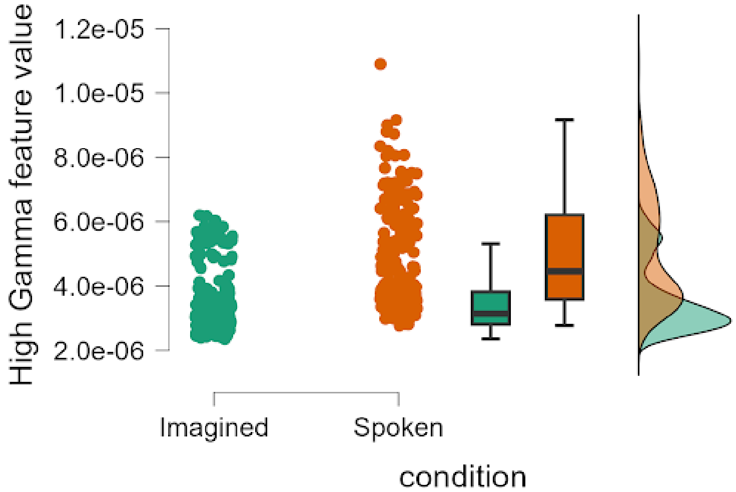


Figure 3: High Gamma Differences in read aloud (Spoken) vs covert (Imagined) conditions

task.

The rationale behind using this algorithm was that the epoched 2 dimensional EEG data could be considered as a snapshot or an image corresponding to the audio data. This snapshot or image of the EEG data was mapped to the one hot encoded vowel data for the VCV task and mapped to the one hot encoded picture category for the picture naming task.

The accuracy measures post running the MNIST algorithm varied for every execution. Therefore, each task was performed 10 times to get a floor and ceiling of the accuracy measures.

To sum up, the vowel classification task accuracies were not better than chance and the picture category classification was accuracy was marginally better than chance when run for 50 epochs.

F05

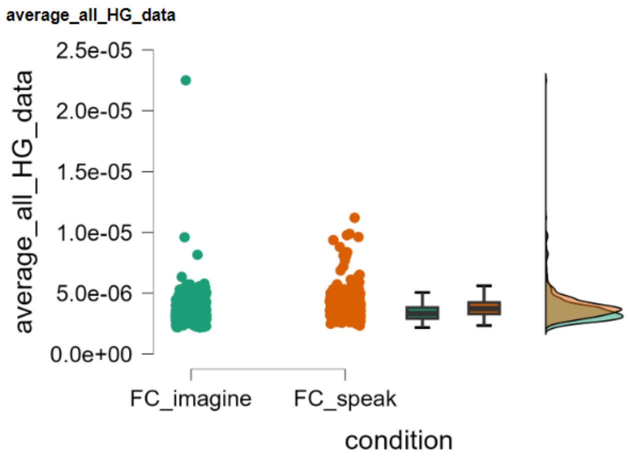
Independent Samples T-Test

	t	df	p
average_all_HG_data	−5.204	783	< .001

Note. Student's t-test.

Descriptives

Raincloud Plots



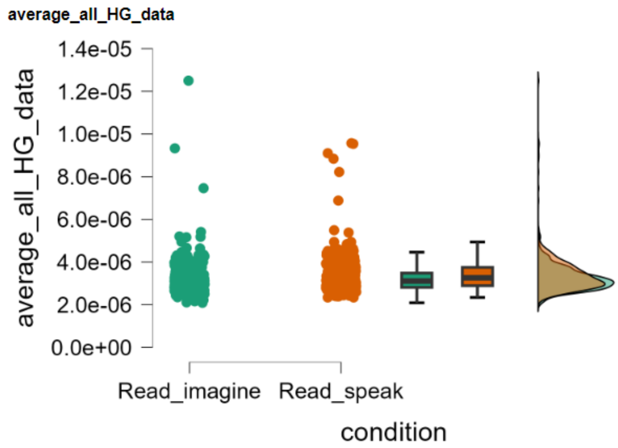
Independent Samples T-Test

	t	df	p
average_all_HG_data	−2.864	783	0.004

Note. Student's t-test.

