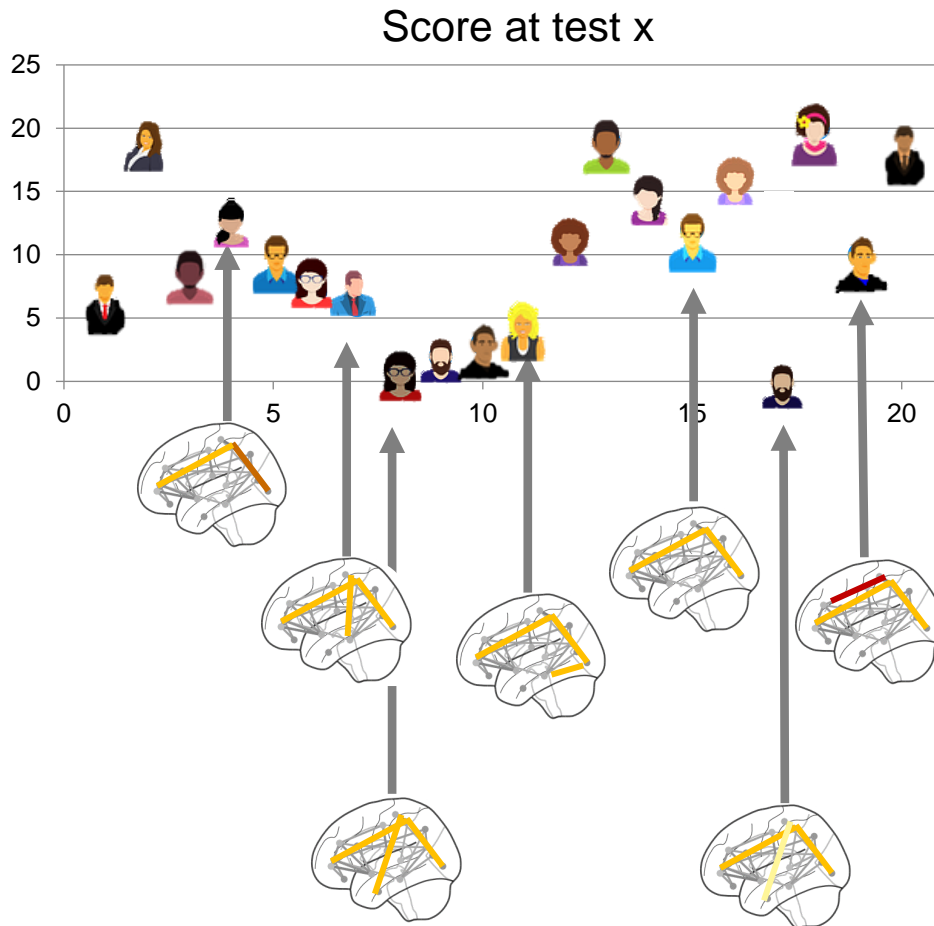


# Generalizability of connectome-based predictive models

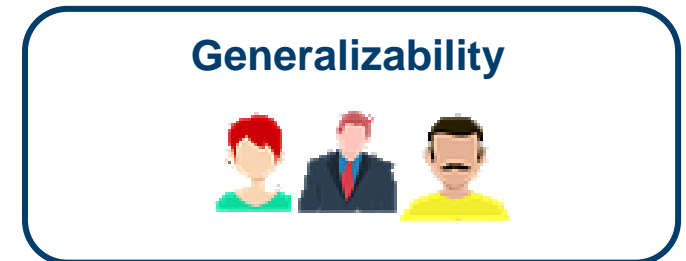
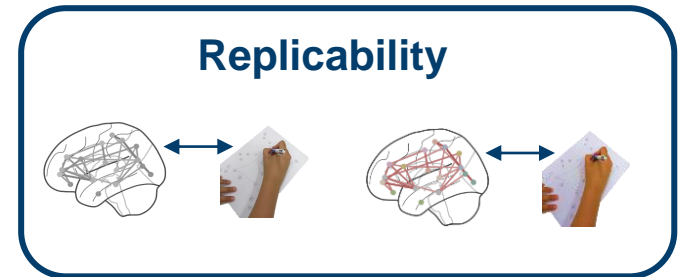
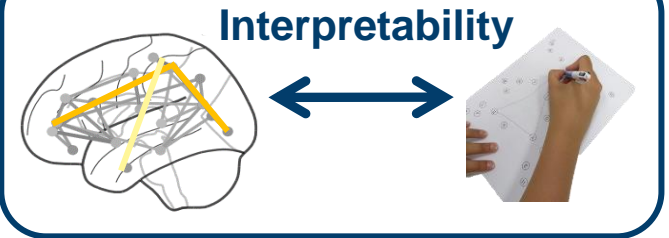
**Sarah Genon**  
**Cognitive Neuroinformatics Lab**  
Research Centre Jülich (INM-7)



