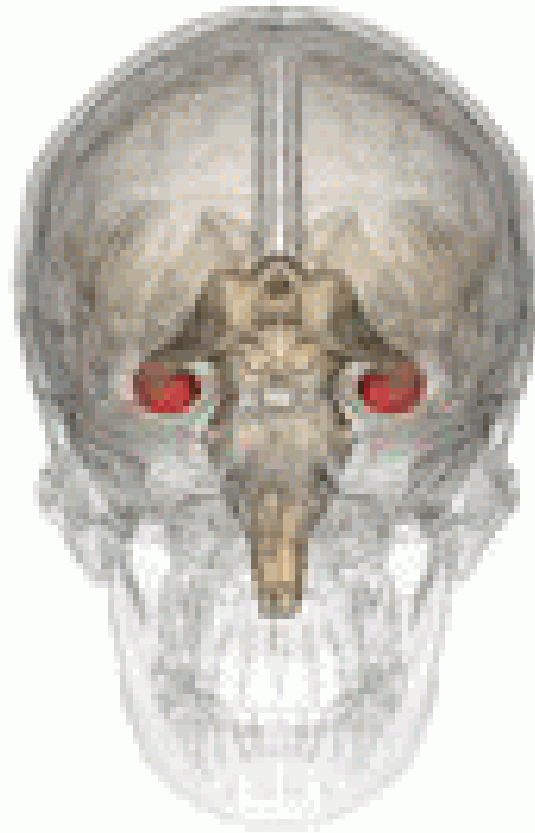


# From the complexity of brain organization to challenges in brain-behaviour mapping

**Sarah Genon**  
**Cognitive NeuroInformatics Lab**  
Research Centre Jülich (INM-7)

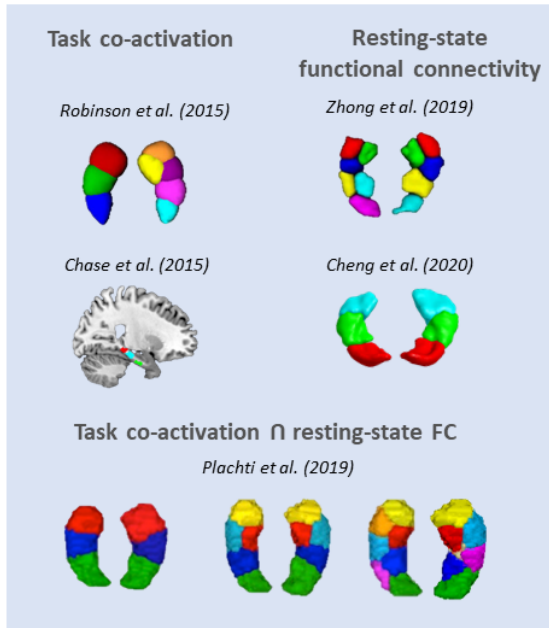


# Understanding brain organization

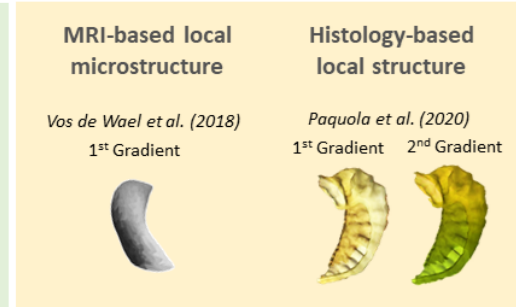
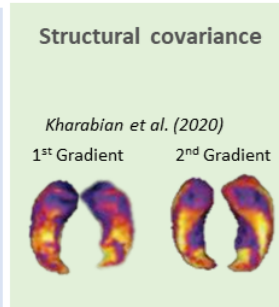
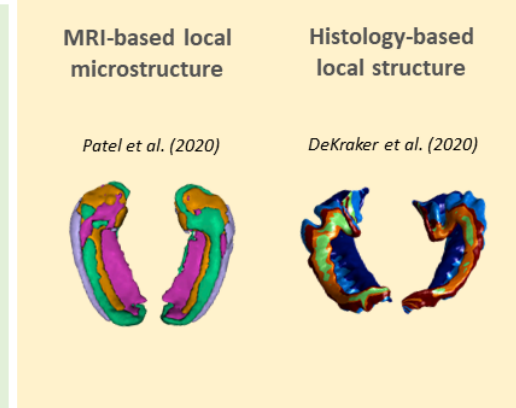
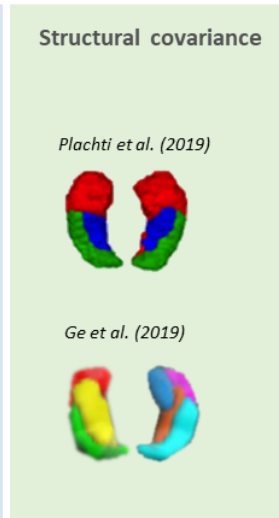
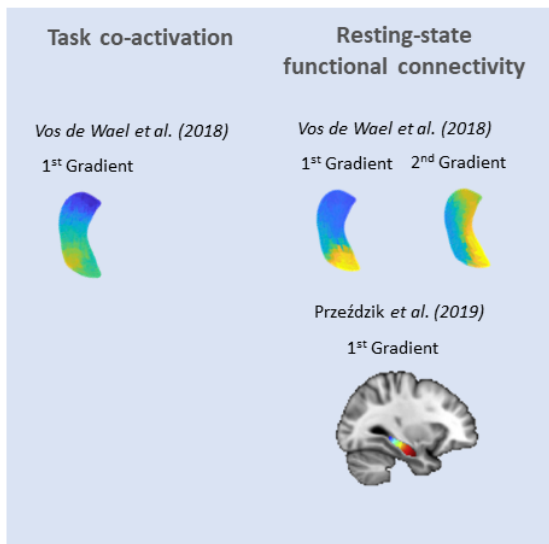


# The complexity of brain organization

## Parcellations

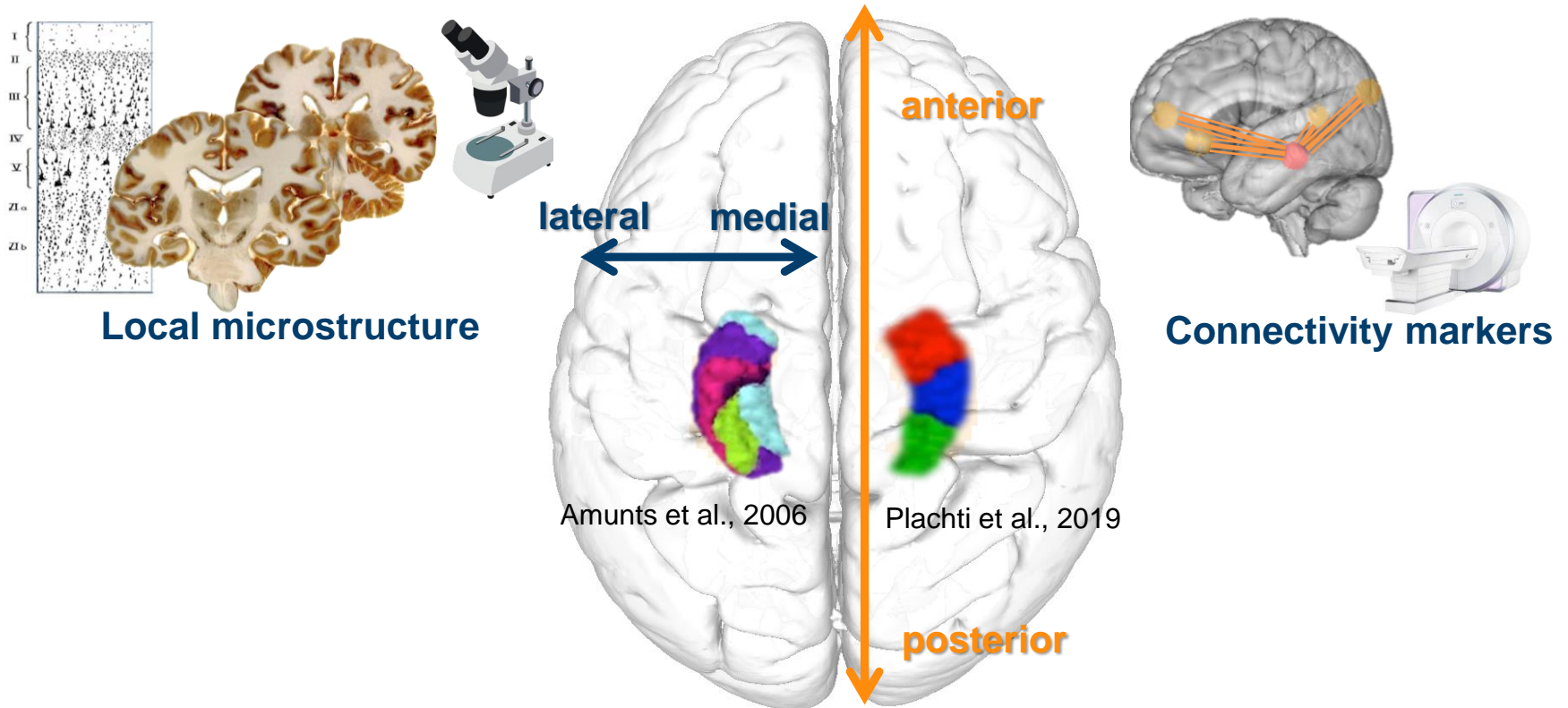


## Gradients

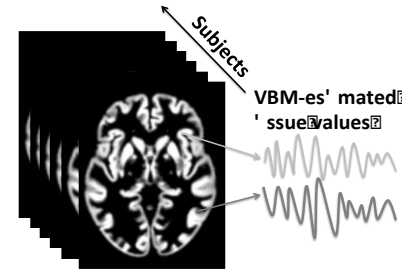
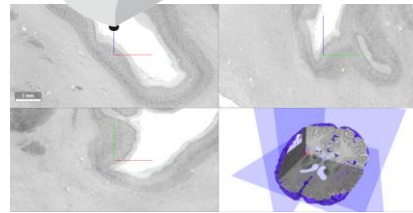
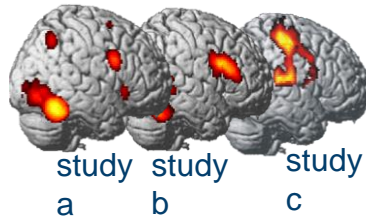


*Eickhoff, Yeo & Genon, 2018, Nat. Rev. Neurosci.*  
*Genon et al., 2022, Trends in Neuroscience*

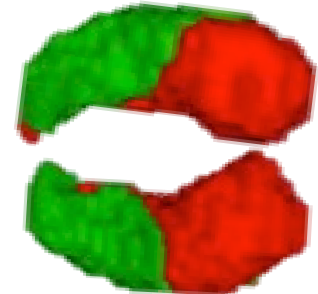
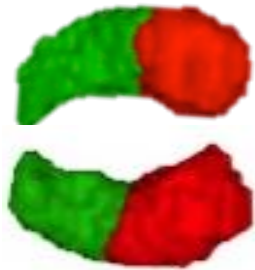
# Local microstructure/processing VS large-scale functional integration



