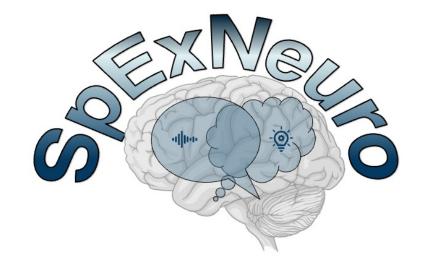


# SpExNeuro – A behavioural and brain imaging data collection of speech and executive functions





However, the

Gianna Kuhles<sup>1,2</sup>, Felix Hoffstaedter<sup>1,2</sup>, Simon B. Eickhoff<sup>1,2</sup> & Susanne Weis<sup>1,2</sup>, Julia A. Camilleri<sup>1,2</sup>

<sup>1</sup>Institute of Systems Neuroscience, Heinrich Heine University Düsseldorf, Düsseldorf, Germany; <sup>2</sup>Institute of Neuroscience and Medicine (INM-7: Brain and Behaviour), Research Centre Jülich, Jülich, Germany



#### INTRODUCTION

**Can Speech predict Cognitive Performance?** 

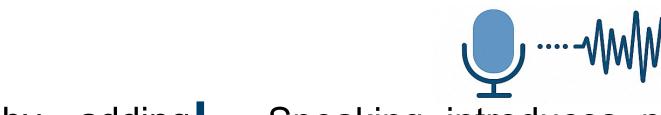


Speech and executive functions (EF) • are related [1, 2].

validity of speech

**METHODS** 

Can we acquire high-quality Neuroimaging during Productive Speech?



- by adding misalignment in fMRI data.
  - Identifying excessive motion is crucial to avoid false neural findings.



- SpEx study collected behavioural data from healthy participants [4].
- We used ML to research if prosodic features can predict EF.

**NEO Five Factor** 

Inventory

**Back Depression** 

Inventory II

Edinburgh

Affective

Neuroscience

Personality Scales

Positive and Negative

Affect Schedule

ADHD Screening for

Adults

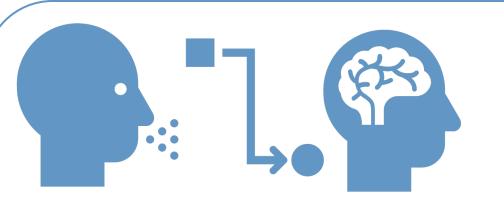
Fig. 1 Experiment Protocol SpExNeuro Study.

- SpExNeuro expands this neuroimaging data.
- →Investigation of neural mechanisms linking speech and EF

# Speaking introduces noise and spatial

#### biomarkers remains inconclusive [3]. PART A **SpEx: Prediction of EF by Prosody** attention cognitive flexibility working memory > inhibition sample: n=231 66 EF target variables picture description story retelling fictional story telling spontaneous speech tasks DATA open**SMILE** audio feature extraction > frequency related features > spectral features > temporal features AUDIO FEATURE EXTRACTION OPEN-SOURCE & CROSS-PLATFORM > energy related features 264 prosodic feature variables

#### FEATURE EXTRACTION



Prediction of EF by prosodic features

- ➤ 10-fold cross-
- validation > stratification (strat.) by
- target performance confound removal (CR) with linear regression model
- > metrics: coefficient of determination (R<sup>2</sup>)

## PART B

**Trail Making Test** 

### SpExNeuro: Expansion of SpEx through the integration of Neuroimaging Data

**General Information** Structural Imaging **Resting State** Diffusion Tensor **Imaging** Stop Signal Task Sternberg Recognition Handedness Inventory Paradigm

Cued Task Switching **Verbal Fluency** Picture Description Narrative Story Telling **Fictional Story Telling** 

Raven's Standard **Progressive Matrices** Wisconsin Card Sorting Tower of London **Cued Task Switching** N-back Non-verbal Test Non-verbal Learning Test

Corsi Block Tapping Task Response Inhibition Simon Task **Stroop Interference Test** Mackworth Clock Test **Divided Attention Test Spatial Attention Test** 

Cortisol Estradiol Progesteron Testosteron

**Luteinising Hormone** Healthy Adults

Monolingual German

20 – 55 Years of Age U

- MRIQC [6] toolbox used to extract automated image quality metrics.