Descriptives

Raincloud Plots



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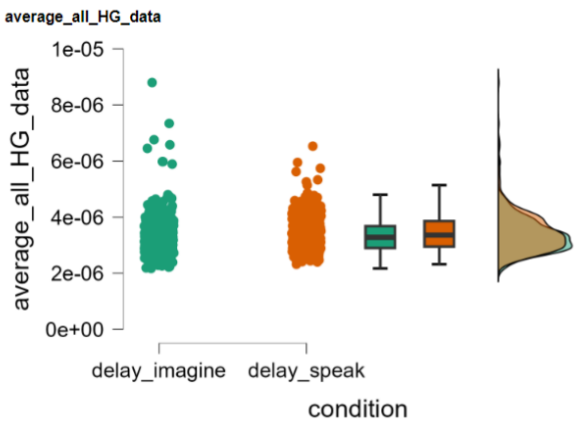
Independent Samples T-Test

	t	df	p
average_all_HG_data	−1.190	783	0.235

Note. Student's t-test.

Descriptives

Raincloud Plots



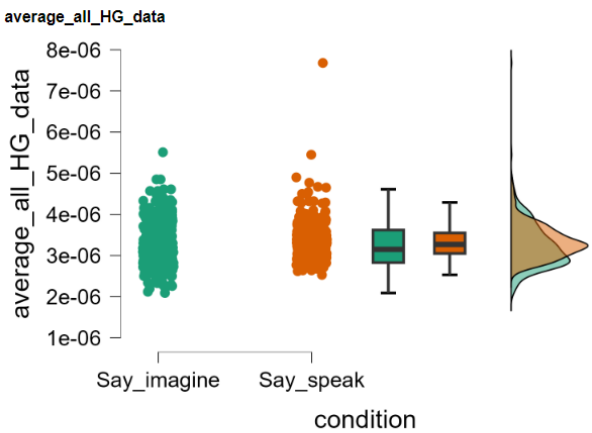
Independent Samples T-Test

	t	df	p
average_all_HG_data	−2.980	783	0.003[a]

Note. Student's t-test.
[a] Brown-Forsythe test is significant ($p < .05$), suggesting a violation of the equal variance assumption

Descriptives

Raincloud Plots



F07

Independent Samples T-Test

Independent Samples T-Test

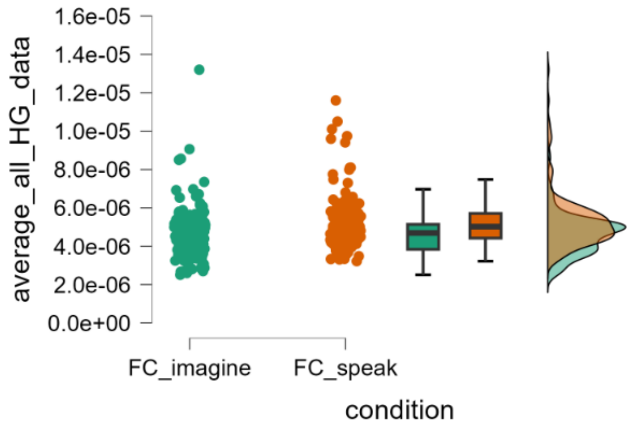
	t	df	p
average_all_HG_data	−4.485	361	< .001

Note. Student's t-test.

Descriptives

Raincloud Plots

average_all_HG_data



Independent Samples T-Test

	t	df	p
average_all_HG_data	−1.844	361	0.066[a]

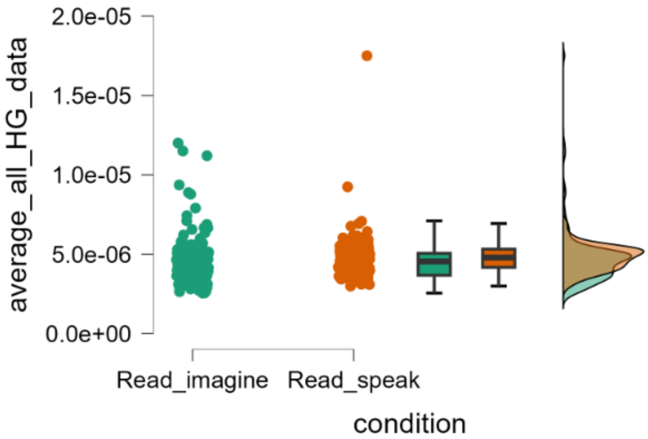
Note. Student's t-test.

