

# Meta-analysis and reproducibility (and responsible data use)

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Neurohackademy | July 2022

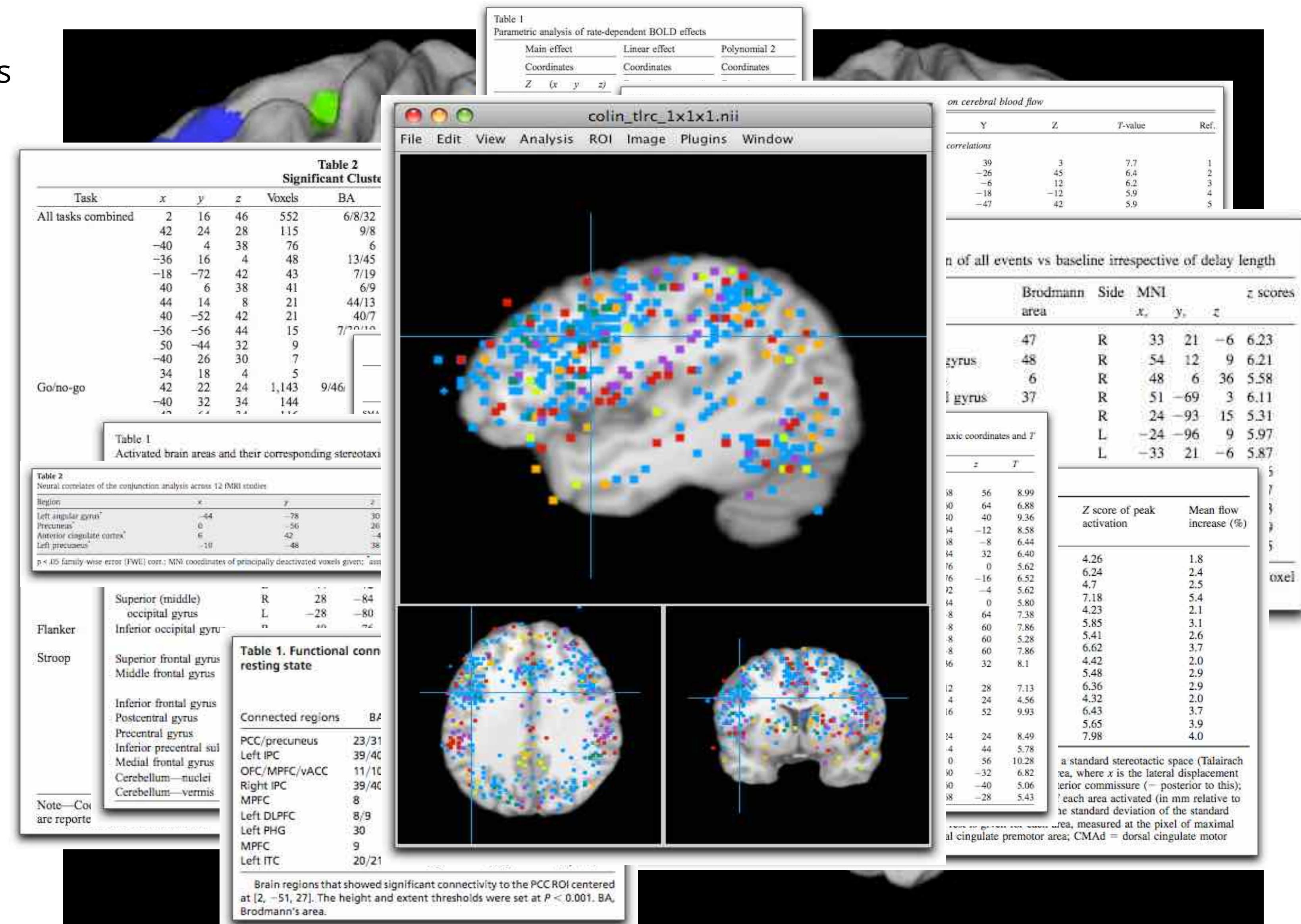


# Coordinate-based neuroimaging meta-analysis: Where do the coordinates converge?

## fMRI Community Standards:

Spatial normalization to standard templates  
Results reported as 3D coordinates (peaks)

