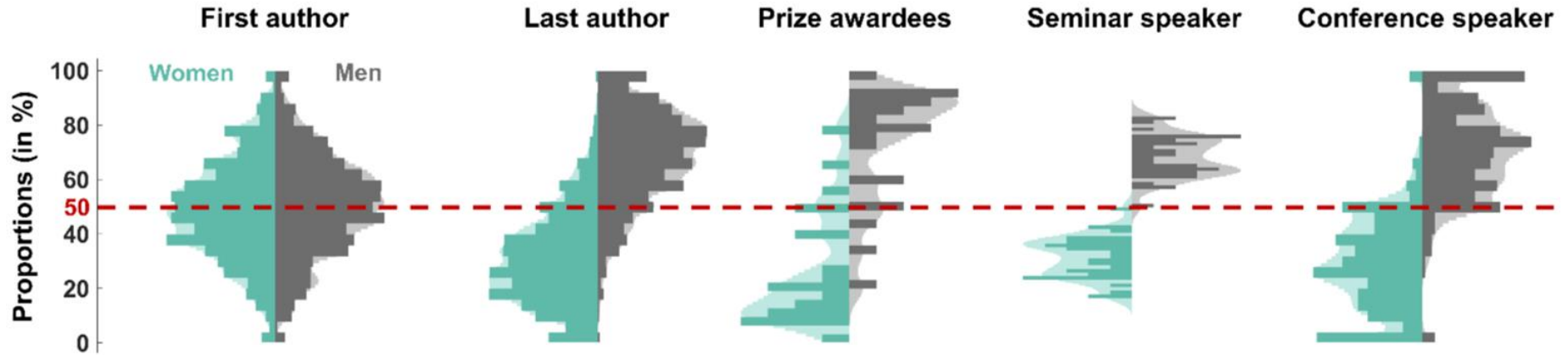


# Diversity and inclusivity in neuroscience

Sarah Genon  
Cognitive Neuroinformatics Lab  
Institute of Neuroscience and Medicine,  
Brain and Behaviour (INM-7)

# Is there a gender bias in neuroscience ?



Histogram in different aspects of **neuroscientific academic life** over the 3 to 10 past years

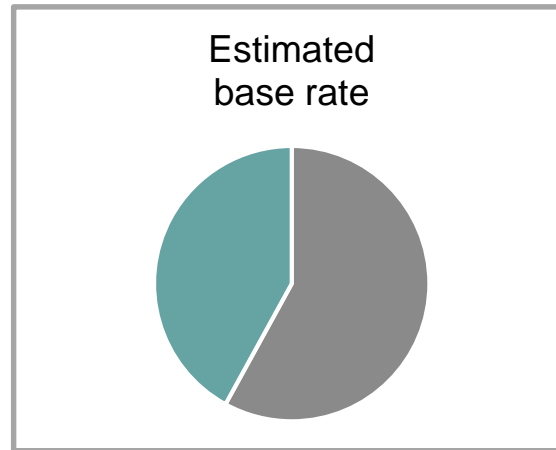
Schrouff et al. 2019

## Bias in most aspects of the research career:

- Funding acceptance rate (Pohlhaus et al., 2011; Kaatz et al., 2016; Sheltzer, 2018)
- Chances of being hired for tenure-track positions at the same competence level (Steinpreis et al., 1999)
- Reviewing and editorial boards, deciding bodies, etc... (Helmer et al., 2017)
- ...