# Connectivity-based psychometric prediction



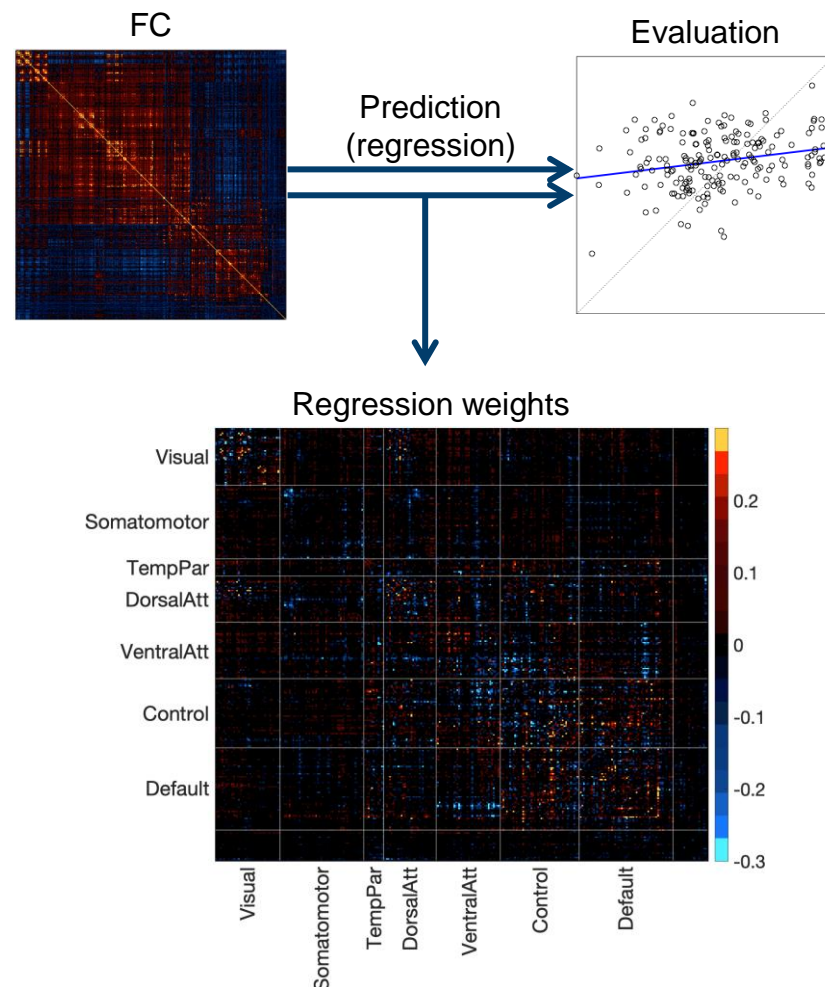
Relating variability in performance to  
variability in brain functional connectivity



# Predictive models of psychometric data

## Interpretability /neurobiological validity issue

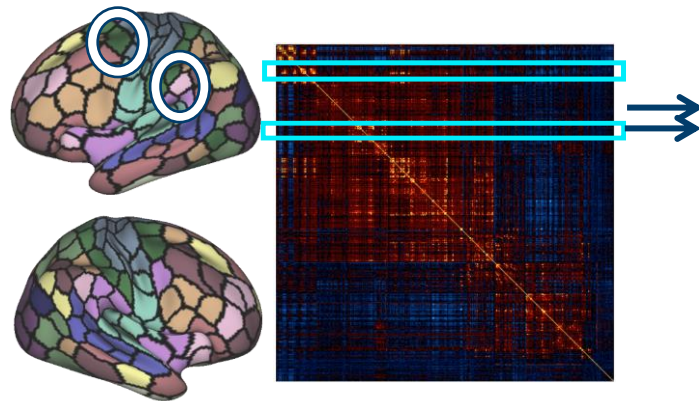
- Hypothesis-driven approach: a priori selection of specific regions/networks for the prediction
- **Data-driven approach:** How do we characterize each region/parcel's association to a psychometric variable?
- **Weight magnitude does not reflect the regions' association strength** with the psychometric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



# Predictive models of psychometric data: interpretability

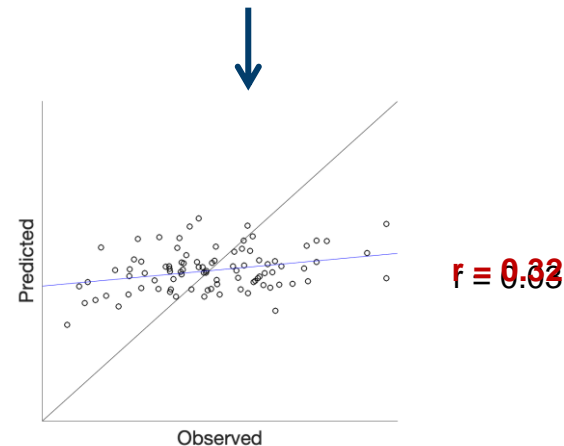
## A region-based approach

- One predictive model for each brain region/parcel



(Schaefer  
et al., 2019)