Table 2 Co-ordinates according to the Talairach and Tournoux Atlas, for the centres of mass of the regions of interest described in the text	
Regions of interest	Talairach and Tournoux co-ordinates
R-M1	-33, 24, 65
L-M1	28, 25, 66
R-S1	-38, 38, 66
L-S1	38, 38, 67
R-LPMC	-30, 5, 65
L-LPMC	30, 5, 65
R-SMA	-7, 4, 67
L-SMA	6, 3, 66
R-CMA	-9, -34, 6
L-CMA	6, -24, 8
R-CRB	-21, 50, -18
L-CRB	18, 50, -18

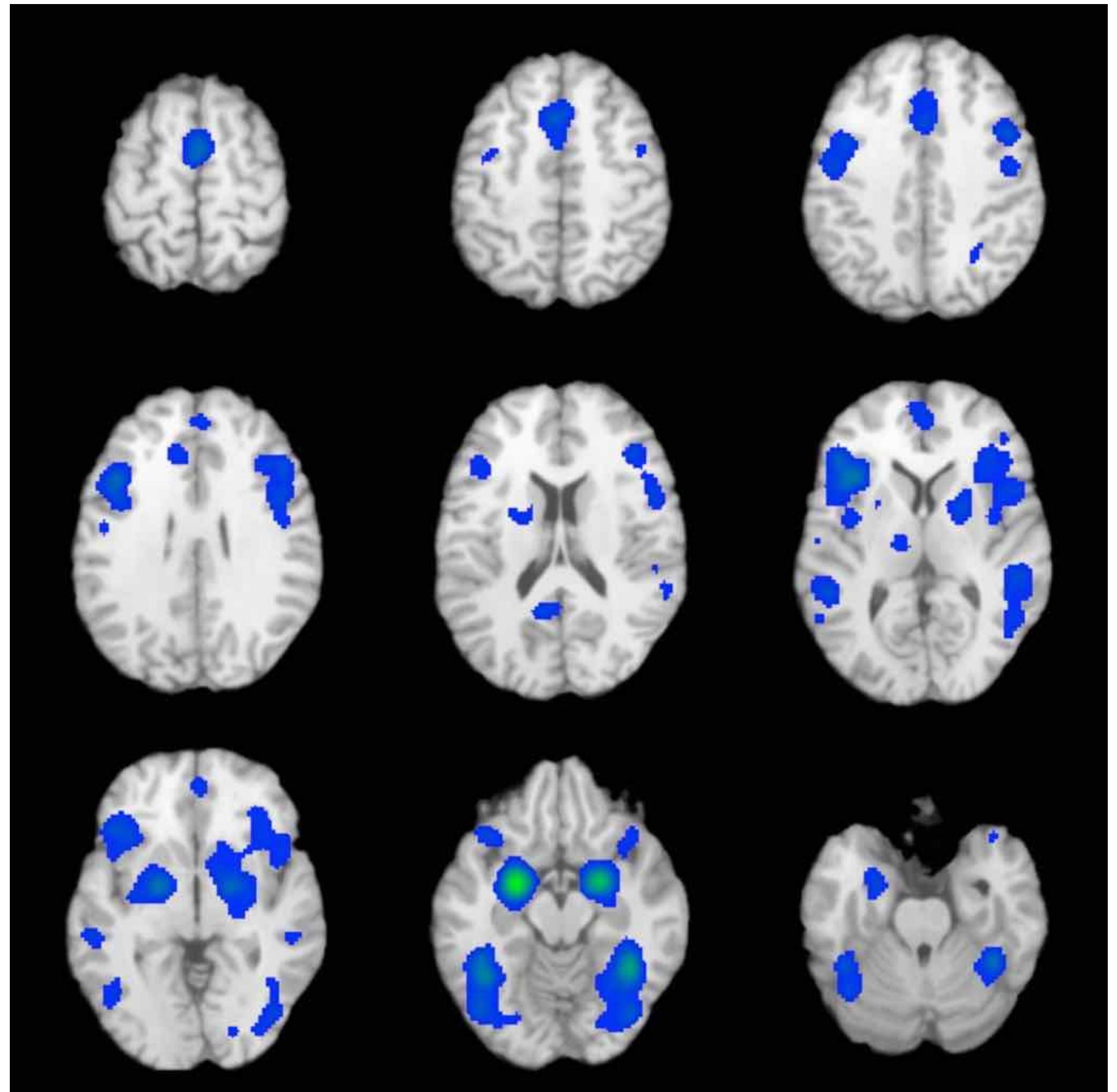


# Coordinate-based neuroimaging meta-analysis: *Where do the coordinates converge?*

~~Effect size meta-analysis:~~ *Is there a statistically significant finding?*

**Location-effects meta-analysis:** *Where do the coordinates converge?*

- Convolve foci with spatial kernel to produce study-specific modeled activation maps
- Combine those MA maps into a sample-wise map
- Compare to null distribution to determine voxel-wise statistical significance



## Coordinate-Based Meta-Analysis

Where do the foci converge?