[a] Brown-Forsythe test is significant (p < .05), suggesting a violation of the equal variance assumption

Descriptives

Raincloud Plots

average_all_HG_data



Independent Samples T-Test

Independent Samples T-Test

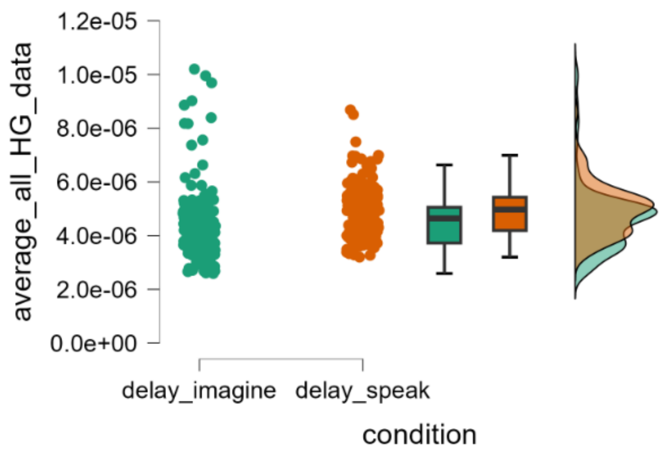
	t	df	p
average_all_HG_data	−3.052	361	0.002

Note. Student's t-test.

Descriptives

Raincloud Plots

average_all_HG_data



Independent Samples T-Test

	t	df	p
average_all_HG_data	−19.993	361	< .001[a]

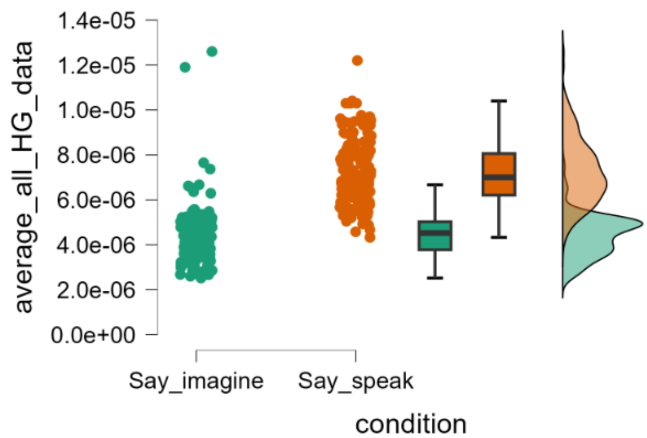
Note. Student's t-test.

[a] Brown-Forsythe test is significant (p < .05), suggesting a violation of the equal variance assumption

Descriptives

Raincloud Plots

average_all_HG_data



F08

Independent Samples T-Test

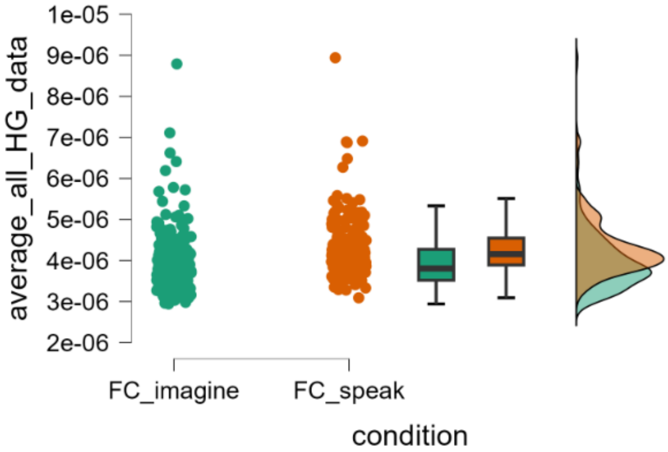
	t	df	p
average_all_HG_data	−4.530	386	< .001

Note. Student's t-test.