> - Metrics used to evaluate data integrity and control for artifacts in analysis:

**Neuroimaging** 

**Quality Control** 

- DVARS,
- Framewise Displacement (FD),
- Probability Score

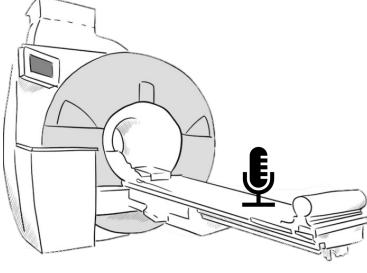
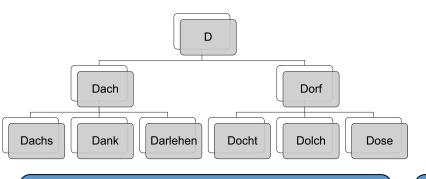


Fig. 2: fMRI speech tasks.



Verbal Fluency



Scanning parameters for fMRI include 64 slices with a resolution of 2.2 mm x 2.2 mm x 2.0 mm<sup>3</sup>, TR = 980 ms, TE =

30 ms, FA = 70, a Multi Band Acceleration factor of 4, and DTI with 100 slices at a resolution of 1.6 mm x 1.6 mm x

1.6 mm³, TR = 3800.0 ms, TE = 70 ms, b-value = 2500 s/mm², and a Multi Band Acceleration factor of 4.

ē 0.5

0.3

0.2

0.1

Picture Description



Retelling a Story



Fictional Story Telling

## **Determination** Coefficient of Mean Trail Making Test A Trail Making Test B without CR with CR without CR – strat. with CR – strat.

PREDICTION

Fig. 3: Prediction of Trail Making Test targets in different conditions [5].

- Trail Making Test performance is predictable from prosodic features, despite small effects.
- Prediction power decreases when not removing the confounding variables, though.
- Careful control of confounding variables is essential.