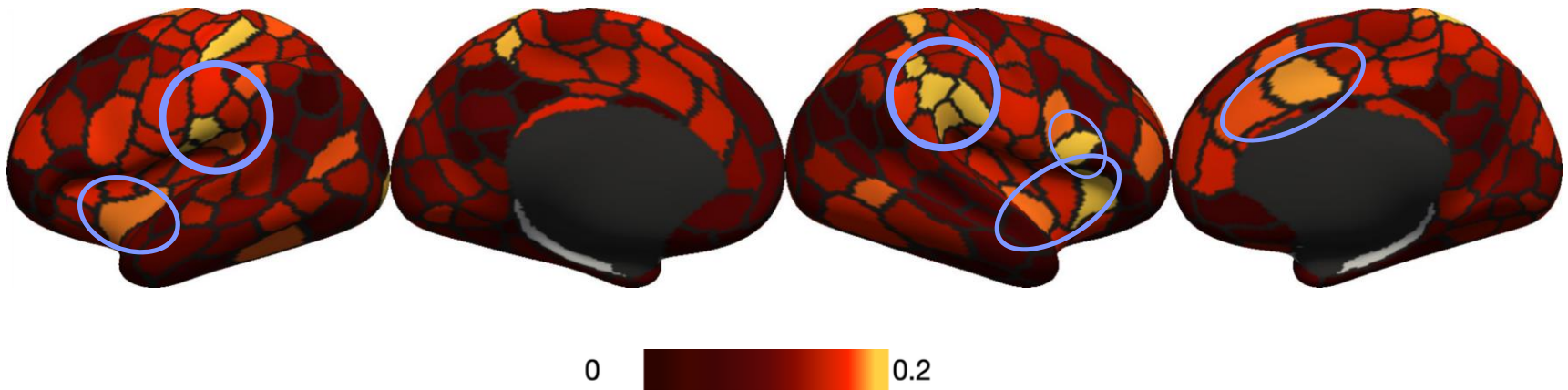
	FC features	Total cognition composite score
Subject 1		133.76
Subject 2		106.85
Subject 3		72.15
...	...	...
Subject N		122.99