# Is there a gender bias in neuroscience ?

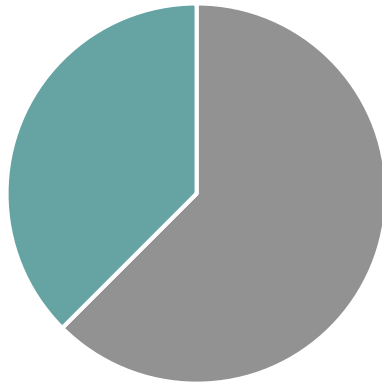
■ Men ■ Women



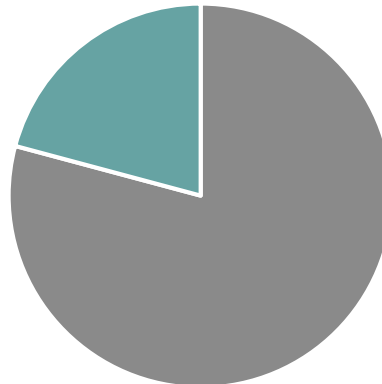
<https://biaswatchneuro.com/>

## 2019 Conference Data

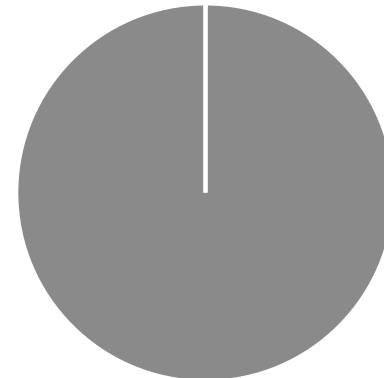
**OHBM 2019**



**Brain Connectivity Workshop**



**Systems Neuroscience Spring School**



# Where does this bias come from ?

## Implicit cognitive biases:

“Implicit” => not deliberate and difficult to be aware of

e.g. : Bohnet et al., 2012

554 American College students asked whether to “hire” the employee presented for a specific task.

Gender was not correlated with task performance

Still, gender stereotypes had a strong and significant impact on evaluators’ candidate assessments:

Higher likelihood for men to be hired for a math task

## => In sciences and research:

- Managers are more likely to hire male scientists (Moss-Racusin et al., 2012)
- Editors are more likely to give a positive review when the senior author is a man (Budden et al., 2008)
- Grant reviewers are more likely to give higher score if the applicant is a man (Bornmann et al., 2007)

## Homophily/Homosociality /“mini-me effect”:

### **Homosociality:**

the preference for similar people and the orientation of the members of this social group towards each other

-> Recruitment and promotion of applicants who appear to be similar in appearance, behaviour and gender to oneself.

Increases with growing hierarchical and leadership levels



# Does diversity matter ?

- **Evolving as a human community**
- **Increase team performance:**

Diverse teams outperform on innovation, problem-solving, flexibility, and decision-making (King, 2005)

- **Research community inclusivity improves research representativity:**
  - “We study people like us”
    - ➔ **Health research: “white male model”** (e.g.: Dresser, 1992)

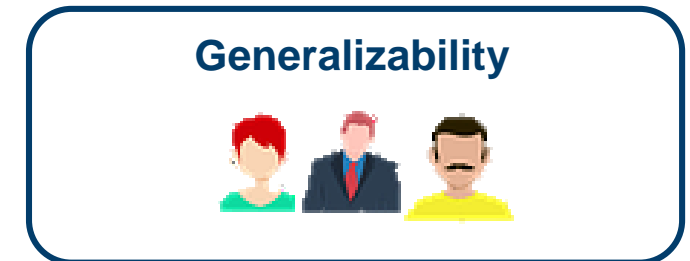
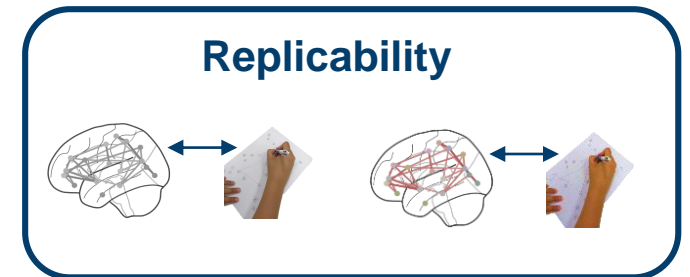
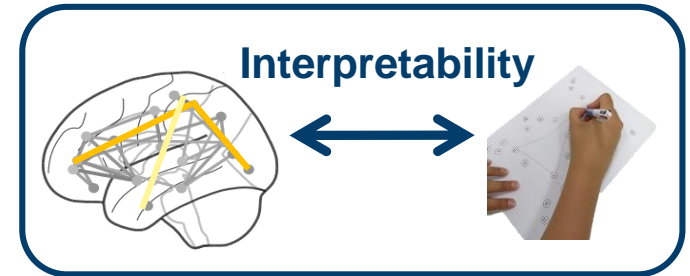
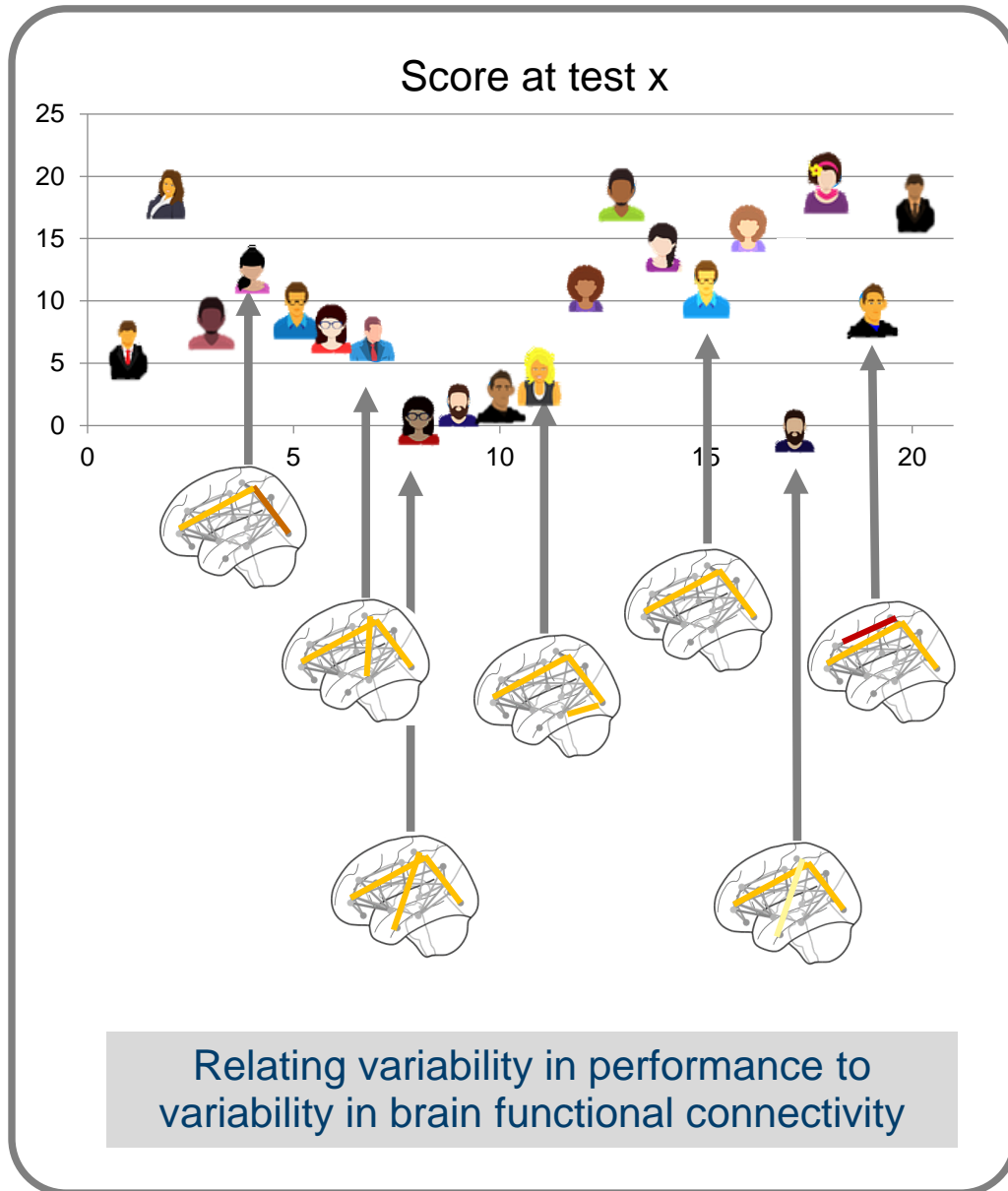
# Does diversity matter ?