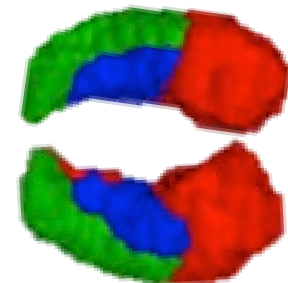
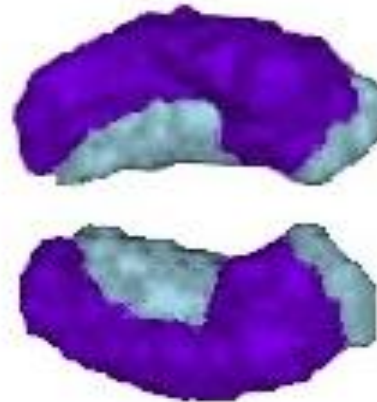
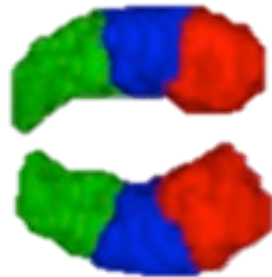
# Local microstructure and large-scale functional integration



2k

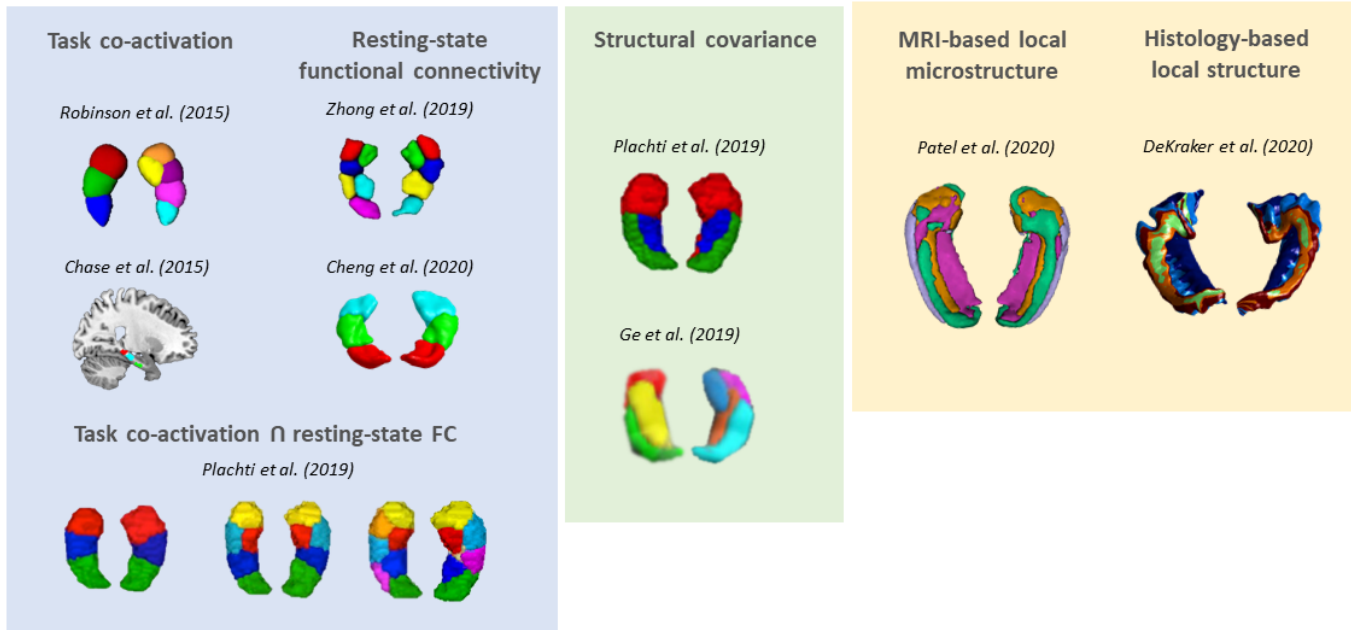


3k

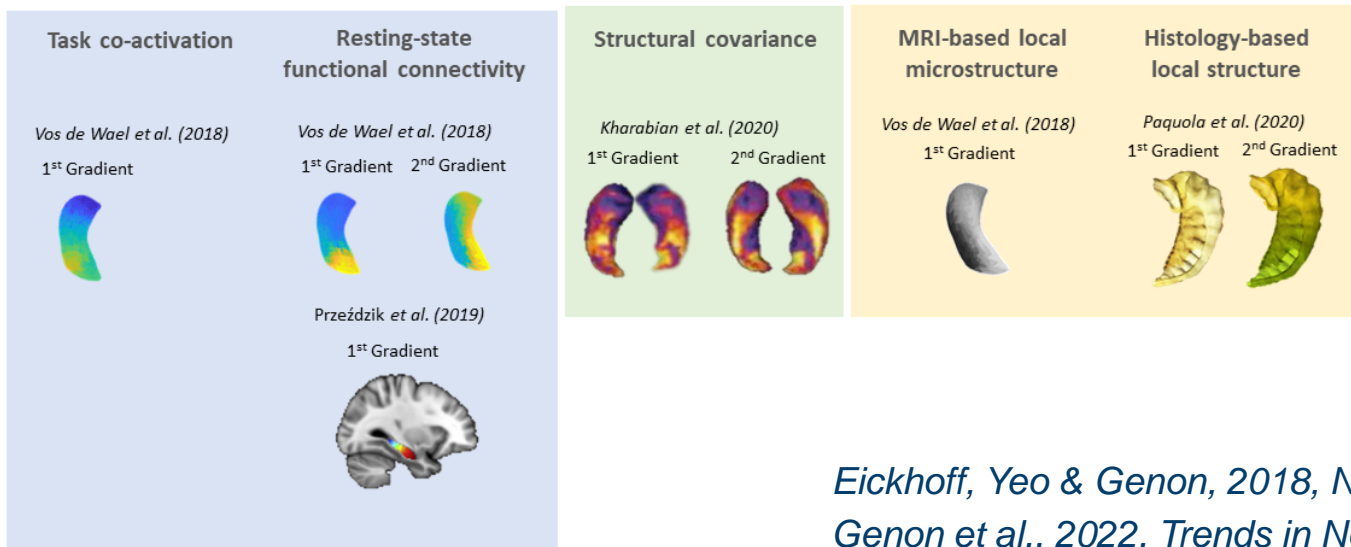


# The complexity of brain organization

## Parcellations



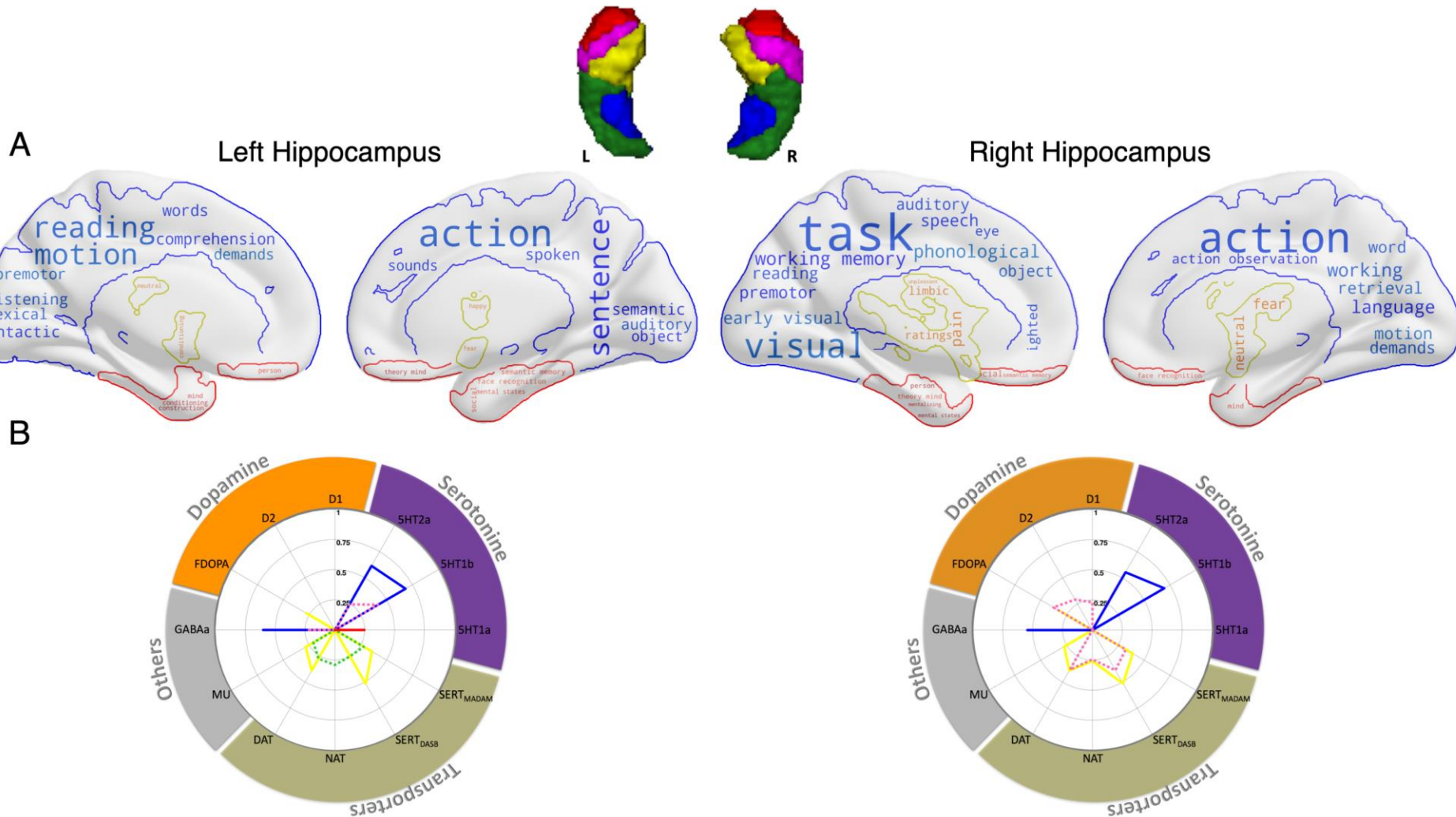
## Gradients



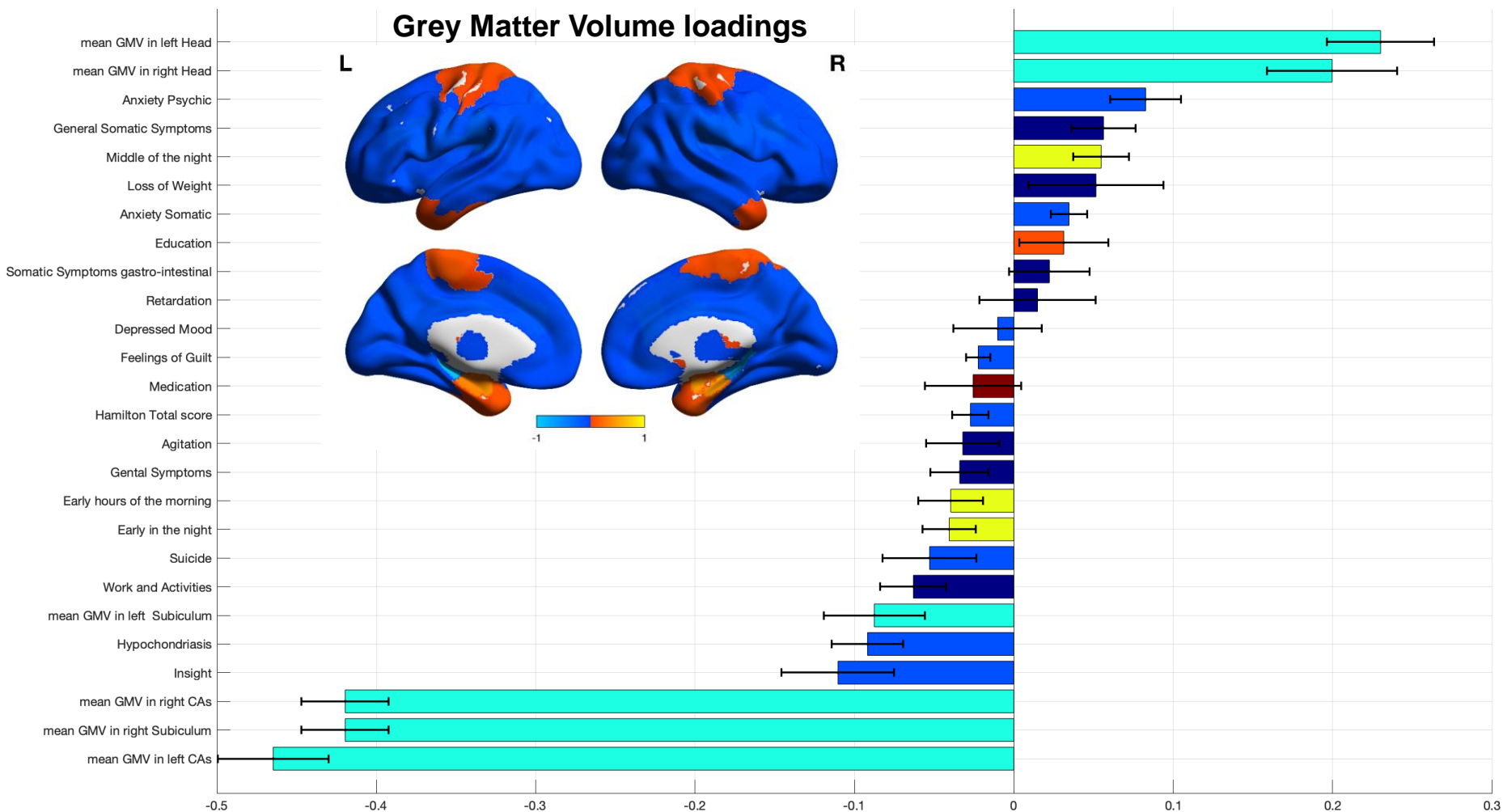
Eickhoff, Yeo & Genon, 2018, *Nat. Rev. Neurosci.*  
 Genon et al., 2022, *Trends in Neuroscience*



# The complexity of brain organization: Hippocampal metabolic networks



# Hippocampal structural covariance networks in Major Depressive Disorders





# Relating behavior to brain structure

---

OPINION

2011

## The structural basis of inter-individual differences in human behaviour and cognition

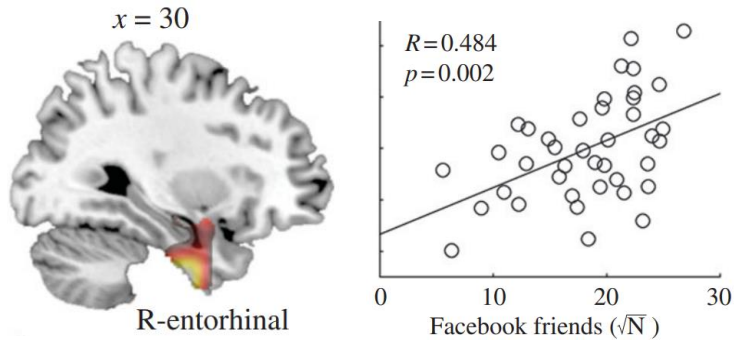
---

*Ryota Kanai and Geraint Rees*

**Abstract** | Inter-individual variability in perception, thought and action is frequently treated as a source of ‘noise’ in scientific investigations of the neural mechanisms that underlie these processes, and discarded by averaging data from a group of participants. However, recent MRI studies in the human brain show that inter-individual variability in a wide range of basic and higher cognitive functions — including perception, motor control, memory, aspects of consciousness and the ability to introspect — can be predicted from the local structure of grey and white matter as assessed by voxel-based morphometry or diffusion tensor imaging. We propose that inter-individual differences can be used as a source of information to link human behaviour and cognition to brain anatomy.

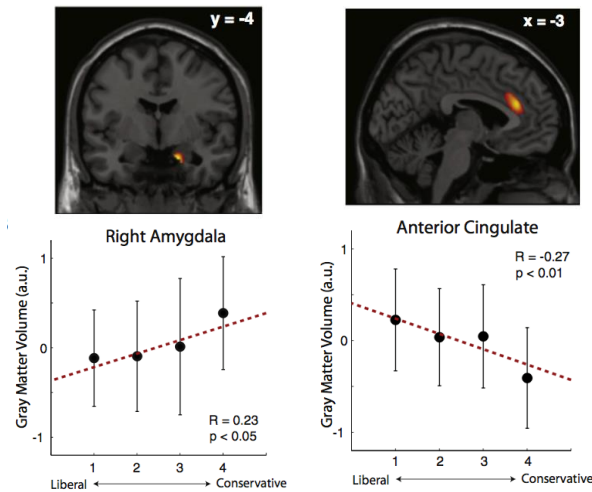
# Relating behavior to brain structure

## Number of facebook friends relates to local grey matter



Kanai et al., 2012

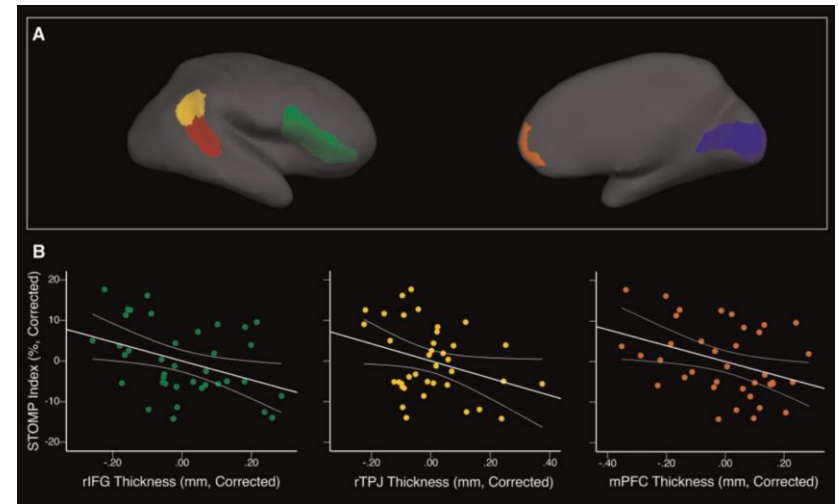
## Political orientation relates to local grey matter



Kanai et al., 2011

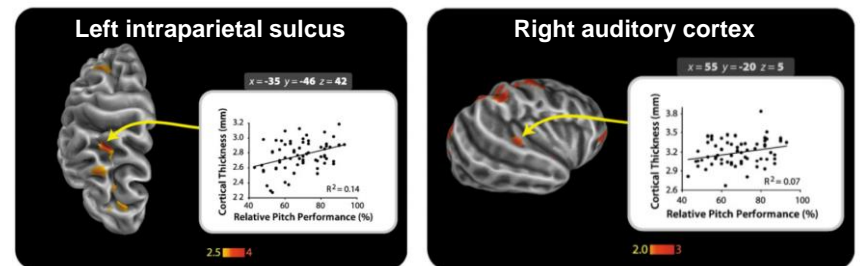
Mitglied der Helmholtz-Gemeinschaft

## Theory of mind performance relates to local cortical thickness



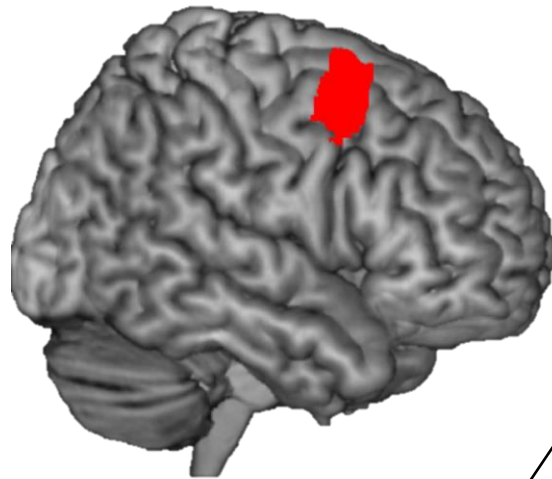
Rice & Redcay, 2015

## Music pitch performance relates to local cortical thickness



Foster & Zatorre, 2012

# Mapping behavior to local brain morphometry: the replication crisis



NKI



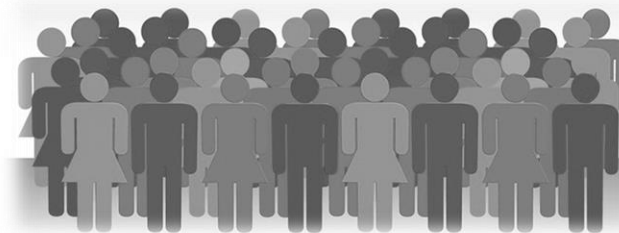
TMT-A

FZJ



N = 135  
61% female  
Age: 20 -> 75

Significant ( $p < .05$ )  
 $r = -.26$

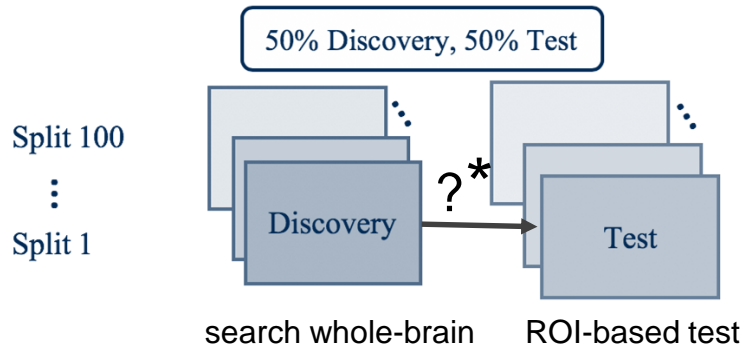


N = 87  
54% female  
Age: 21 -> 71

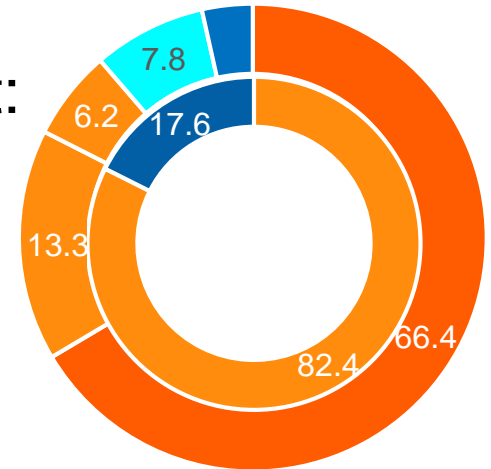
Not significant ( $p > .05$ )  
 $r \approx 0$