# Predictive models of psychometric data: interpretability

## Prediction Performance Distribution

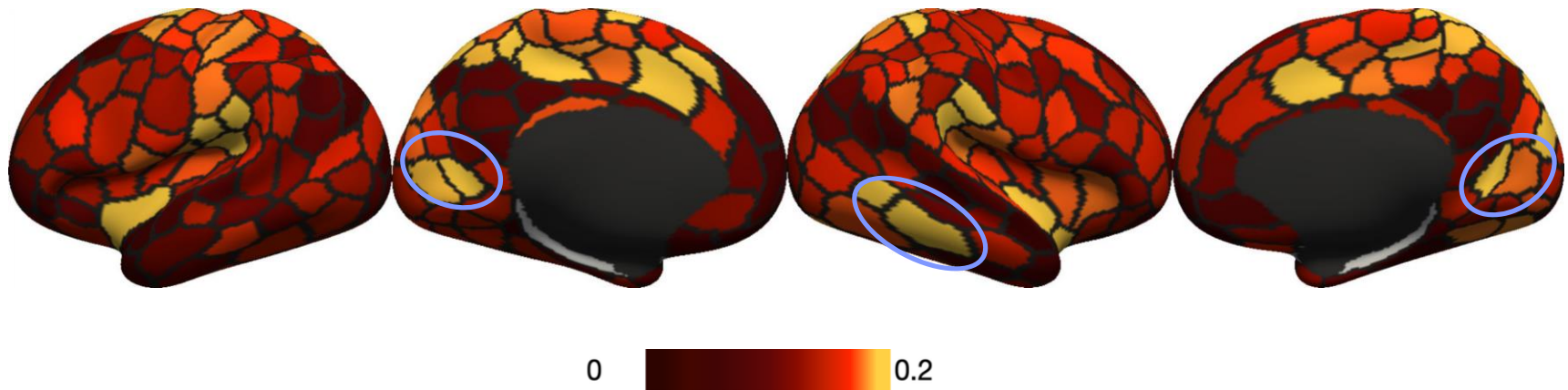
(working memory) 2-back task accuracy



# Predictive models of psychometric data: interpretability

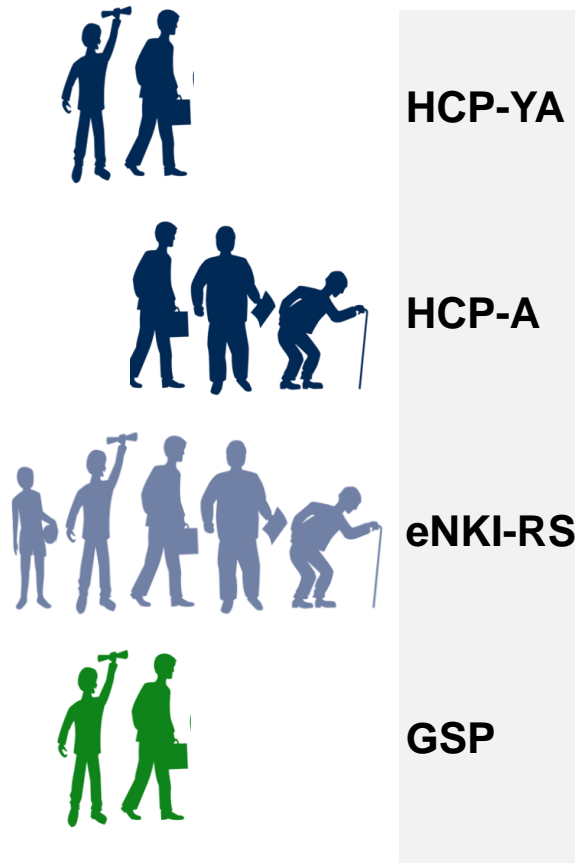
## Prediction Performance Distribution

(working memory) 2-back face task accuracy



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

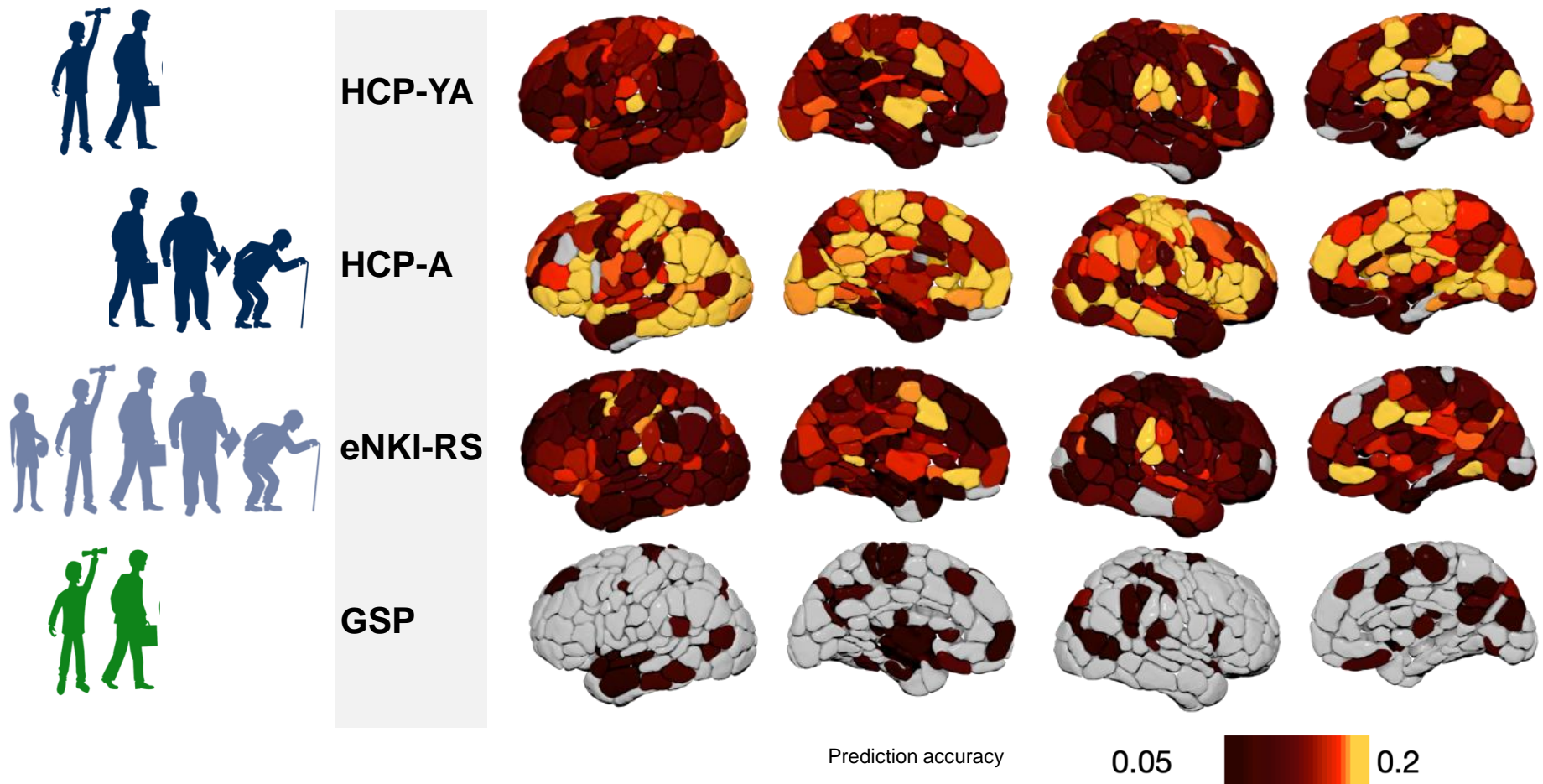
Cross-dataset replicability of brain predictive patterns for fluid cognition





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

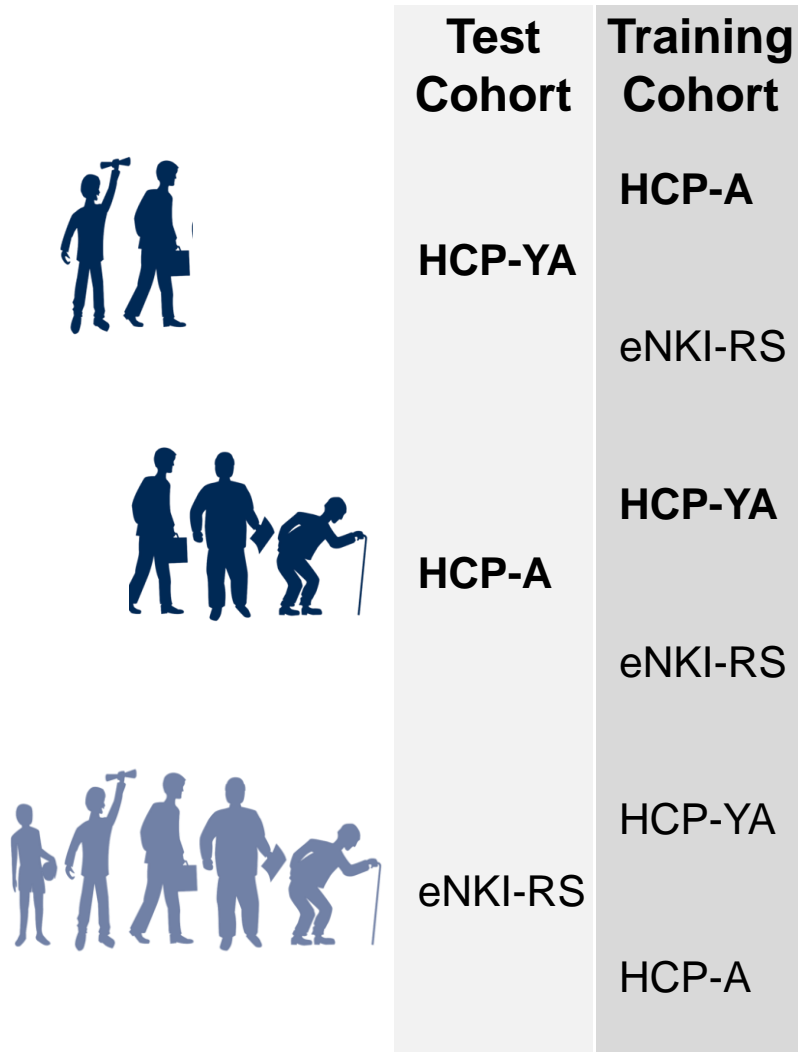
Cross-dataset replicability of brain predictive patterns for fluid cognition