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→ **Health research: “white male model”** (e.g.: Dresser, 1992)
  - Future of science and **AI**: data are **biased**, so models are (e.g.: Bolukbasi et al., 2016)

# Connectivity-based psychometric prediction



# Does diversity matter ?

Future and **AI**:

SCIENCE ADVANCES | RESEARCH ARTICLE

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NEUROSCIENCE

## Cross-ethnicity/race generalization failure of behavioral prediction from resting-state functional connectivity

Jingwei Li<sup>1,2,3\*</sup>, Danilo Bzdok<sup>4,5</sup>, Jianzhong Chen<sup>3</sup>, Angela Tam<sup>3</sup>, Leon Qi Rong Ooi<sup>3</sup>, Avram J. Holmes<sup>6,7</sup>, Tian Ge<sup>7,8,9</sup>, Kaustubh R. Patil<sup>1,2</sup>, Mbemba Jabbi<sup>10,11,12,13</sup>, Simon B. Eickhoff<sup>1,2</sup>, B. T. Thomas Yeo<sup>3,14\*†</sup>, Sarah Genon<sup>1,2\*†</sup>

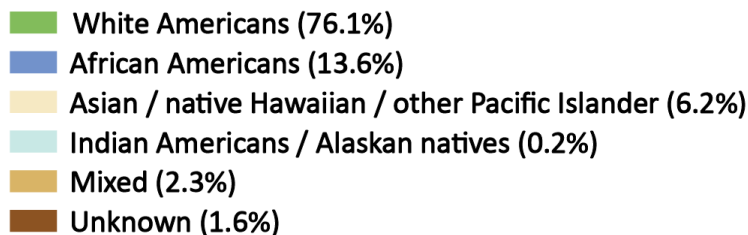
Algorithmic biases that favor majority populations pose a key challenge to the application of machine learning for precision medicine. Here, we assessed such bias in prediction models of behavioral phenotypes from brain functional magnetic resonance imaging. We examined the prediction bias using two independent datasets (pre-adolescent versus adult) of mixed ethnic/racial composition. When predictive models were trained on data dominated by white Americans (WA), out-of-sample prediction errors were generally higher for African Americans (AA) than for WA. This bias toward WA corresponds to more WA-like brain-behavior association patterns learned by the models. When models were trained on AA only, compared to training only on WA or an equal number of AA and WA participants, AA prediction accuracy improved but stayed below that for WA. Overall, the results point to the need for caution and further research regarding the application of current brain-behavior prediction models in minority populations.