Descriptives

Raincloud Plots

average_all_HG_data



Independent Samples T-Test

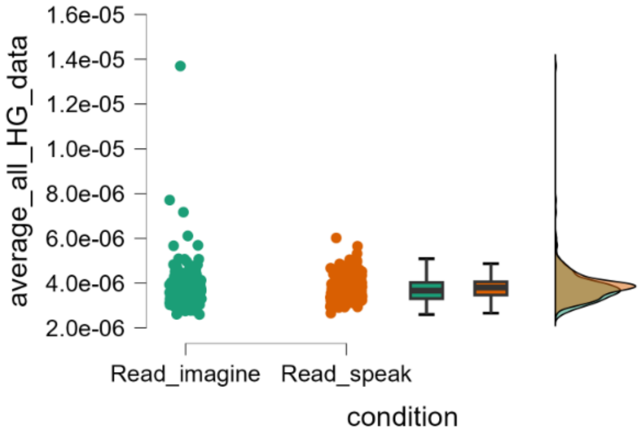
	t	df	p
average_all_HG_data	−0.211	386	0.833[a]

Note. Student's t-test.
[a] Brown-Forsythe test is significant ($p < .05$), suggesting a violation of the equal variance assumption

Descriptives

Raincloud Plots

average_all_HG_data



Independent Samples T-Test

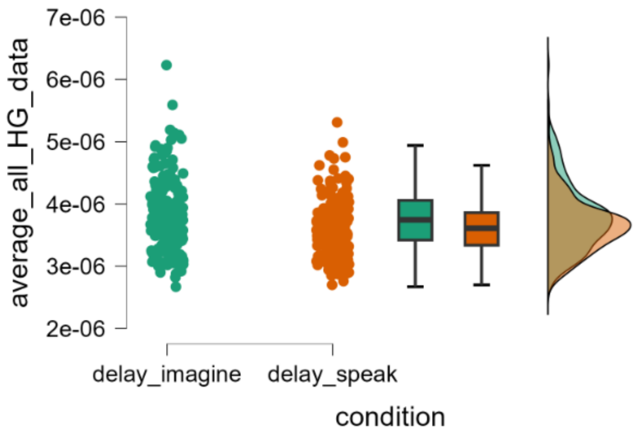
	t	df	p
average_all_HG_data	3.247	386	0.001[a]

Note. Student's t-test.
[a] Brown-Forsythe test is significant ($p < .05$), suggesting a violation of the equal variance assumption

Descriptives

Raincloud Plots

average_all_HG_data



Independent Samples T-Test

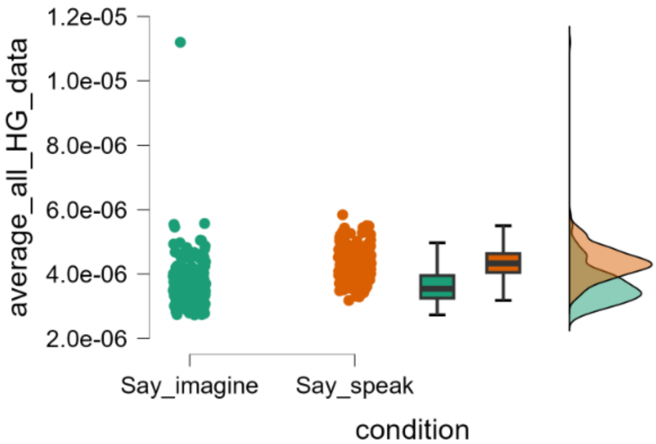
	t	df	p
average_all_HG_data	−9.999	386	< .001

Note. Student's t-test.

Descriptives

Raincloud Plots

average_all_HG_data



F09

Independent Samples T-Test

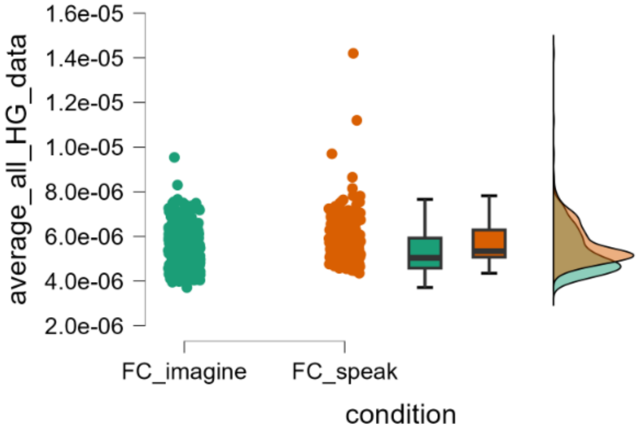
	t	df	p
average_all_HG_data	−5.390	611	< .001

Note. Student's t-test.