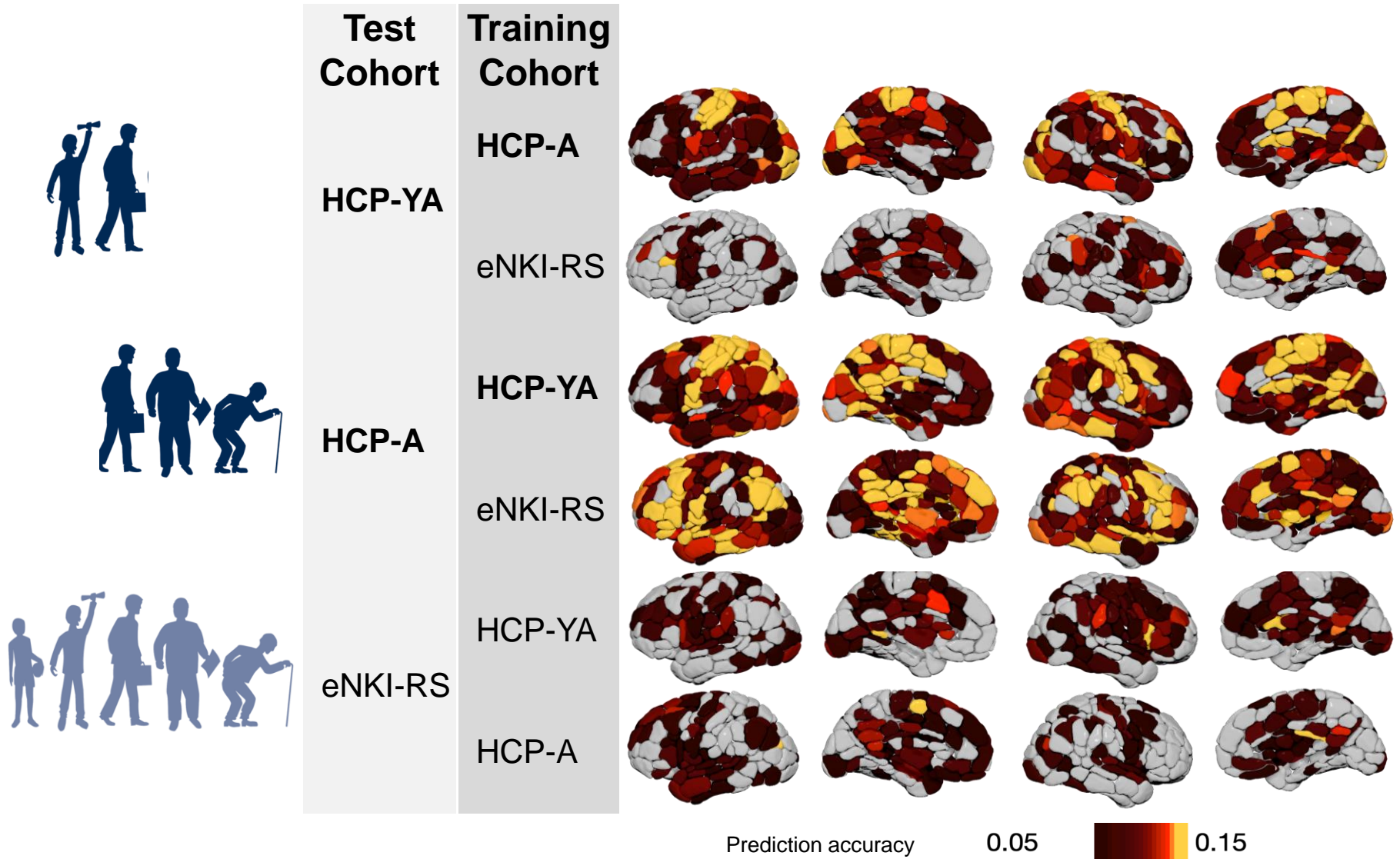
# Predictive models of psychometric data: cross-dataset generalizability