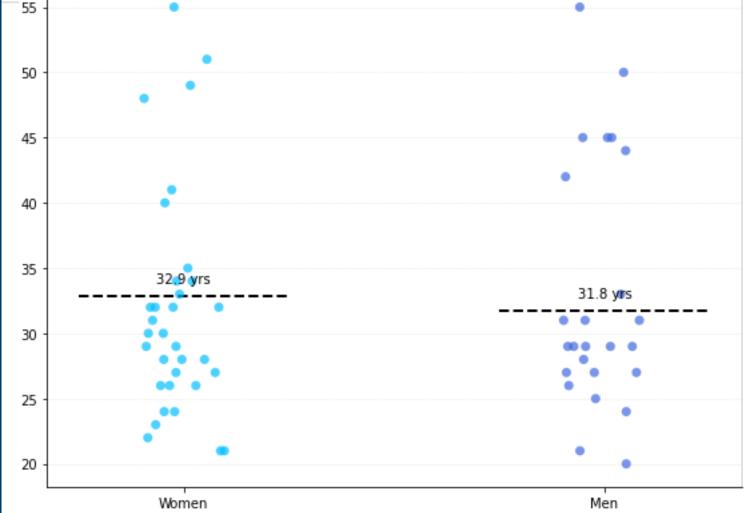


Fig. 4: Age Distribution by Gender SpExNeuro. Data acquisition is ongoing

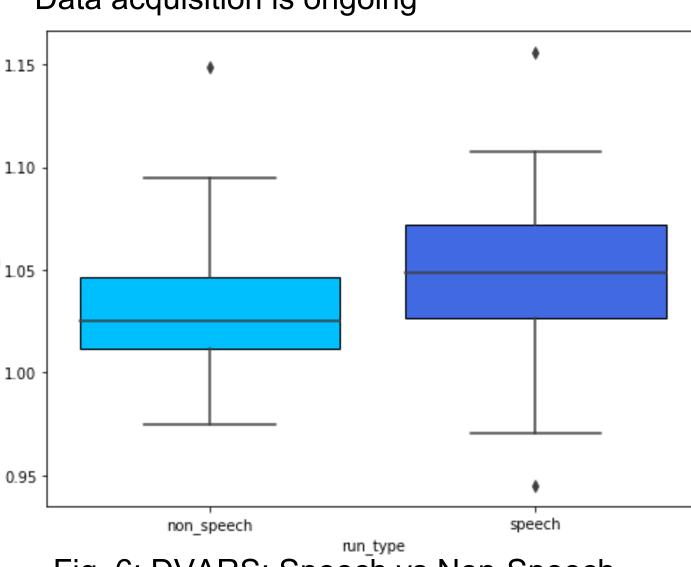
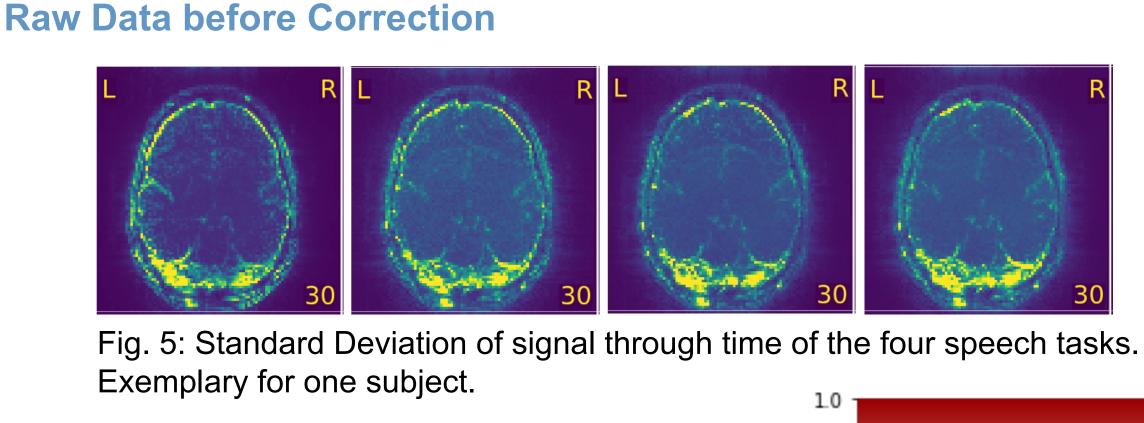


Fig. 6: DVARS: Speech vs Non-Speech. Higher signal variability observed during speech production.



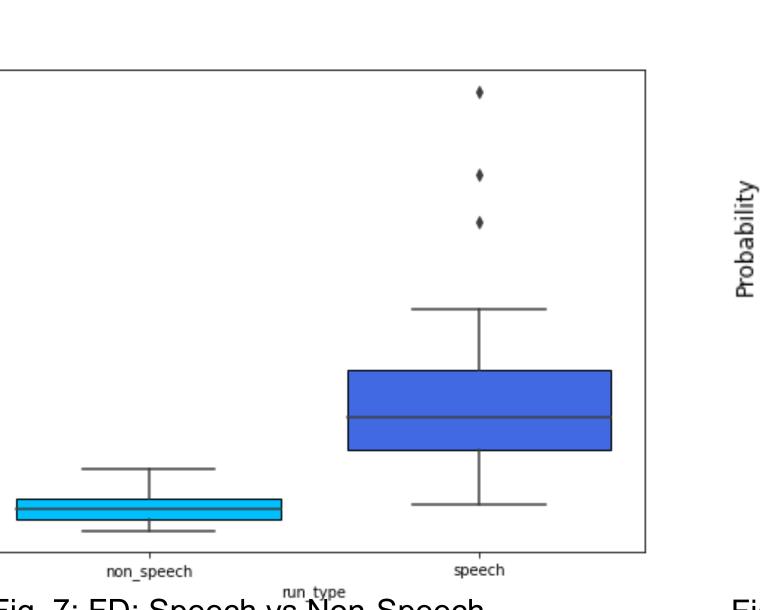
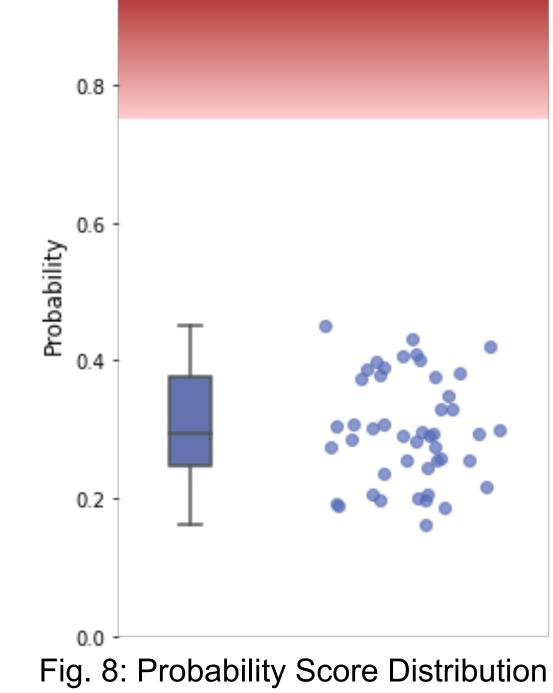