# Which replicability for local GMV-behavior associations ?

## ROI-based confirmatory:



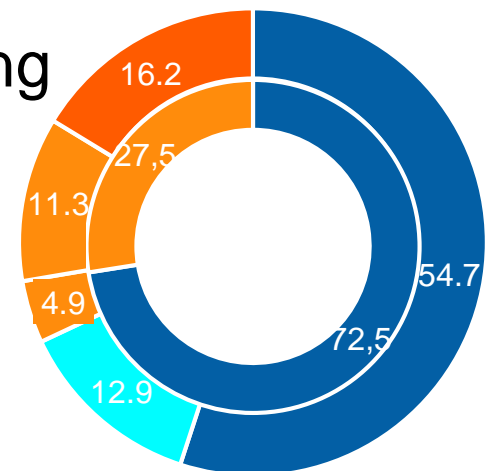
Healthy adults cohort:  
(n = 466)  
Perceptual IQ



## \* Replication indexes:

|                  |                             |
|------------------|-----------------------------|
| Sign + $p < .05$ | Replicate                   |
|                  | Not replicate               |
| Bayes factor     | Moderate-strong evidence H1 |
|                  | Anecdotal evidence H1       |
|                  | Anecdotal evidence H0       |
|                  | Moderate-strong evidence H0 |

Clinical dataset:  
(n = 371)  
Verbal learning



# Which replicability for local **CT**-behavior associations ?

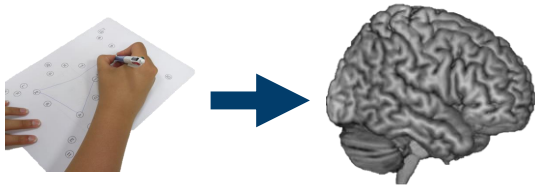
**Young healthy adults** **N = 1206**  
34 behavioral measures **CT (Freesurfer)**



Including **composite score**

## **Exploratory: spatial consistency**

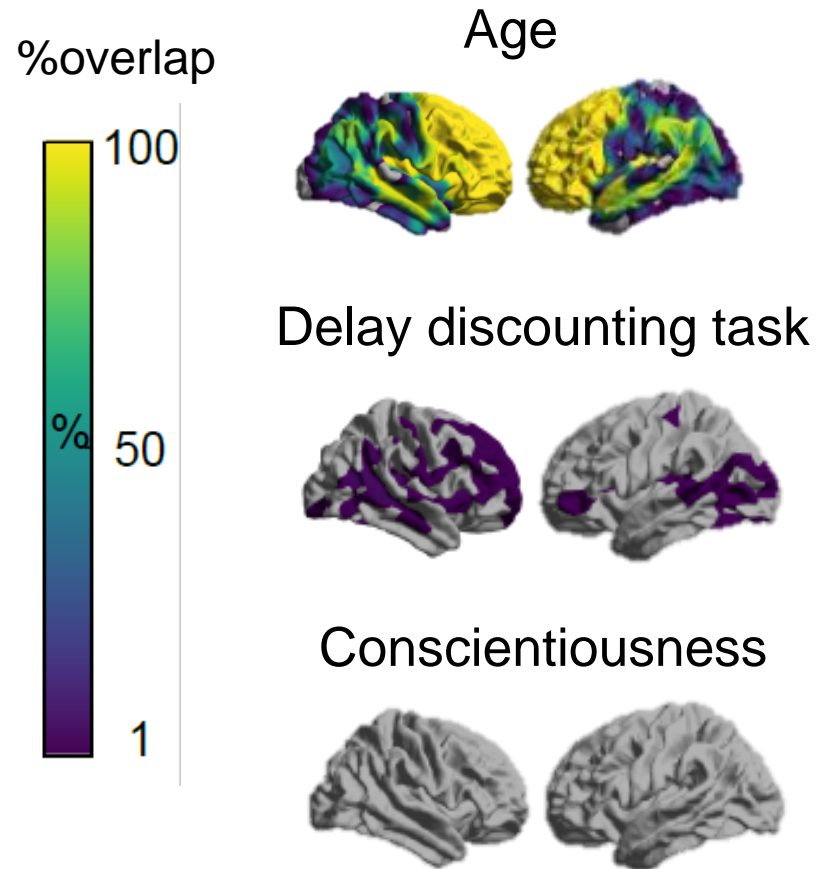
Search whole-brain, 100 split-half



## **Benchmarks:**

Healthy adults data: Age

## **Spatial consistency:**




# Relating brain structure to behavior

PERSPECTIVES

2022

## Linking interindividual variability in brain structure to behaviour

Sarah Genov , Simon B. Eickhoff and Shahrzad Kharabian

Abstract | What are the key challenges in relating brain structure to behaviour? This new avenue of research is progressing rapidly, but replication and searching for behavioural methodological mapping of these not only relationship the relationship dimensions the study of address cur

**Large Datasets**

**Confounds modelling**

**Multivariate analyses**

**Cross-validation scheme**

**Out-of-cohort replicability**

ences in  
promising  
ch then  
s, and a  
involved  
omy and  
n these  
e-to-one  
merged.  
behaviour  
tation of  
y latent  
resent of  
ons and



# Relating brain structure to behavior

## Brain structural data:

- *Cortical Thickness (CT)*
- *Surface Area (SA)*
- *Grey Matter Volume (GMV)*



Regularized  
Canonical  
Correlation Analysis  
(RCCA)

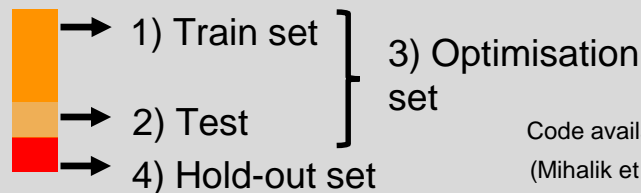
## Behavioural data:

- *Alertness*
- *Cognition*
- *Emotion*



Machine Learning Framework: **Multiple Holdouts**

Within-dataset  
generalizability



Code available at: [https://github.com/anaston/cca\\_pls\\_toolkit](https://github.com/anaston/cca_pls_toolkit)  
(Mihalik et al., 2020, Monteiro et al., 2016)