## Cross-dataset generalizability of fluid cognition



# Predictive models of psychometric data: cross-dataset generalizability

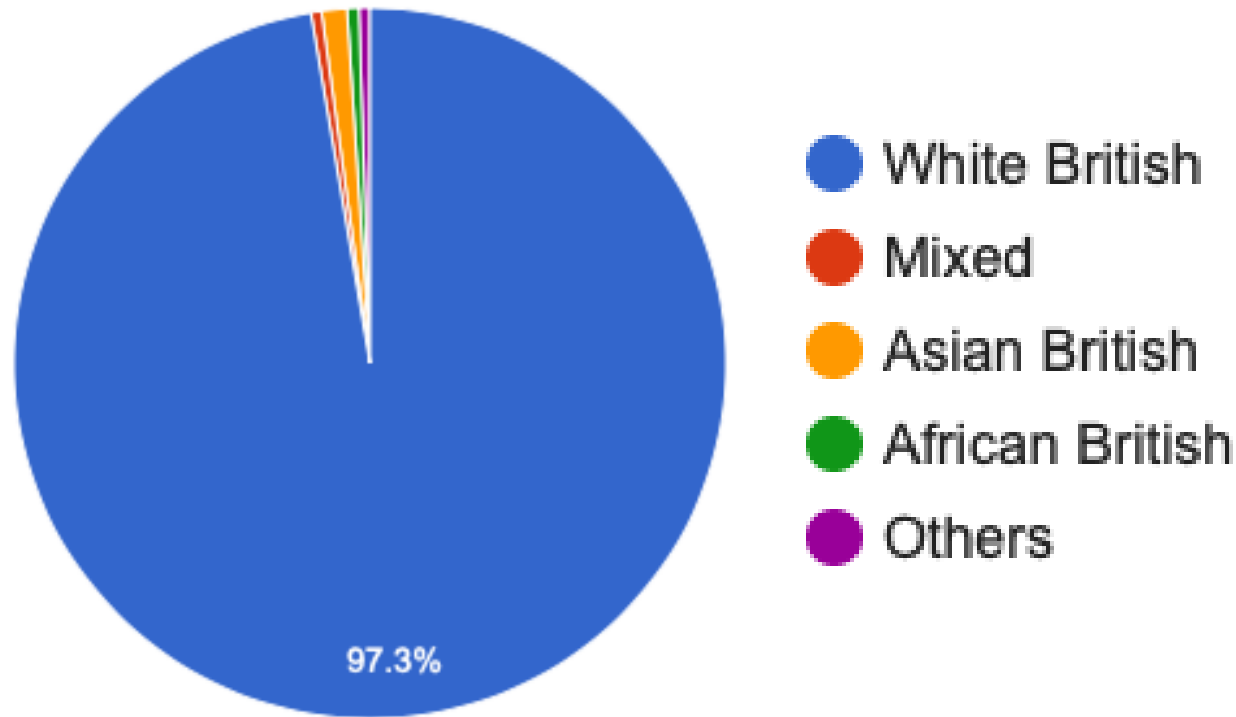
## Cross-dataset generalizability of fluid cognition



# Predictive models of psychometric data

## Underrepresented populations in neuroimaging datasets

Ethnicities in UK-Biobank



# Predictive models of psychometric data: biases in population minority

## Human Connectome Project (HCP)

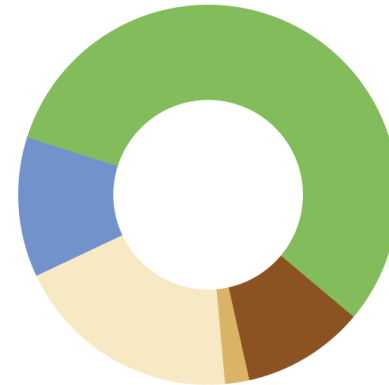
- N = 948; 22-37years
- 58 behavioral measures
- #WA = 721, #AA = 129



- 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

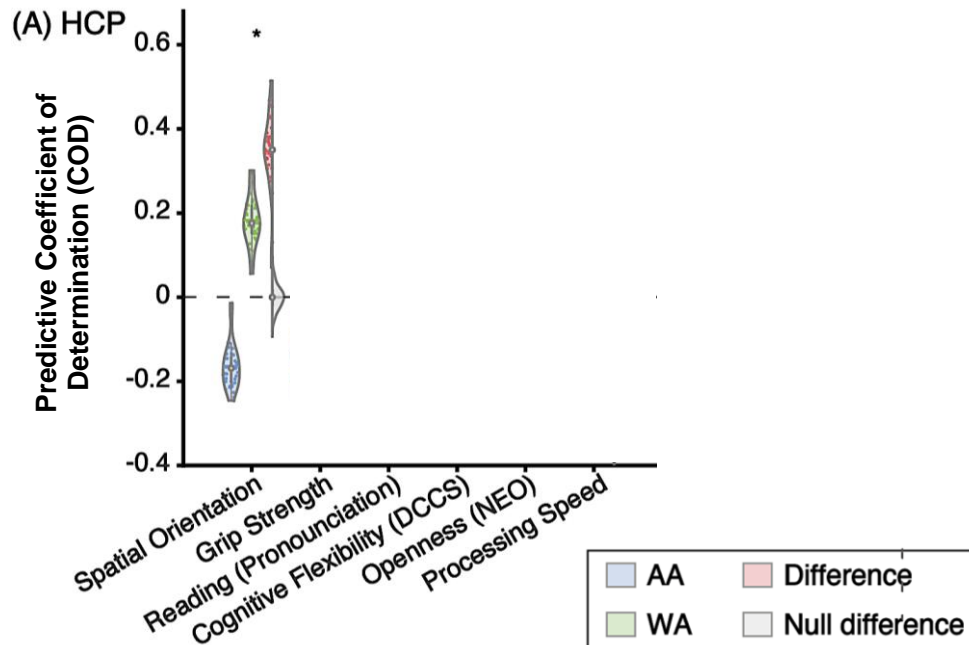


- White Americans (56.0%)
- African Americans (11.9%)
- Hispanic (19.7%)
- Asian (2.1%)
- Others (10.4%)