Fig. 7: FD: Speech vs Non-Speech. Lenient (FD = 0.5 mm) and strict (FD = 0.2 mm) thresholds [7].



for T1. Overall quality score derived from all IQMs – all subjects < 0.75.

#### DISCUSSION



provide SpEx(Neuro) datasets comprehensive multimodal resource to investigate individual differences.

ML analyses can uncover shared brain activation patterns of speech and EF.



- Quality control is crucial for maintaining data integrity and ensuring that observed effects reflect true neural and cognitive processes - particularly in productive speech data, which is highly sensitive to noise and motion.
- Despite expected variability, our results suggest that acquiring productive speech in the scanner is feasible without major loss in image quality.



- We encourage scientists to leverage this dataset for collaborative growing research.
- → Available data paper: Camilleri & Volkening et al., 2024 [4]

References: Hagoort, P. (2017). The core and beyond in the language-ready brain. Neuroscience & Biobehavioral Reviews, 81, 194-204.

National Institute on Aging (R01AG067103).

[2] Novick, J. M., Trueswell, J. C., & Thompson-Schill, S. L. (2005). Cognitive control and parsing: Reexamining the role of Broca's area in sentence comprehension. Cognitive, Affective, & Behavioral Neuroscience, 5(3), 263-281. [3] Robin, J., Harrison, J. E., Kaufman, L. D., Rudzicz, F., Simpson, W., & Yancheva, M. (2020). Evaluation of speech-based digital biomarkers: review and recommendations. Digital Biomarkers, 4(3), 99-108.

[4] Camilleri, J. A., Volkening, J., Heim, S., Mochalski, L. N., Neufeld, H., Schlothauer, N., Kuhles, G., Eickhoff, S. B. & Weis, S. (2024). SpEx: a German-language dataset of speech and executive function performance. Scientific Reports, 14(1), 9431. [5] Kuhles, G., Hamdan, S., Heim, S., Eickhoff, S., Patil, K. R., Camilleri, J., & Weis, S. (in review). Pitfalls in using ML to predict cognitive function performance. Research Square.

[6] Esteban, O., Birman, D., Schaer, M., Koyejo, O. O., Poldrack, R. A., Gorgolewski, K. J. MRIQC: Advancing the Automatic Prediction of Image Quality in MRI from Unseen Sites; PLOS ONE 12(9):e0184661.

[7] Power, J. D., Barnes, K. A., Snyder, A. Z., Schlaggar, B. L., & Petersen, S. E. (2012). Spurious but systematic correlations in functional connectivity MRI networks arise from subject motion. Neuroimage, 59(3), 2142-2154.

**Acknowledgments:** Deutsche Forschungsgemeinschaft (DFG, GE 2835/2-1, EI 816/16-1 and EI 816/21-1), National Institute of Mental Health (R01-MH074457), Helmholtz Portfolio Theme "Supercomputing and Modeling for the Human Brain", Virtual Brain Cloud (EU H2020, no. 826421) & **Preprint: PART A** 

Scan me!  $\rightarrow \rightarrow \rightarrow$ 



g.kuhles@fz-juelich.de