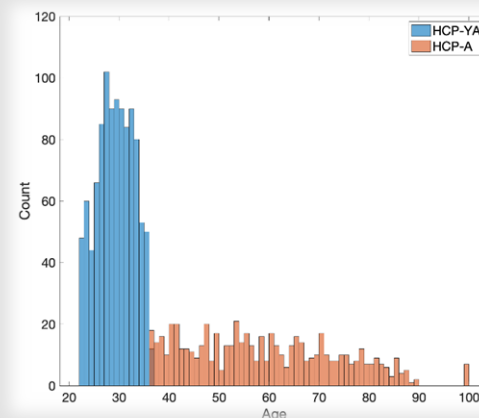
Cross-dataset  
replicability

Large datasets  
with **similar**  
brain and  
**behavioral**  
measurements

HCP young adults

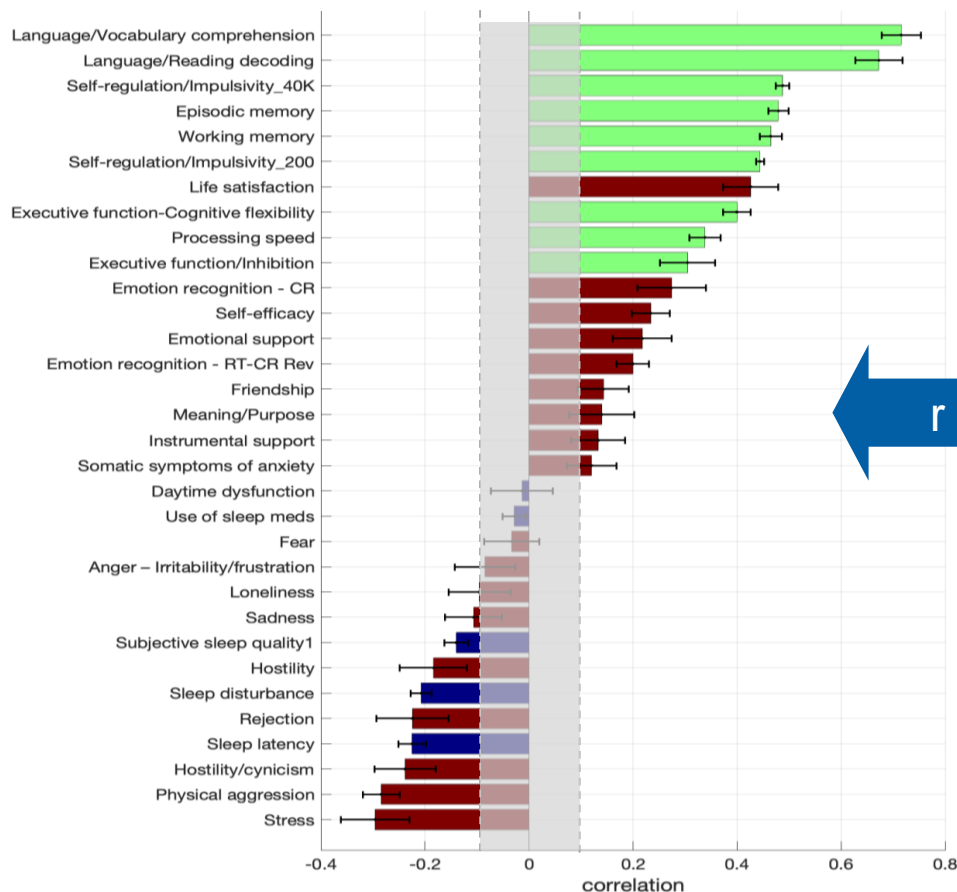


HCP aging



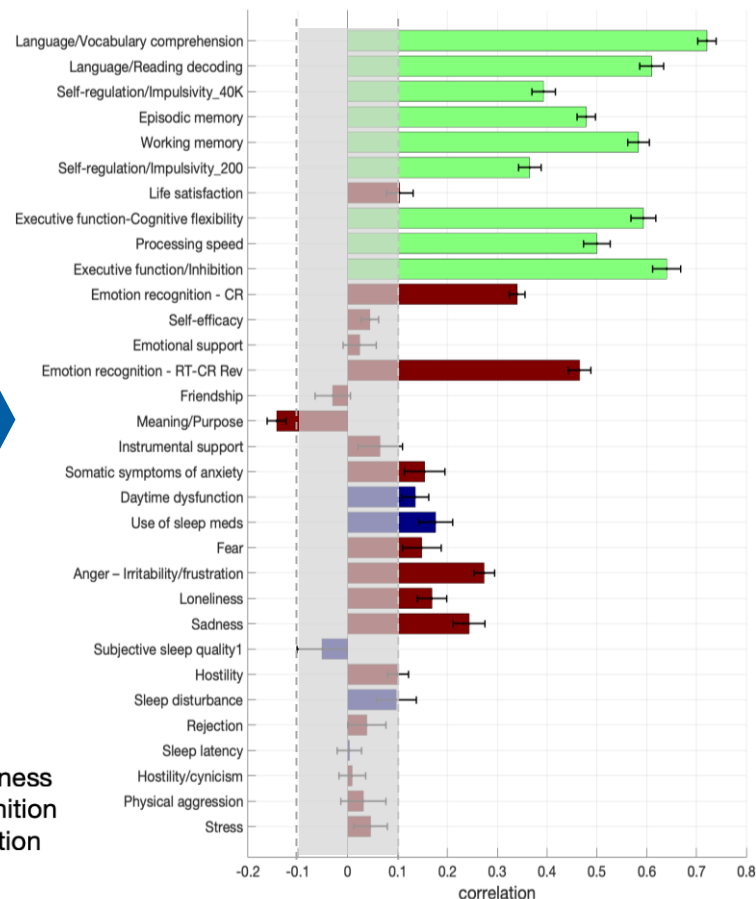
# Relating brain structure to behavior

## HCP young adults



$r = .73$

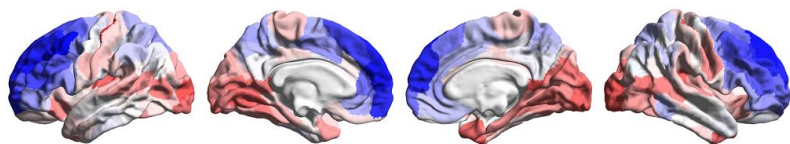
## HCP aging



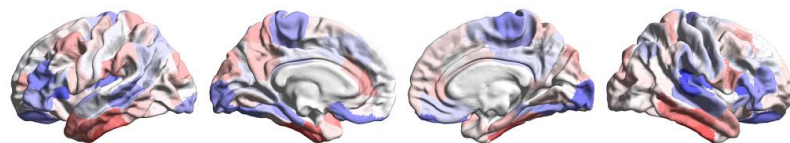
# Relating brain structure to behavior

HCP young adults

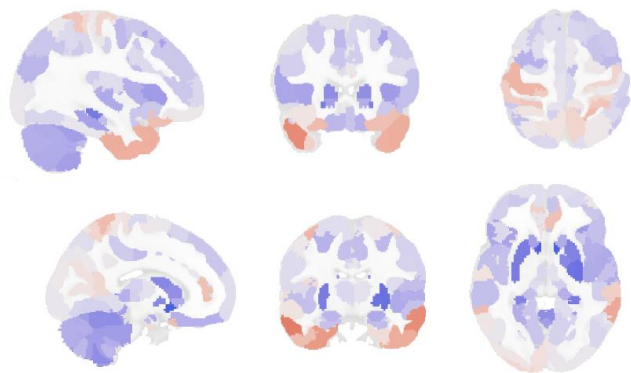
Cortical thickness loadings



Surface area loadings

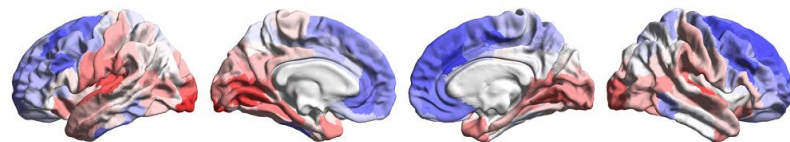


Grey Matter Volume loadings

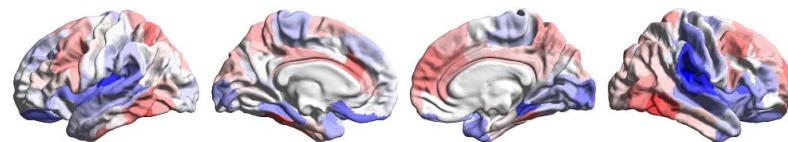


HCP aging

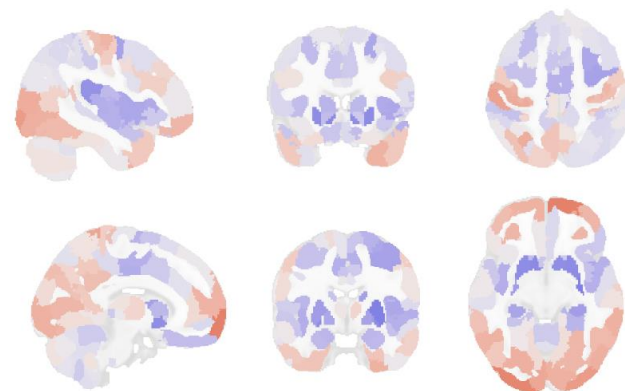
Cortical thickness loadings



Surface area loadings



Grey Matter Volume loadings

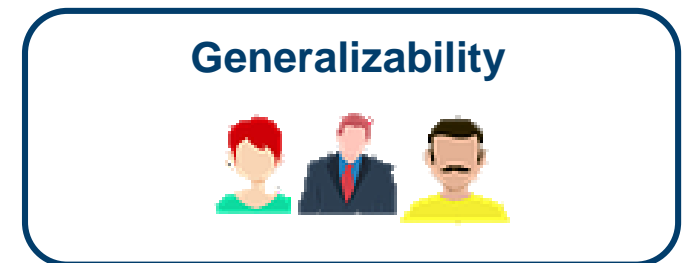
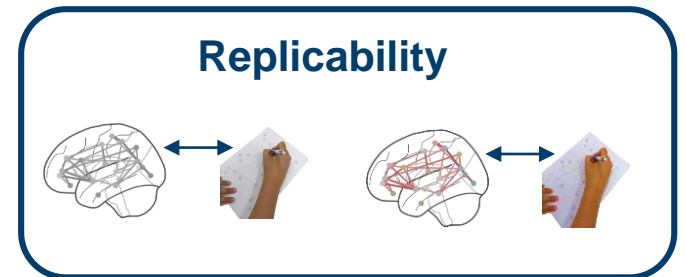
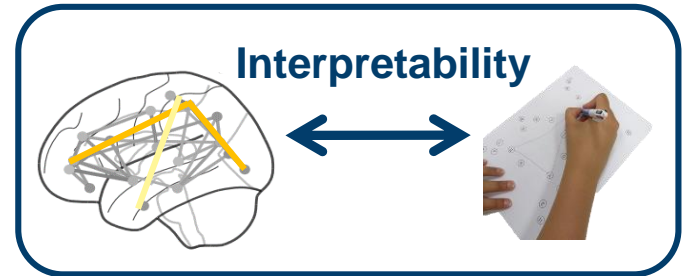
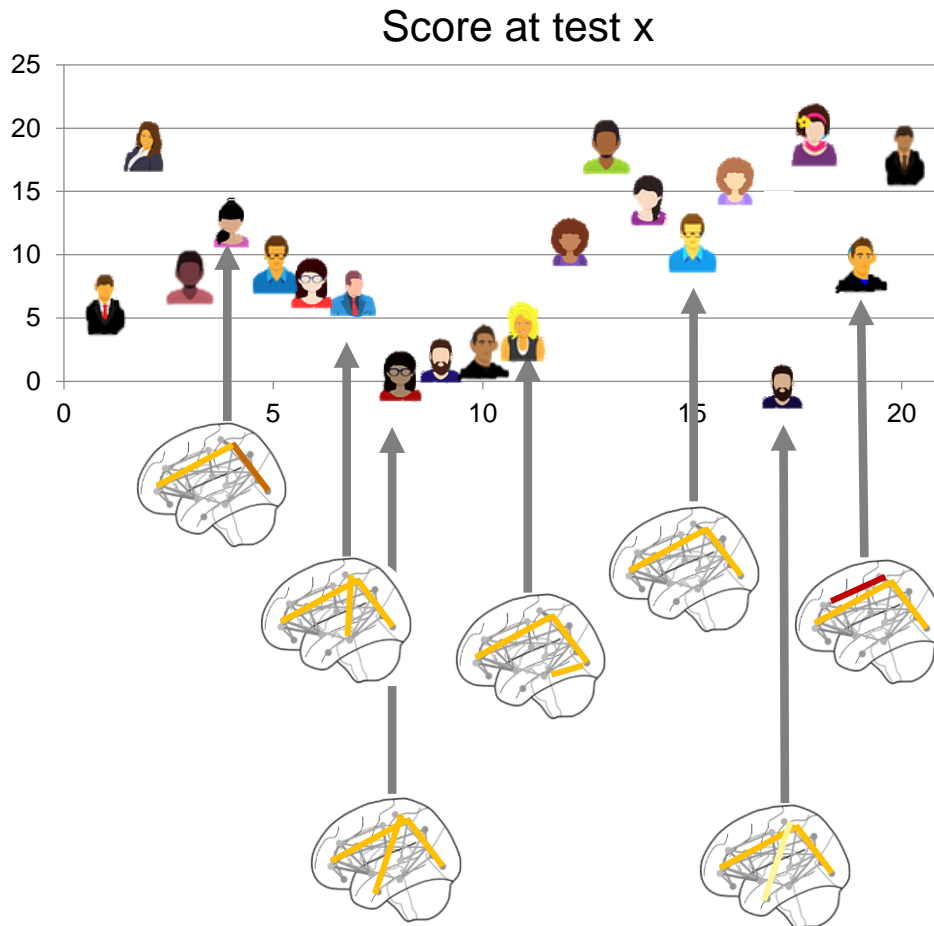


$r = .81$

$r = .56$

$r = .69$

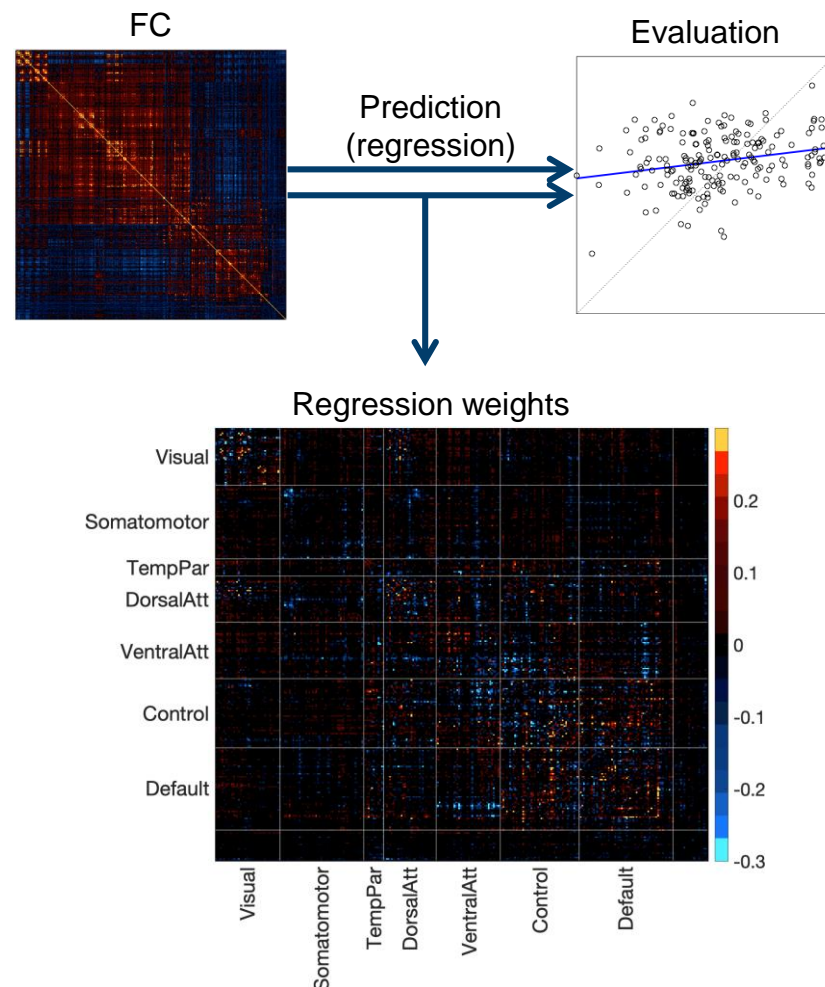
# Connectivity-based psychometric prediction