# Predictive models of psychometric data: biases in population minority

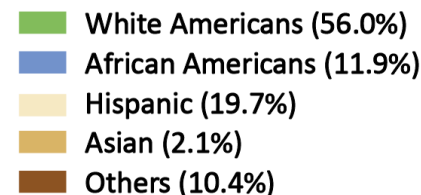
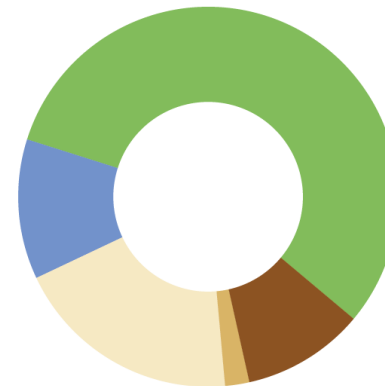
## Human Connectome Project (HCP)

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



## Adolescent Brain Cognitive Development (ABCD)

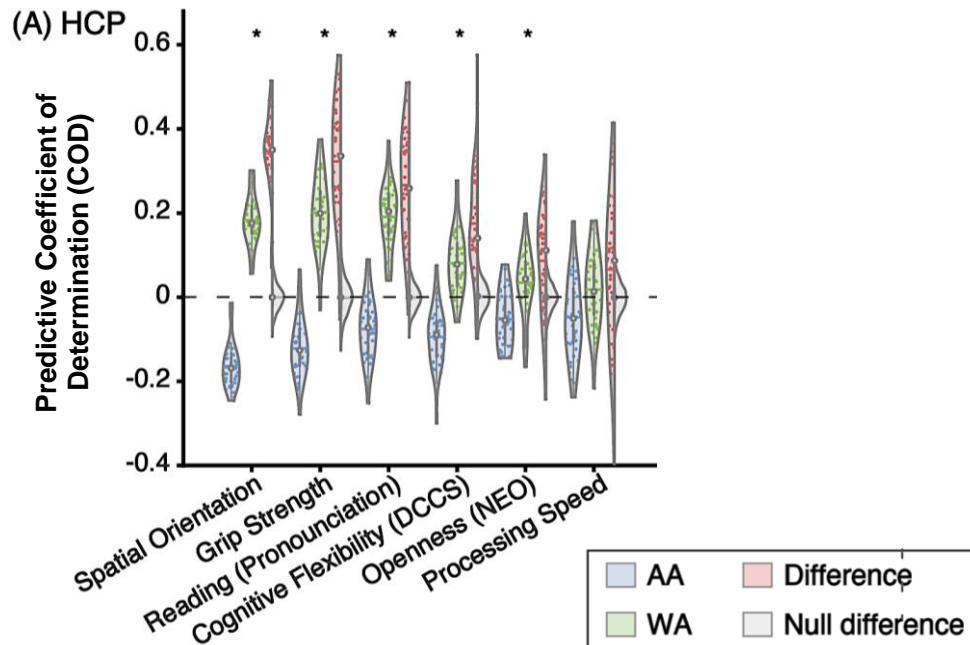
- N = 5351; 9-11years
- 36 behavioral measures
- #WA = 2997, #AA = 642