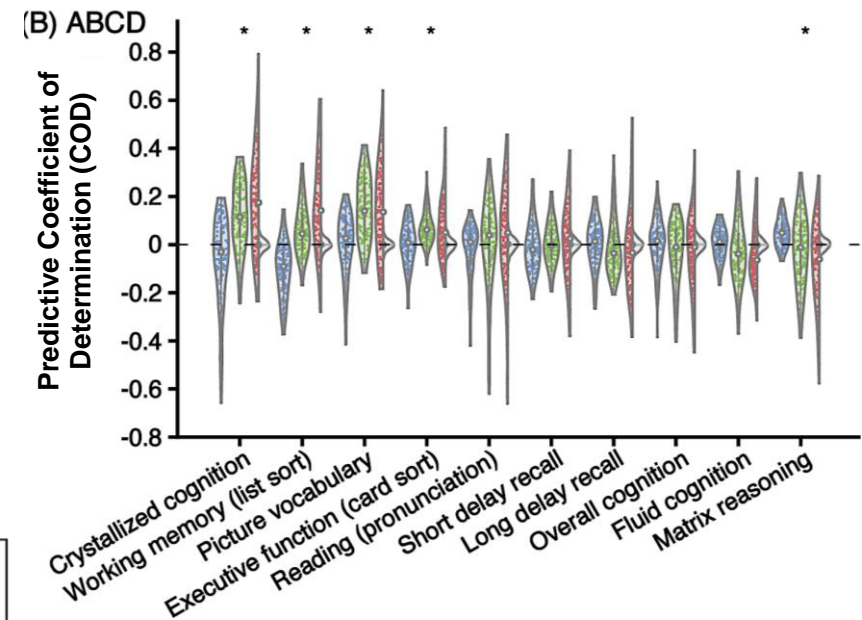
# Predictive models of psychometric data: biases in population minority

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

### Human Connectome Project (HCP)



### Adolescent Brain Cognitive Development (ABCD)



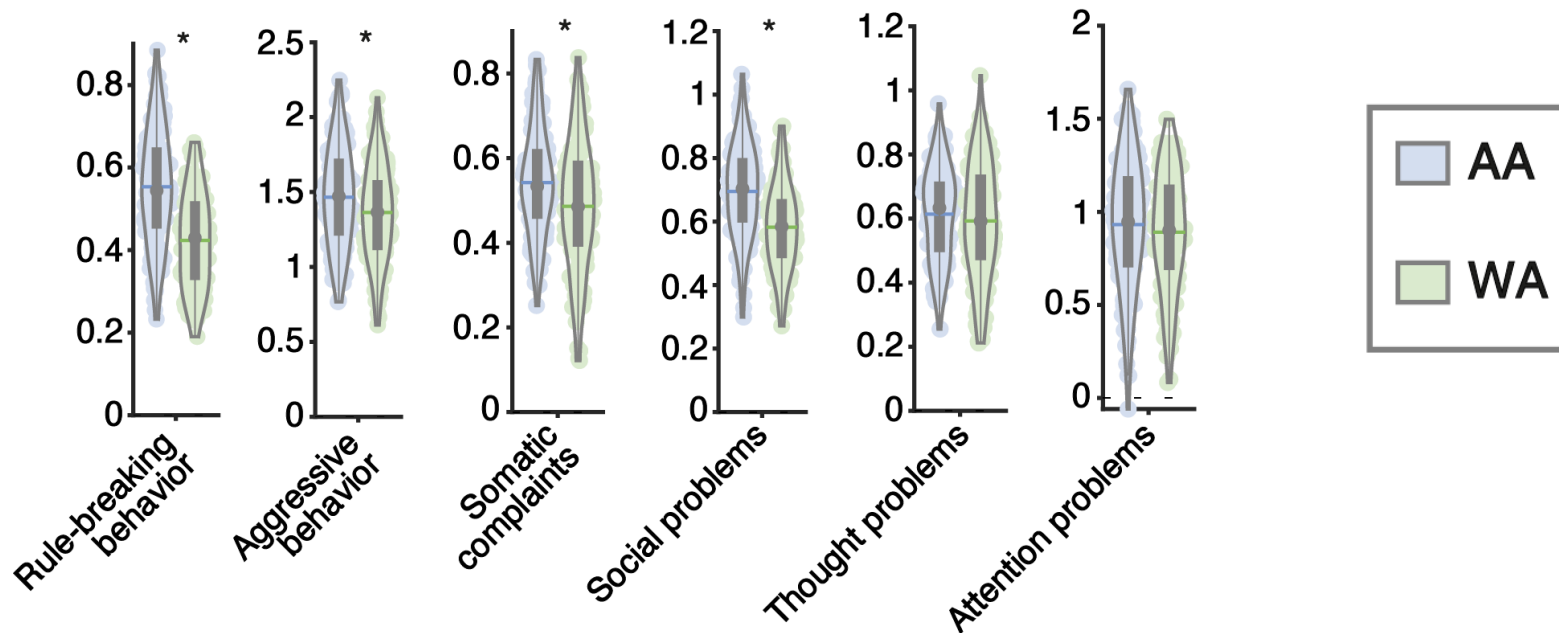
Only predictable behavioral measures are shown here.