Descriptives

Raincloud Plots

average_all_HG_data



Independent Samples T-Test

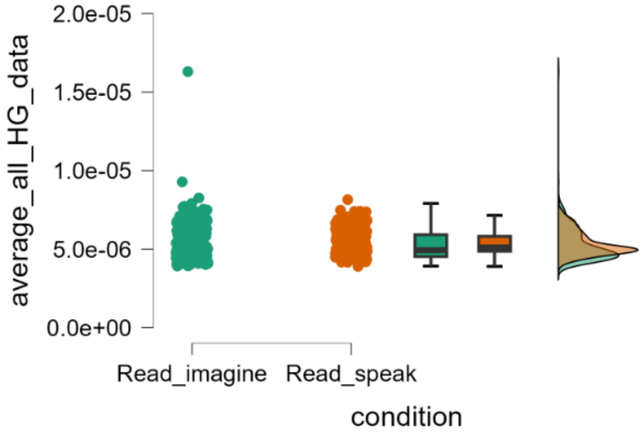
	t	df	p
average_all_HG_data	−1.002	611	0.317[a]

Note. Student's t-test.
[a] Brown-Forsythe test is significant (p < .05), suggesting a violation of the equal variance assumption

Descriptives

Raincloud Plots

average_all_HG_data



Independent Samples T-Test

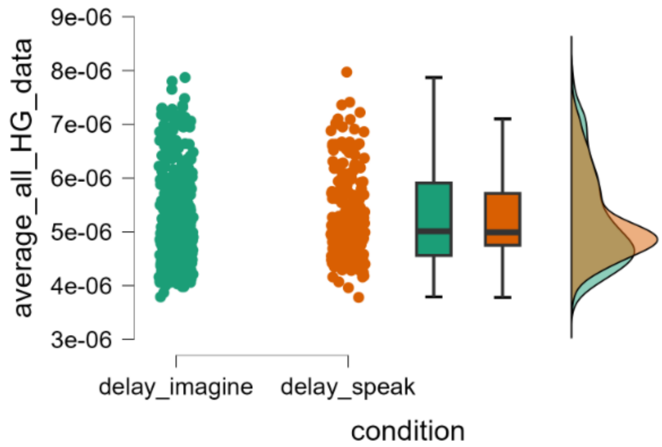
	t	df	p
average_all_HG_data	0.185	611	0.853[a]

Note. Student's t-test.
[a] Brown-Forsythe test is significant (p < .05), suggesting a violation of the equal variance assumption

Descriptives ▼

Raincloud Plots ▼

average_all_HG_data



Independent Samples T-Test

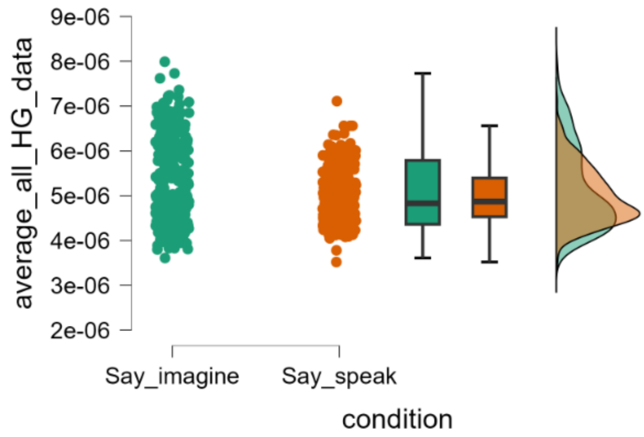
	t	df	p
average_all_HG_data	1.989	611	0.047[a]

Note. Student's t-test.
[a] Brown-Forsythe test is significant (p < .05), suggesting a violation of the equal variance assumption

Descriptives ▼

Raincloud Plots ▼

average_all_HG_data



F10

Independent Samples T-Test

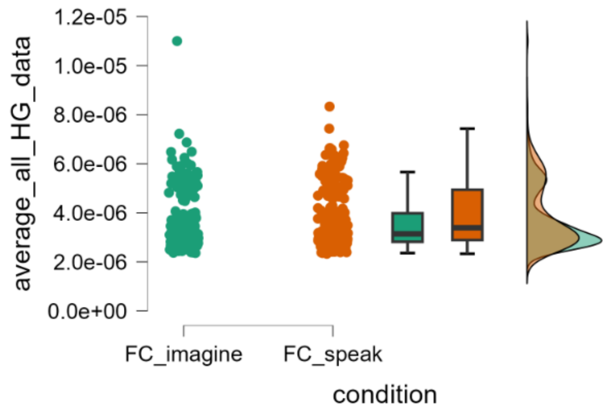
	t	df	p
average_all_HG_data	−1.958	395	0.051

Note. Student's t-test.