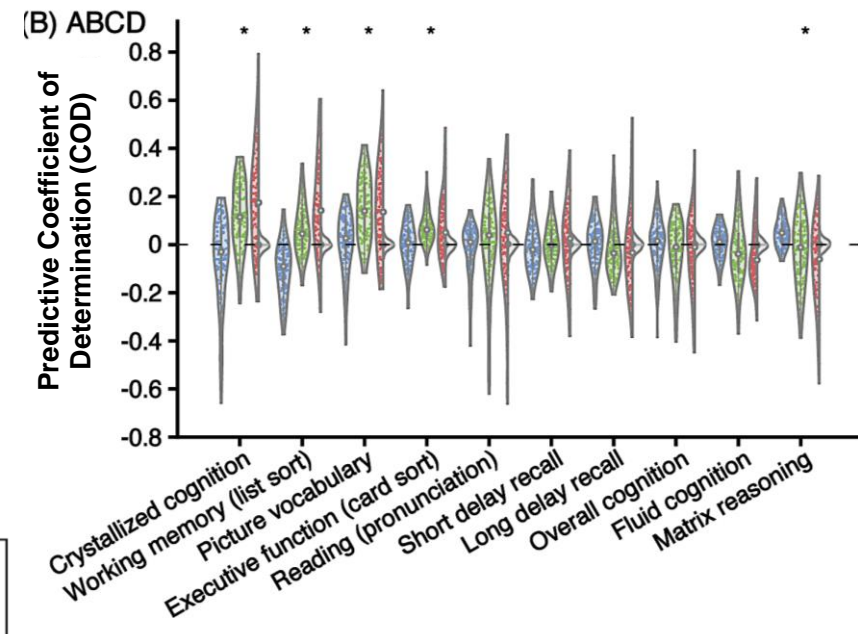
# Predictive models of psychometric data: biases in population minority

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

### Human Connectome Project (HCP)



### Adolescent Brain Cognitive Development (ABCD)



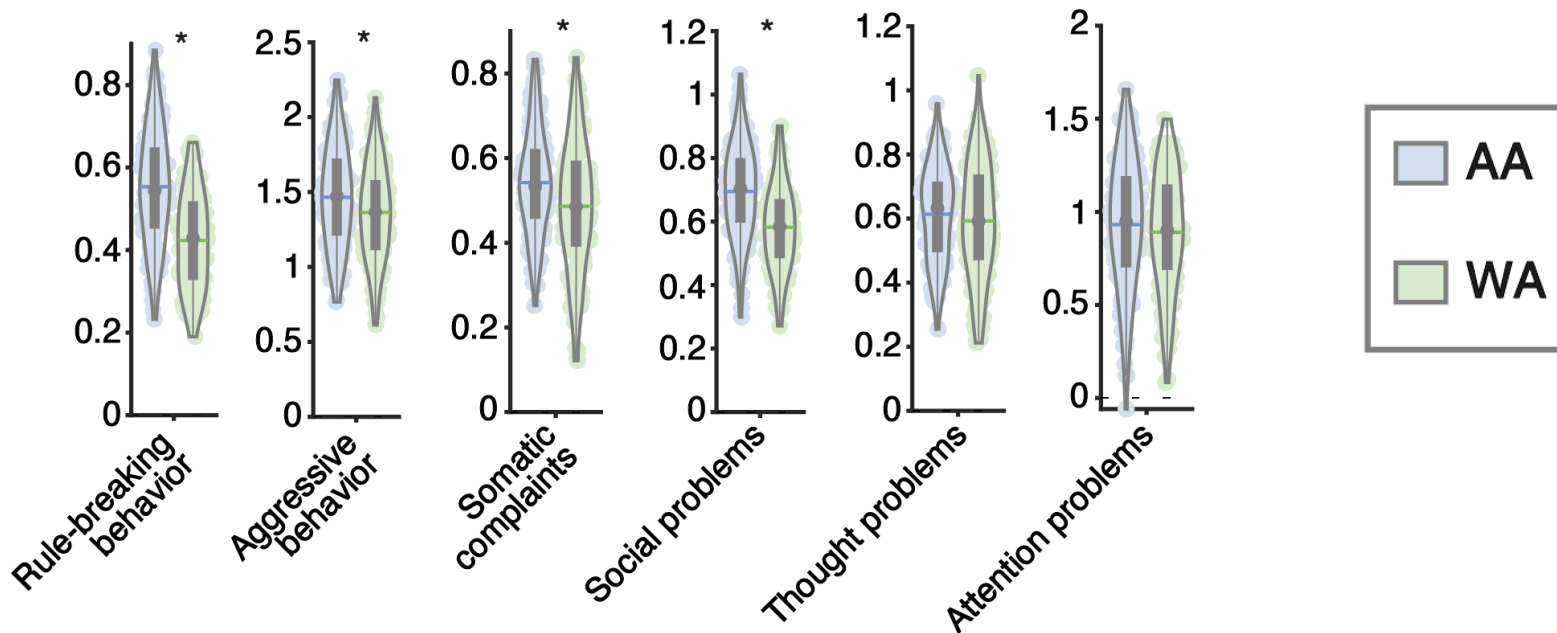
Only predictable behavioral measures are shown here.