# Predictive models of psychometric data

## Interpretability /neurobiological validity issue

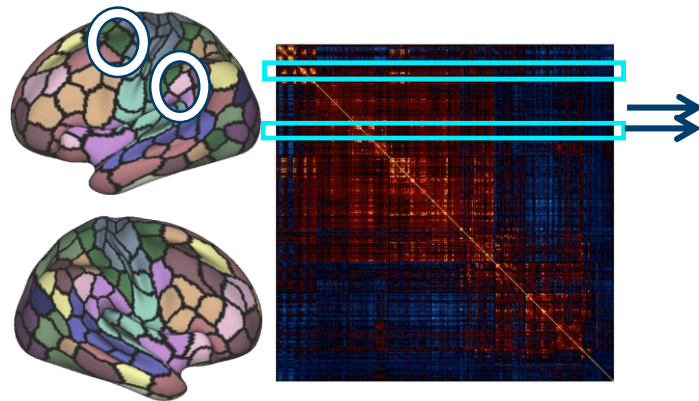
- Hypothesis-driven approach: a priori selection of specific regions/networks for the prediction
- **Data-driven approach:** How do we characterize each region/parcel's association to a psychometric variable?
- **Weight magnitude does not reflect the regions' association strength** with the psychometric variable
- Hard to get neurobiological insights



# Predictive models of psychometric data: interpretability

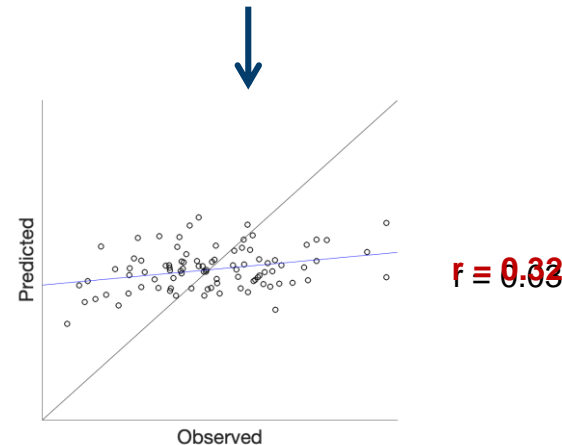
## A region-based approach

- One predictive model for each brain region/parcel



(Schaefer  
et al., 2019)

|           | FC features | Total cognition<br>composite<br>score |
|-----------|-------------|---------------------------------------|
| Subject 1 |             | 133.76                                |
| Subject 2 |             | 106.85                                |
| Subject 3 |             | 72.15                                 |
| ...       | ...         | ...                                   |
| Subject N |             | 122.99                                |

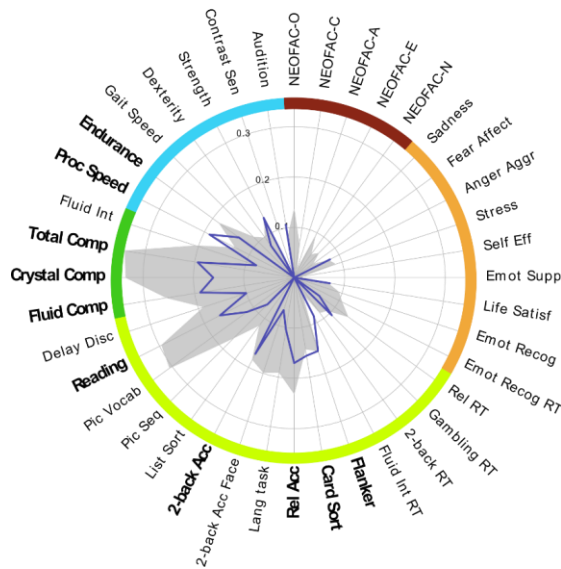




# Predictive models of psychometric data: interpretability

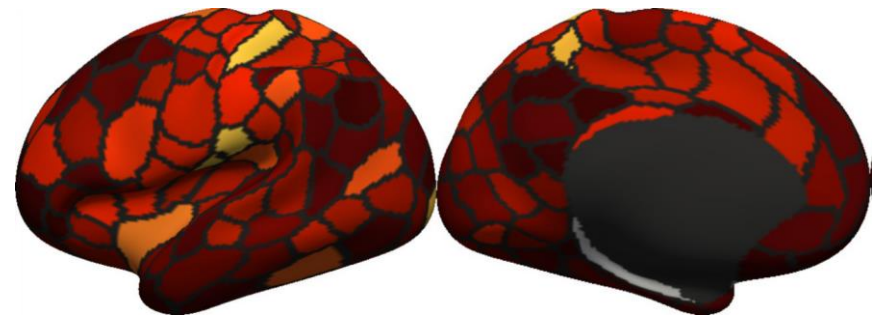
## A region-based approach

1. **Brain region's perspective:**  
psychometric profile across  
psychometric variables



- Primary visual cortex
- Broca region
- Anterior hippocampus

2. **Psychometric variable's perspective:** prediction performance  
distribution across brain regions

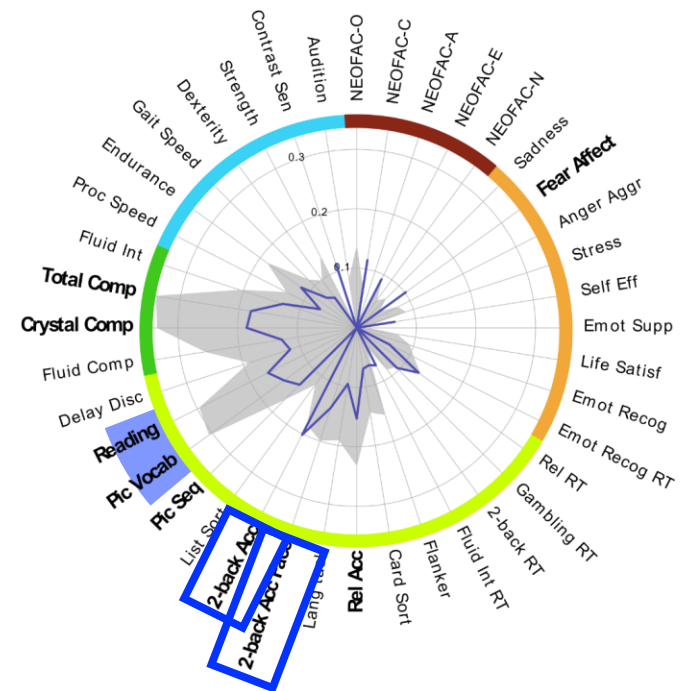
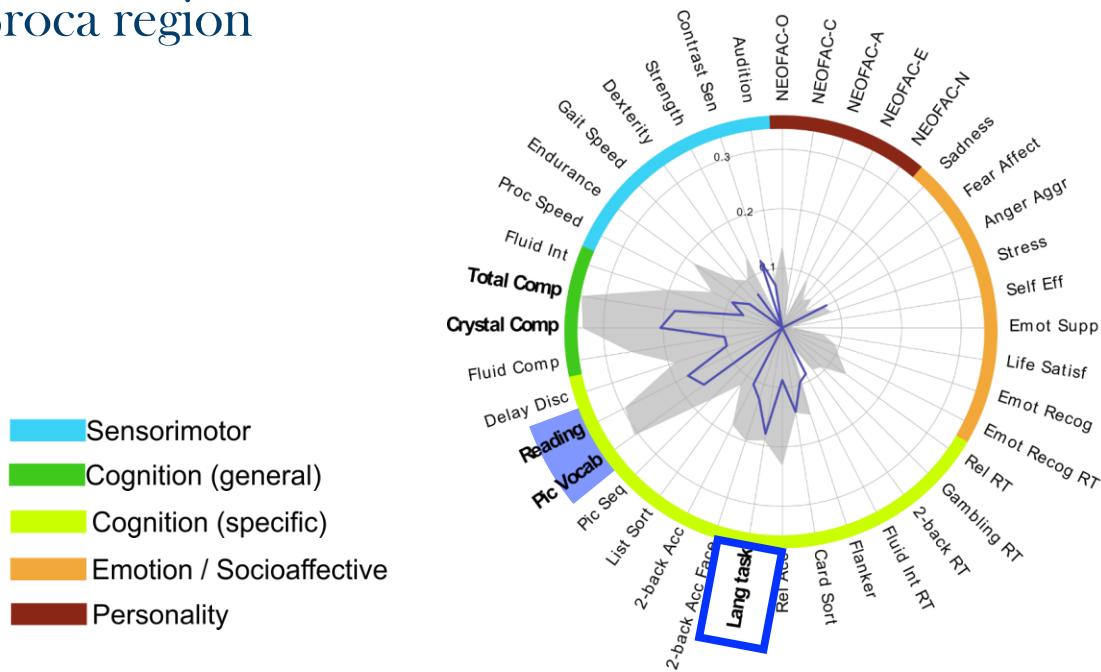
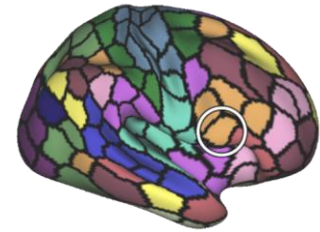
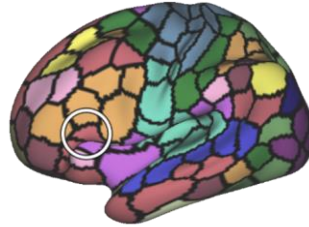


- Crystallized cognition composite score
- (Working memory) 2-back task accuracy
- (Working memory) 2-back face task accuracy