Descriptives ▼

Raincloud Plots ▼

average_all_HG_data



Independent Samples T-Test

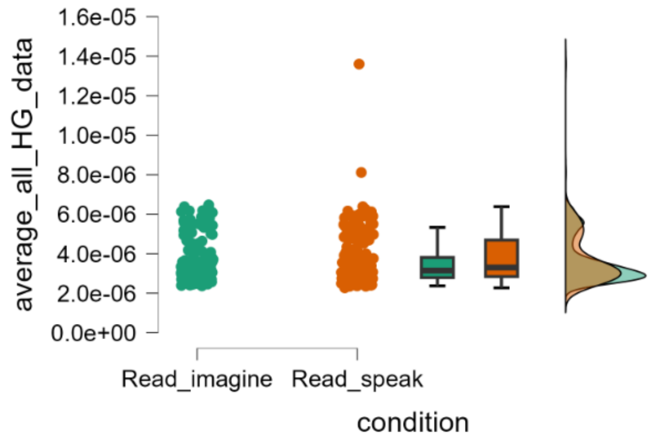
	t	df	p
average_all_HG_data	−1.532	395	0.126

Note. Student's t-test.

Descriptives ▼

Raincloud Plots ▼

average_all_HG_data



Independent Samples T-Test

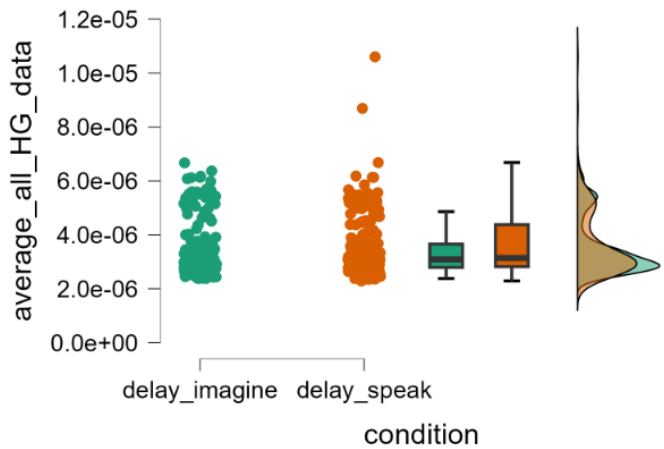
	t	df	p
average_all_HG_data	−1.178	395	0.239

Note. Student's t-test.

Descriptives

Raincloud Plots

average_all_HG_data



Independent Samples T-Test

	t	df	p
average_all_HG_data	−10.375	395	< .001[a]

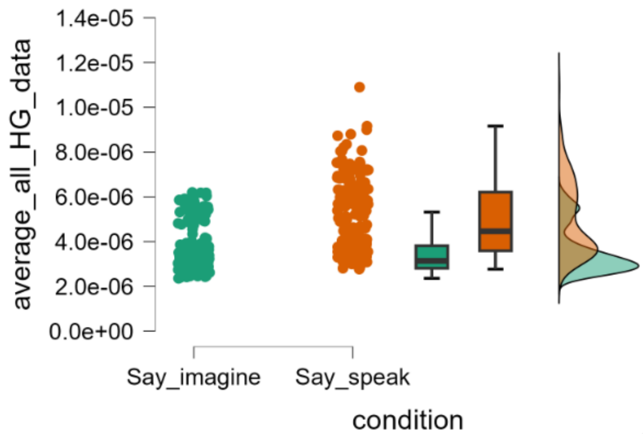
Note. Student's t-test.