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

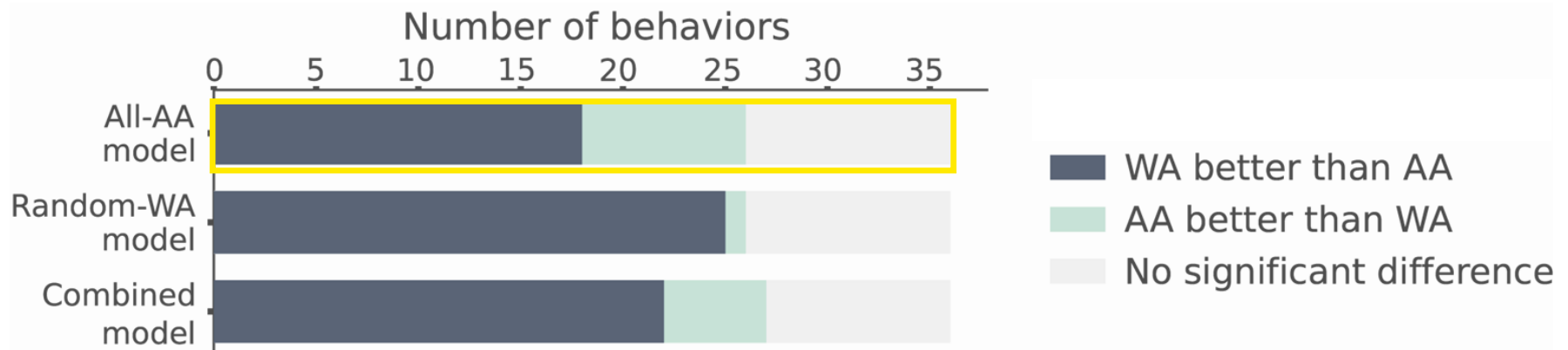
# Predictive models of psychometric data: biases in population minority

## EFFECTS OF TRAINING POPULATION

### ABCD dataset

Compare 3 types of models, trained on:

- AA only
- WA only (same sample size as AA)
- 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 ≠ 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.  
NO conclusion regarding neurobiological / neurocognitive difference across groups should be drawn.  
Structural inequality: historical, societal, educational factors play important roles in the outcome.

# When neuroscience contributes to stereotypes: Neurosexism and neuroracism

Neurosexism =

a bias in the neuroscience of sex differences towards reinforcing harmful gender stereotypes

**PLOS BIOLOGY**

PERSPECTIVE

## How hype and hyperbole distort the neuroscience of sex differences

Gina Rippon<sup>1\*</sup>, Lise Eliot<sup>2</sup>, Sarah Genon<sup>3,4</sup>, Daphna Joel<sup>5,6</sup>

*Sex/gender differences in the human brain attract attention far beyond the neuroscience community. Given the interest of nonspecialists, it is important that researchers studying human female–male brain difference assume greater responsibility for the accurate communication of their findings.*

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PLOS BIOLOGY

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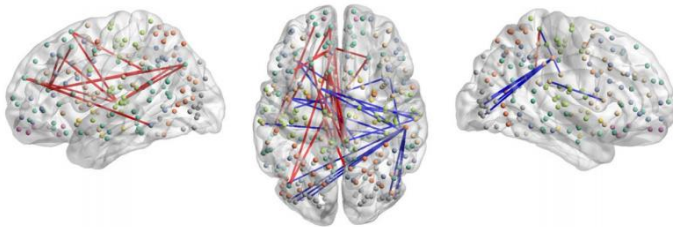
Gina Rippon<sup>1\*</sup>, Lise Eliot<sup>2</sup>, Sarah Genon<sup>3,4</sup>, Daphna Joel<sup>5,6</sup>

- The qualitative terminology used to describe the results does not accurately reflect the actual findings
- Gender comparisons are conducted by investigators naïve to the field or as an “add-on” to the main objective of the study:
  - => adopt an essentialist binary framework and an evolutionary perspective that biases the analysis, design, and interpretation of results
- Post-hoc rationalization for discovery-based findings of sex/gender brain differences

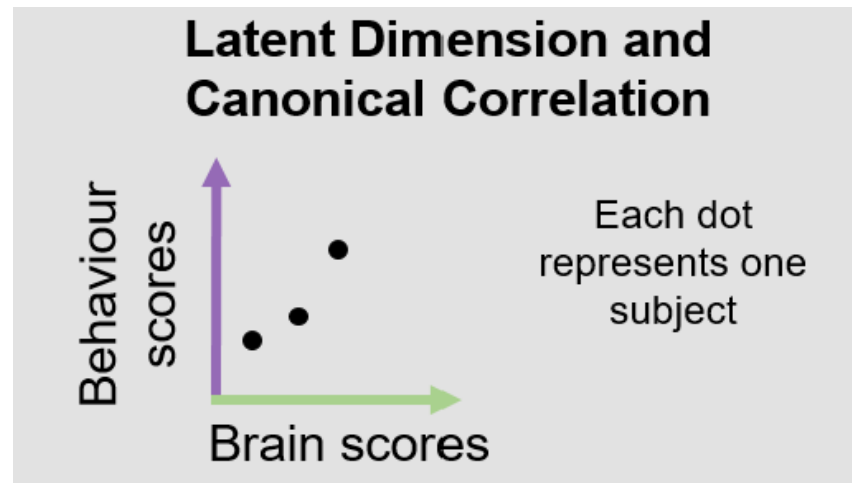
# Sex/gender differences are easy to find but they are not easy to explain