# Predictive models of psychometric data: interpretability

## Psychometric Profile

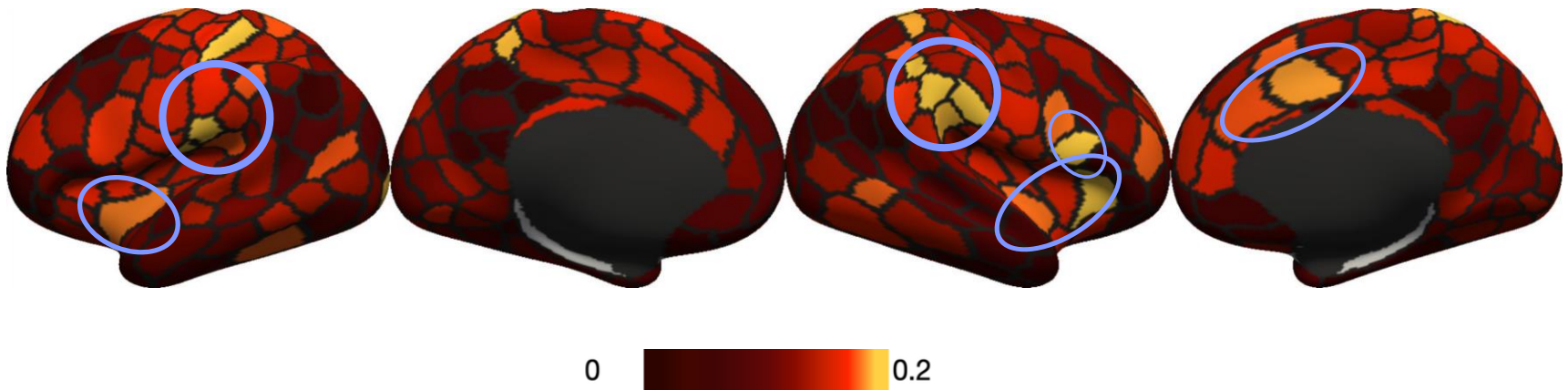
Broca region



# Predictive models of psychometric data: interpretability

## Prediction Performance Distribution

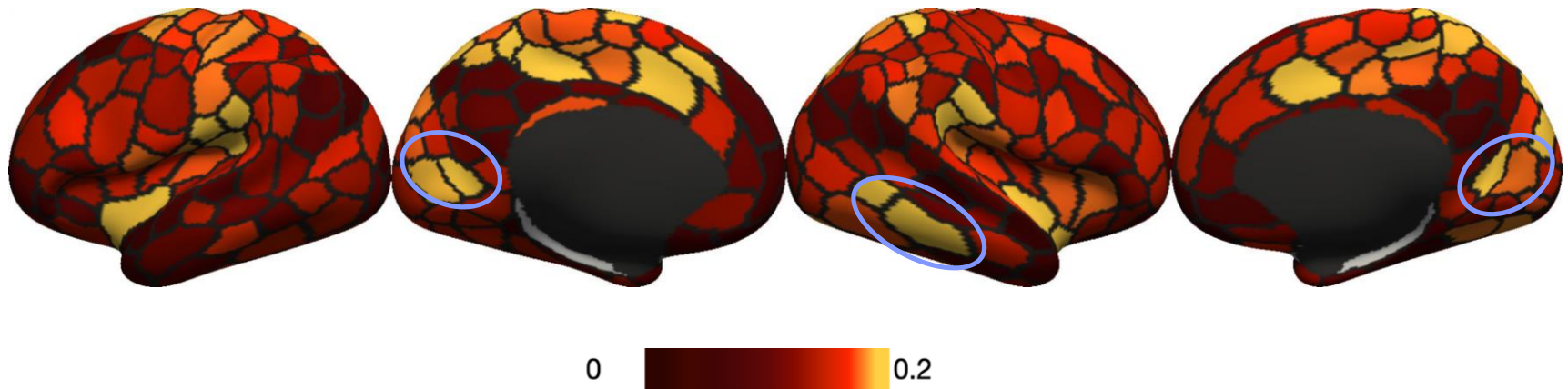
(working memory) 2-back task accuracy



# Predictive models of psychometric data: interpretability

## Prediction Performance Distribution

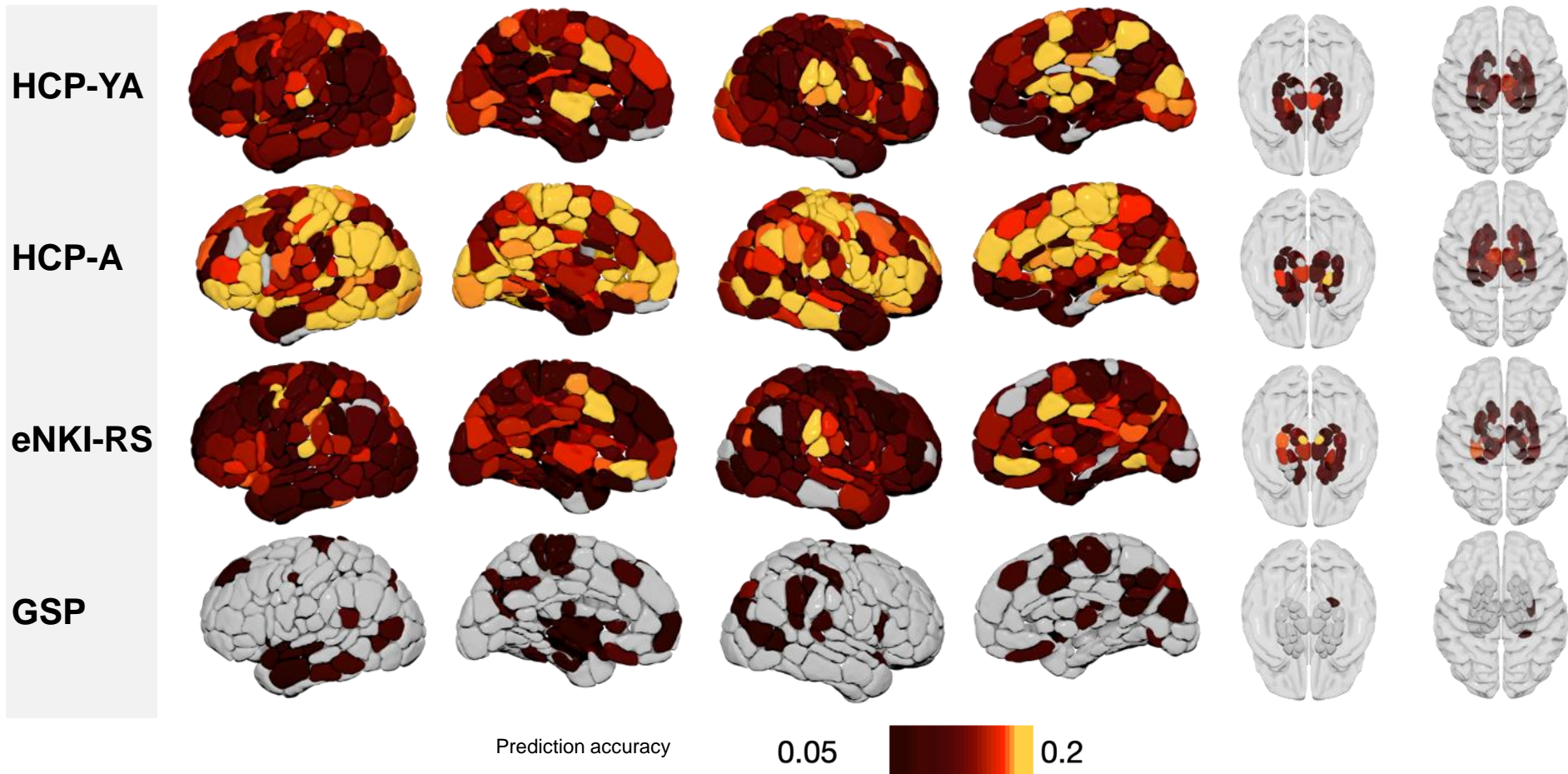
(working memory) 2-back face task accuracy





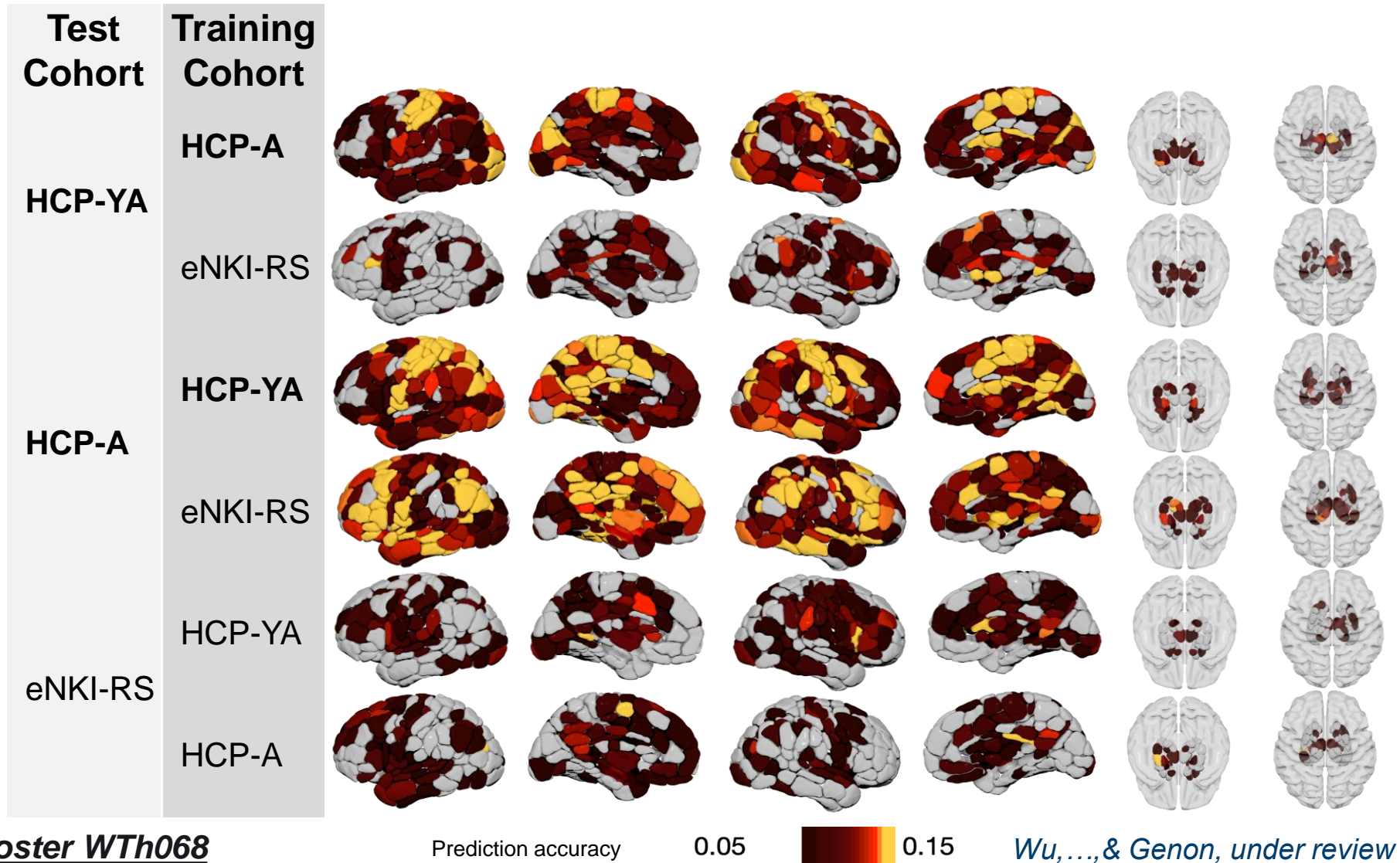
# Predictive models of psychometric data: replicability of brain-behavior patterns

Cross-dataset replicability of brain predictive patterns for fluid cognition



# Predictive models of psychometric data: cross-dataset generalizability

## Cross-dataset generalizability of fluid cognition





# Predictive models of psychometric data: biases in population minority

## Human Connectome Project (HCP)

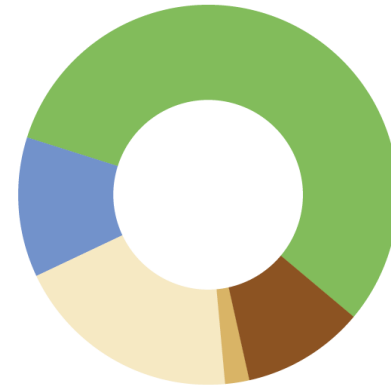
- N = 948; 22-37years
- 58 behavioral measures
- #WA = 721, #AA = 129



- White Americans (76.1%)
- African Americans (13.6%)
- Asian / native Hawaiian / other Pacific Islander (6.2%)
- Indian Americans / Alaskan natives (0.2%)
- Mixed (2.3%)
- Unknown (1.6%)