[a] Brown-Forsythe test is significant ($p < .05$), suggesting a violation of the equal variance assumption

Descriptives ▼

Raincloud Plots ▼

average_all_HG_data ▼



M06

Independent Samples T-Test ▼

Independent Samples T-Test

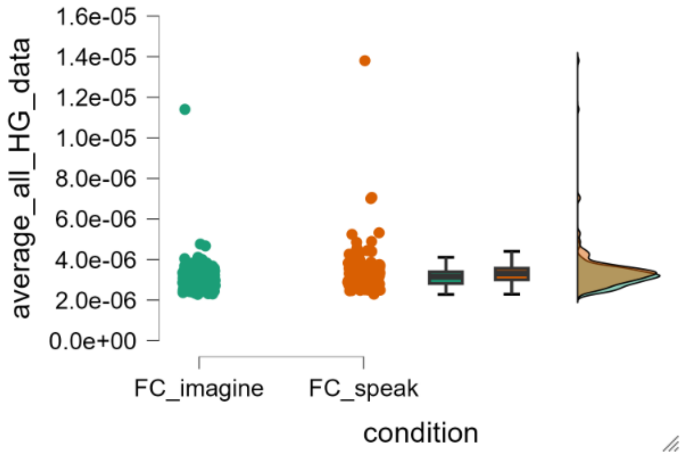
	t	df	p
average_all_HG_data	−2.928	392	0.004

Note. Student's t-test.

Descriptives ▼

Raincloud Plots ▼

average_all_HG_data ▼



Independent Samples T-Test ▼

	t	df	p
average_all_HG_data	−3.942	392	< .001[a]

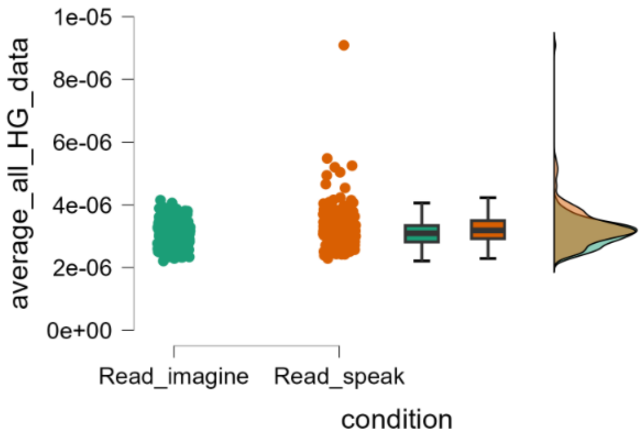
Note. Student's t-test.

[a] Brown-Forsythe test is significant (p < .05), suggesting a violation of the equal variance assumption

Descriptives

Raincloud Plots

average_all_HG_data



Independent Samples T-Test

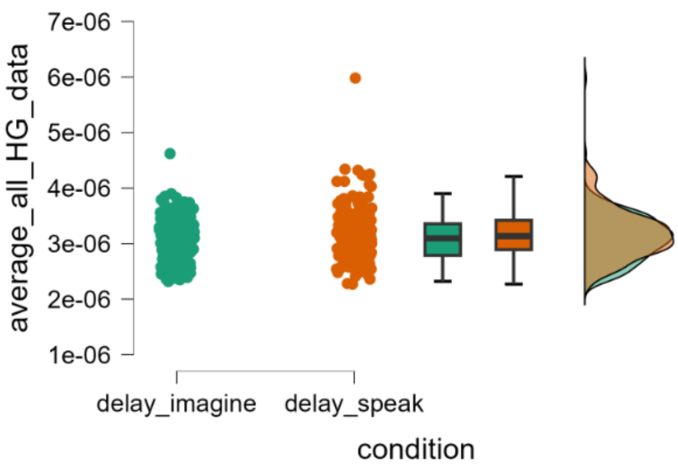
	t	df	p
average_all_HG_data	−2.181	392	0.030

Note. Student's t-test.

Descriptives

Raincloud Plots

average_all_HG_data



Independent Samples T-Test

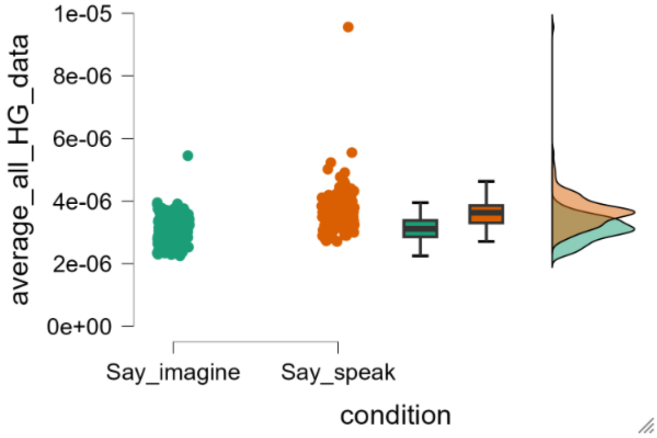
	t	df	p
average_all_HG_data	−10.391	392	< .001

Note. Student's t-test.