306 adolescents/young adults

Brain functional connectivity



**Behavioural data:**  
Questionnaire (depression, anxiety,...)

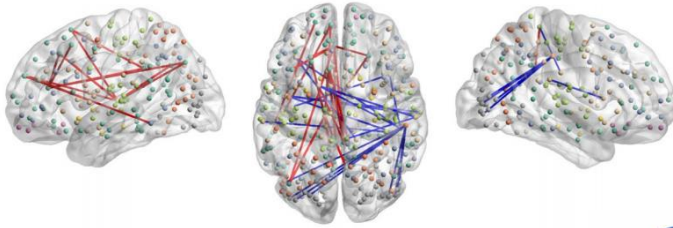


*Mihalik et al., Scientific Report 2019*



# Sex/gender differences are easy to find but they are not easy to explain

Brain functional connectivity in 306 adolescents/young adults



## Essentialist approach:

- The underlying assumption is that female– male differences are determined by biological factors (i.e., “sex”),
- ignore the myriad of psychosocial influences (i.e., “gender”) that can affect the brain

## Simplified reasoning:

*Differences appear early -> this is nature:*

*Depressive symptoms in women are driven by biological factors (hormones)*

**BUT** environmental influences start very early as well

# When neuroscience contributes to stereotypes: Neurosexism and neuroracism

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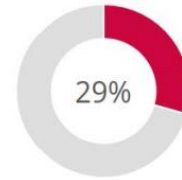
- Post-hoc rationalization for discovery-based findings of sex/gender brain differences

**=> neuroscientists need to think carefully about how they present findings about brain differences between socially segregated groups of humans**

# How can we take actions ?

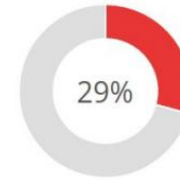
# Repository for Women in Neuroscience

- [www.winrepo.org](http://www.winrepo.org)
- > **1800** profiles
- > **120** recommendations
- Easy search



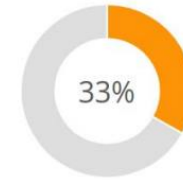
PhD

544 profiles



Post-doc

542 profiles



Senior

615 profiles



Other

153 profiles

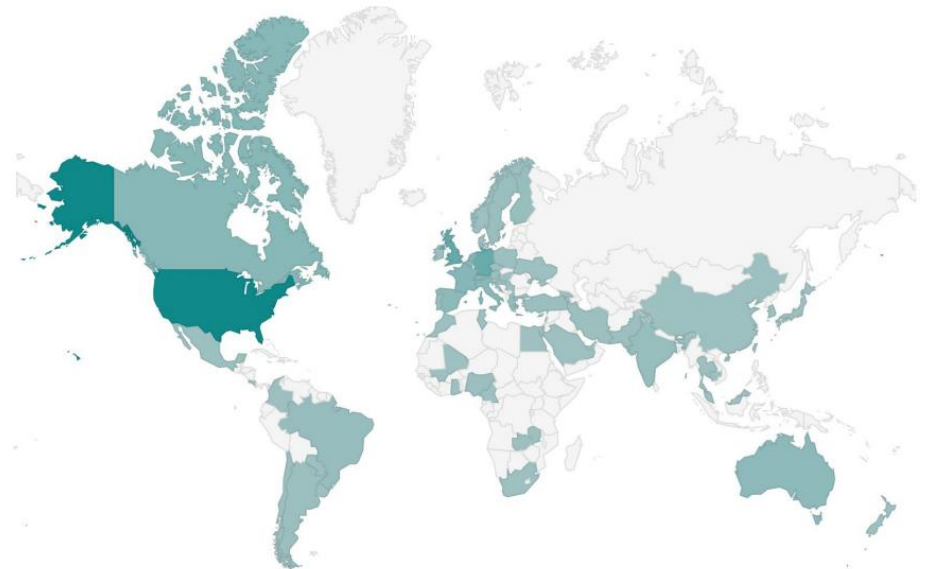
## Support the project:

- Sign up
- Spread the word
- Submit recommendations

 WINRePo1

 [www.facebook.com/WiNRepository/](http://www.facebook.com/WiNRepository/)