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



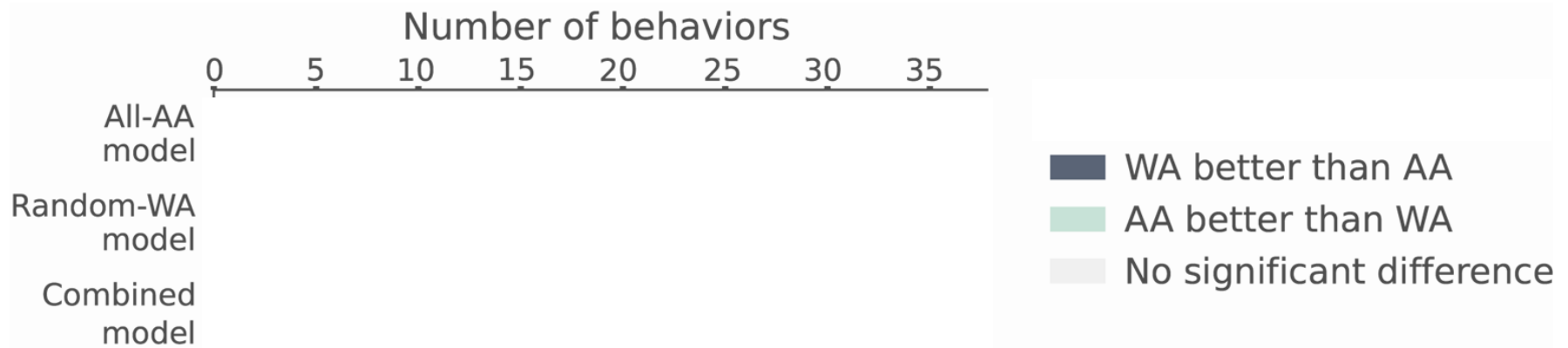
# Predictive models of psychometric data: biases in population minority

## 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.*)



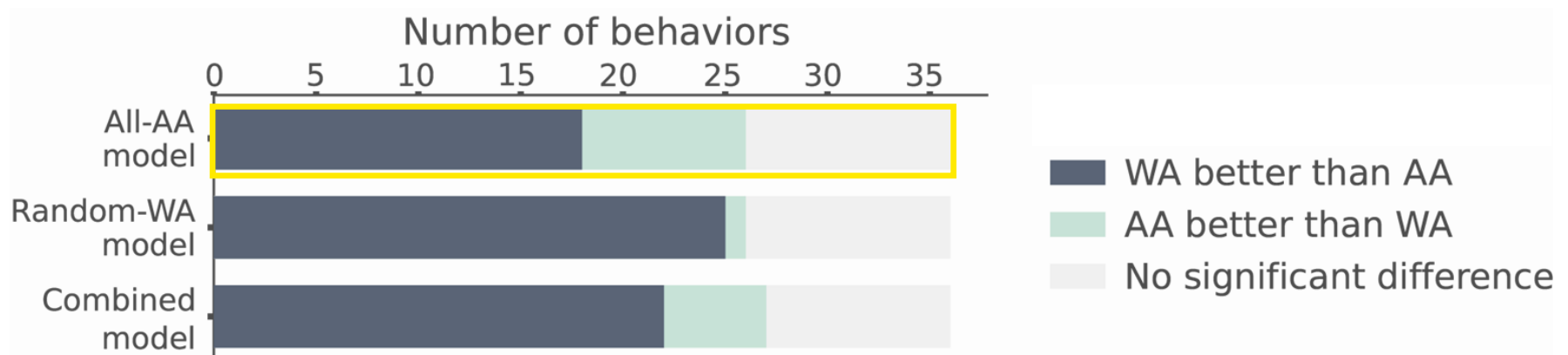
# Predictive models of psychometric data: biases in population minority

## 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.)



- Training only on AA helped to reduce prediction bias against AA
- Prediction accuracy was still in favor of WA
  - Brain Imaging side:  
preprocessing strategies/parameters were optimized on white-dominated samples (e.g. [brain templates](#), [functional atlases](#))
  - Behavioral side:  
standard measures (or tools) suitable / valid for minorities?
- Call for more data collection from non-European-descendant / non-white populations, to learn better representation of minor populations.
  - Consider even more minor groups (e.g. native Americans in the US population)
  - Africans in Africa  $\neq$  African Americans
- Subgroups in the currently defined ethnic/racial categories (e.g. Chinese vs Indian, both as “Asian”)
  - Be aware of similar issue in other countries (e.g. Chinese datasets dominated by Han)
  - Other minority groups, e.g. lower social class
- Assess & promote fairness of future artificial intelligence applications across populations.

## Düsseldorf (Germany)

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Agoston Mihalik

## WashU (USA)

Aris Sotiras

## Yale University (USA)

Todd Constable  
Avram Holmes

## NUS (Singapore)

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