Descriptives ▼

Raincloud Plots ▼

average_all_HG_data ▼



M11

Independent Samples T-Test

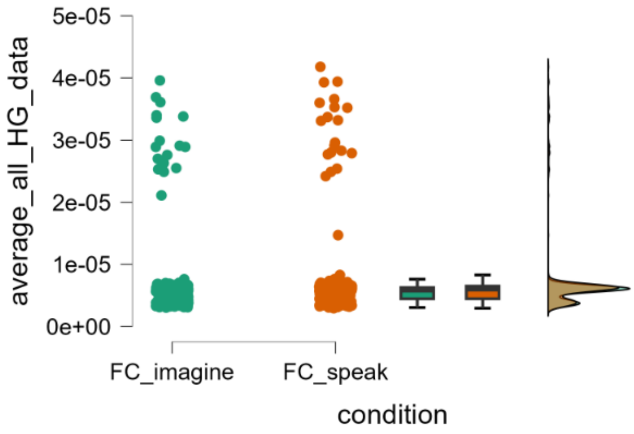
	t	df	p
average_all_HG_data	−0.905	674	0.366

Note. Student's t-test.

Descriptives

Raincloud Plots

average_all_HG_data



Independent Samples T-Test

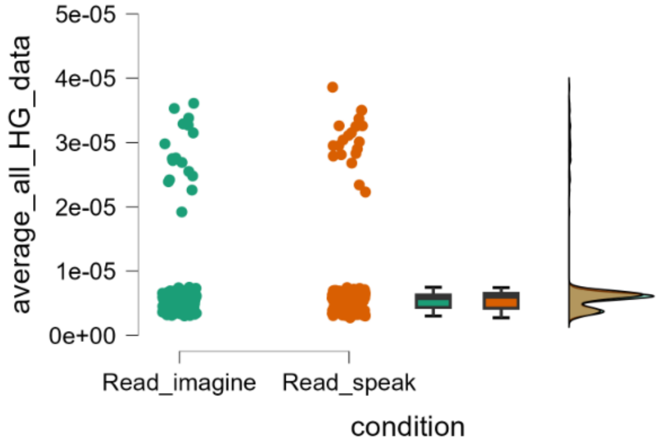
	t	df	p
average_all_HG_data	−1.030	674	0.303

Note. Student's t-test.

Descriptives

Raincloud Plots

average_all_HG_data



Independent Samples T-Test

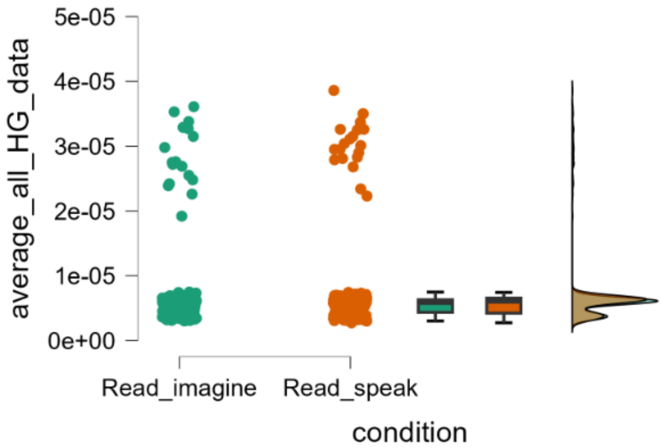
	t	df	p
average_all_HG_data	−1.030	674	0.303

Note. Student's t-test.

Descriptives

Raincloud Plots

average_all_HG_data



Independent Samples T-Test

	t	df	p
average_all_HG_data	−2.012	674	0.045

Note. Student's t-test.

Descriptives ▼

Raincloud Plots ▼

average_all_HG_data ▼