 <https://discord.gg/YHc9g3rN>



# Some additional resources:

## “Information” resources:

Data about diversity in neuroscience: <https://biaswatchneuro.com/>

Information about the challenges facing women and minorities in science: Women in Stem Resources

[http://www.sarahrugheimer.com/Women in STEM Resources.html](http://www.sarahrugheimer.com/Women_in_STEM_Resources.html)

A free online test to track implicit biases:

<https://implicit.harvard.edu/implicit/>

## “Action” resources:

#MeTooSTEM: <https://metoostem.com/>

Databases for diversity in sciences:

<https://www.winrepo.org/>

<https://diversesources.org/>

<https://www.embo.org/science-policy/women-in-science/wils-database-of-women-in-life-sciences>

<https://www.nexxt.rub.de/>

<https://anneslist.net/>

<http://www.academia-net.org/>

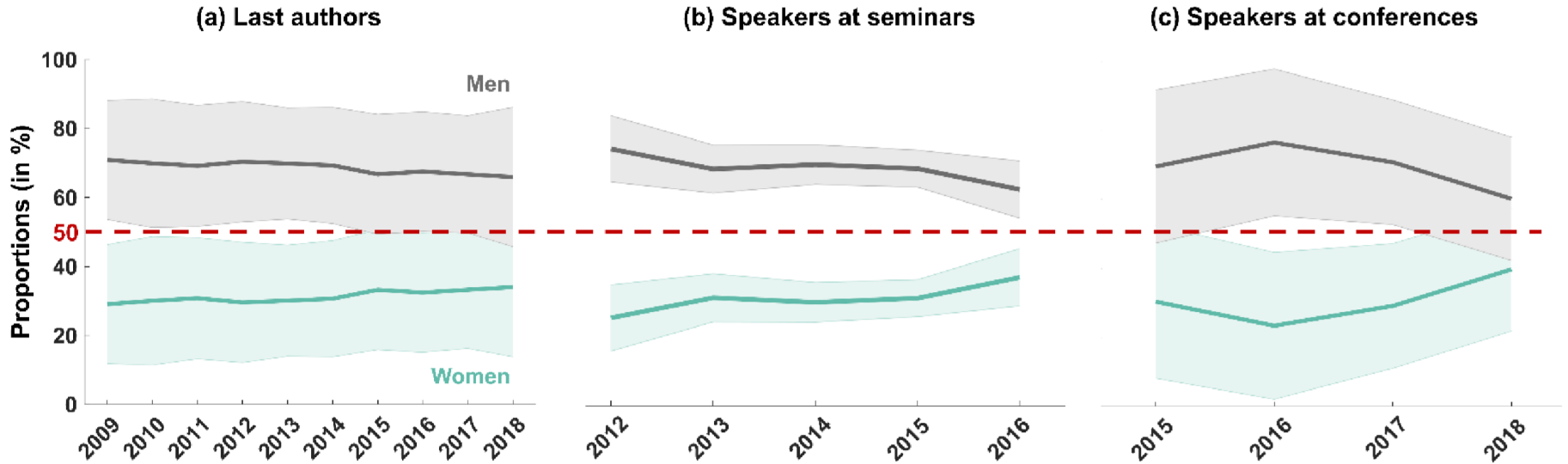
For gender diversity in policy debates:

<https://brusselsbinder.org/>  
Mitglied der Helmholtz-Gemeinschaft



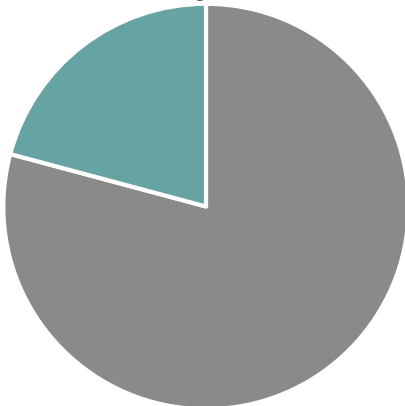
# Discussion

Progress is visible when we take action!

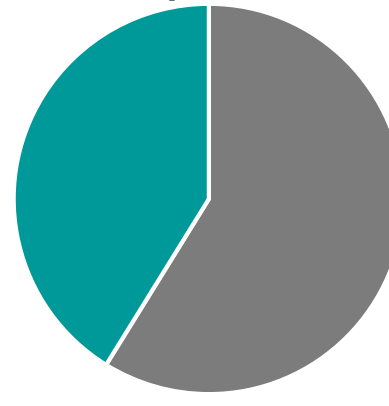


Schrouff et al., 2019

Brain connectivity workshop 2019



Brain connectivity workshop 2021 & 2022



# Thank you

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