## Adolescent Brain Cognitive Development (ABCD)

- N = 5351; 9-11years
- 36 behavioral measures
- #WA = 2997, #AA = 642

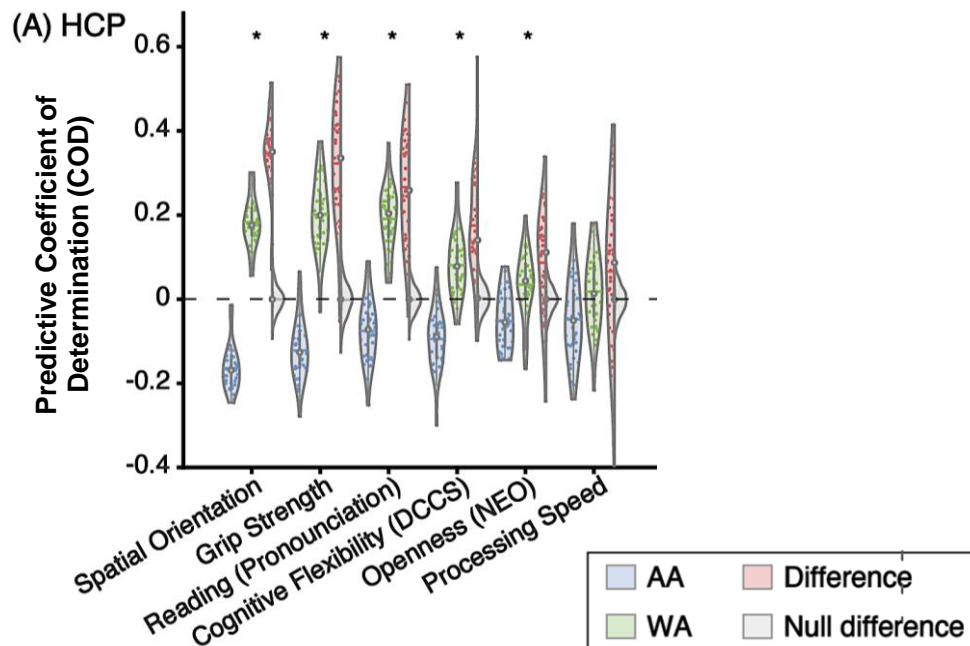


- White Americans (56.0%)
- African Americans (11.9%)
- Hispanic (19.7%)
- Asian (2.1%)
- Others (10.4%)

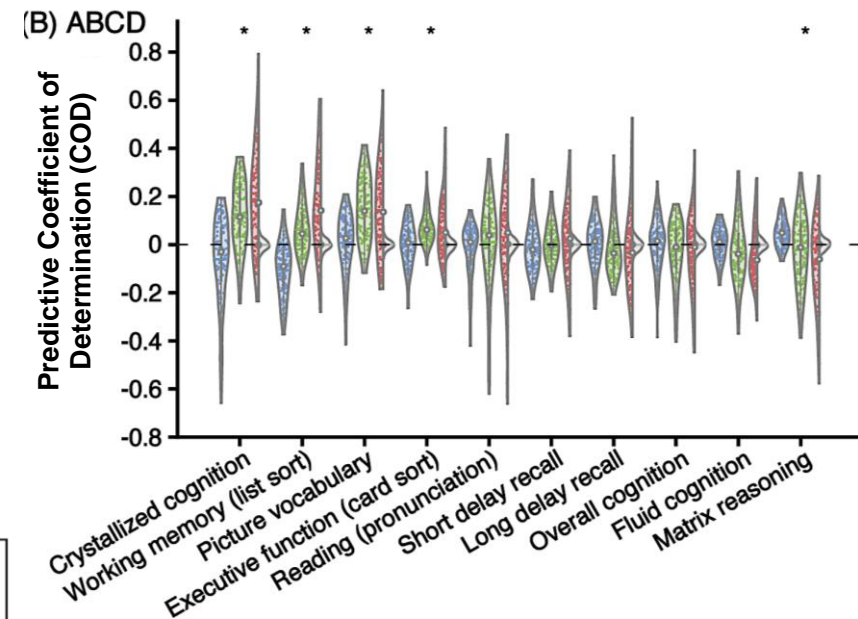
# Predictive models of psychometric data: biases in population minority

## LARGER PREDICTION ERROR IN AFRICAN AMERICANS THAN MATCHED WHITE AMERICANS

### Human Connectome Project (HCP)



### Adolescent Brain Cognitive Development (ABCD)



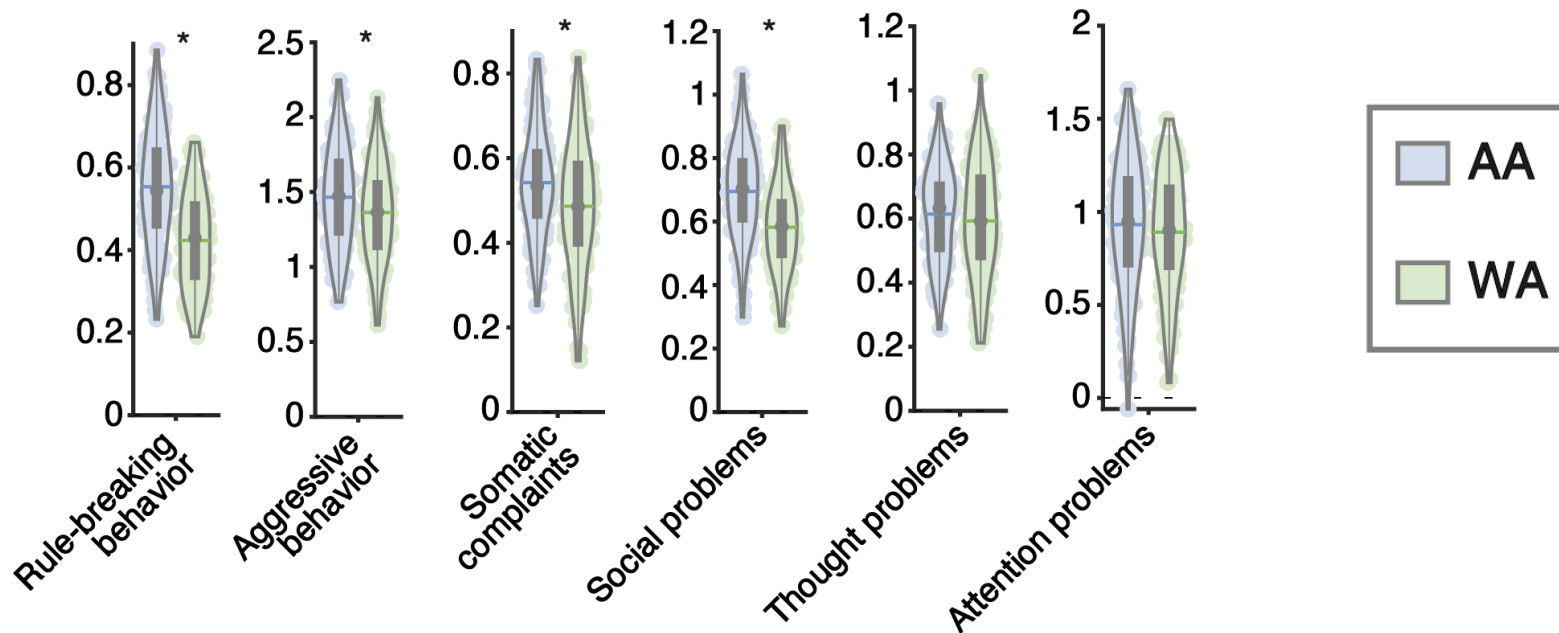
Only predictable behavioral measures are shown here.

Similar pattern by looking into all behavioral measures, or regressing different confounds, or modelling with a different algorithm.

# Predictive models of psychometric data: biases in population minority

## DIRECTION OF PREDICTION ERROR & POTENTIAL CONSEQUENCES

Predicted – observed behavioral scores



ABCD data - Achenbach Child Behavior Checklist

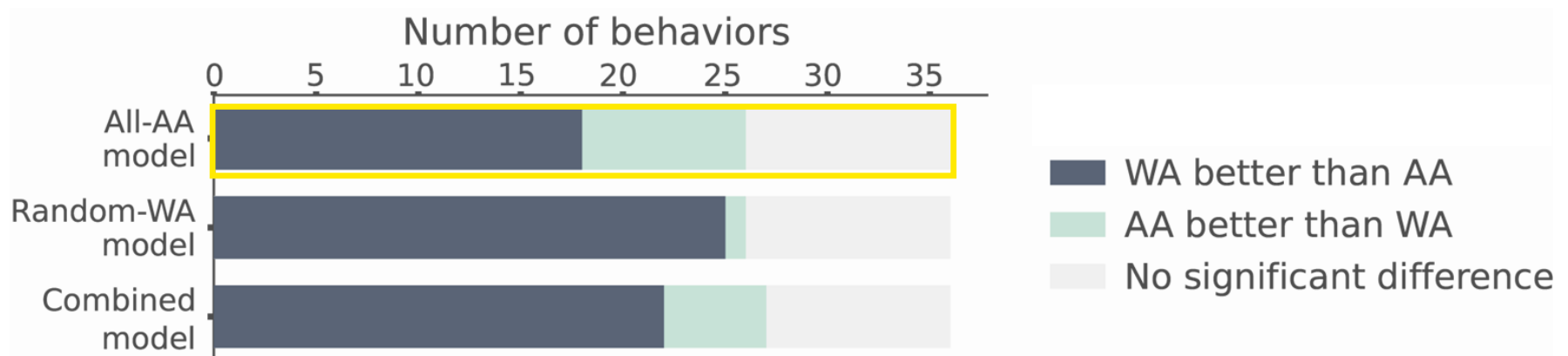
# Predictive models of psychometric data: biases in population minority

## EFFECTS OF TRAINING POPULATION

### ABCD dataset

Compare 3 types of models, trained on:

- a. AA only
- b. WA only (same sample size as AA)
- c. Half AA, half WA (combination of a. & b.)



# Conclusions

- Different brain parcellations reflect the complexity of brain organization
  - Brain structural-behaviour (BSB) associations using traditional approaches show poor replicability
    - Multivariate BSB mapping reveals new global, robust and cross-cohort replicable patterns
  - Connectivity-based predictions of behavioral phenotype
    - Benefit from frameworks promoting interpretability
    - Show limited cross-cohort replicability and generalizability
    - Show fairness issues for minority groups
- ⇒ More diverse datasets are needed to address replicability, interpretability and generalizability issues

## Düsseldorf (Germany)

Katrin Amunts  
Svenja Caspers  
Simon Eickhoff  
Nicola Palomero-Gallagher

## GIGA-ULiege (Belgium)

Steven Laureys  
Gilles Vandewalle  
Eric Salmon  
Christina Schmidt

## UCL Brussels (Belgium)

Julie Duque

## Neurospin/INRIA (France)

Bertrand Thirion  
Demian Wassermann

## UCL (UK)

Janaina Mourao-Miranda  
Agoston Mihalik

## WashU (USA)

Aris Sotiras

## Yale University (USA)

Todd Constable  
Avram Holmes

## NUS (Singapore)

Thomas Yeo

## Cognitive NeuroInformatics Lab