- Convolve foci with spatial kernel to produce study-specific modeled activation maps
- Combine those MA maps into a sample-wise map
- Compare to null distribution to determine voxel-wise statistical significance

**Activation Likelihood Estimation (ALE)**

**Kernel Density Analysis (KDA)**

**Multilevel Kernel Density Analysis (MKDA)**

**Specific Coactivation Likelihood Estimation (SCALE)**

**Seed-Based d-Mapping**

**MKDA Chi2 Extension**

Described in detail by Samartsidis  
et al., Stat Sci, 2017

## Image-Based Meta-Analysis

Where do the images converge?

**Mixed-Effects GLM (gold standard)**

**Fixed-Effects GLM**

**Fisher's IBMA**

**Stouffer's IBMA**

**z permutation**

Described in detail by Maumet and Nichols, 2016  
doi: <https://doi.org/10.1101/048249>

Please upload  
your maps!



# NiMARE: A neuroimaging meta-analysis research environment

## NiMARE: A Neuroimaging Meta-Analysis Research Environment



**FIU** FLORIDA INTERNATIONAL UNIVERSITY

### Motivation

- Meta-analysis is crucial for neuroimaging, which suffers from low power, sample sizes, and signal-to-noise
- Meta-analyses and derivative analyses may use databases, algorithms, annotation models, and decoding models
- No common interface across several meta-analysis packages that perform similar tasks
- Available tools are often closed source, GUI-based, and/or written in languages unfamiliar to most neuroimagers
- No available implementations for many algorithms or workflows

### Features

- NiMARE is a Python package for performing meta-analyses and related analyses of the neuroimaging literature
- Provides a standard syntax for a variety of analyses and to interact with coordinate and image databases from fMRI studies (e.g., Neurosynth, Brainspell, and NeuroVault)
- Joins the burgeoning Python neuroimaging ecosystem including nipype, nistats, and nilearn
- Is open source, collaboratively developed, and built for simplicity

### Want to get involved?

Visit  
<https://github.com/neurostuff/NiMARE>

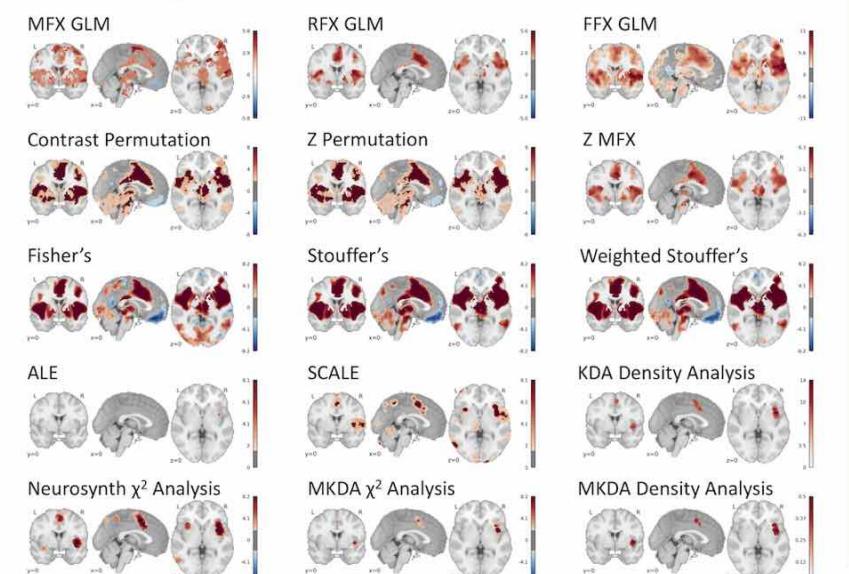


or scan this QR code:  
Check out our contributing guidelines  
and open Issues

### Test Methods

- NiDM Results packs for 21 pain studies from NeuroVault collection 1425
- Convert to json for NiMARE
- Apply meta-analytic algorithms to all datasets
- Code available at <https://github.com/NBCLab/nimare-incf-2018>

### Test Results



This work was supported by awards from the National Science Foundation (NSF 1631325) and the National Institutes of Health (NIH U24 DA039832 & NIH R01 DA041353)

Contact Information: Taylor Salo • tsalo006@fiu.edu

### (Proposed) Interface

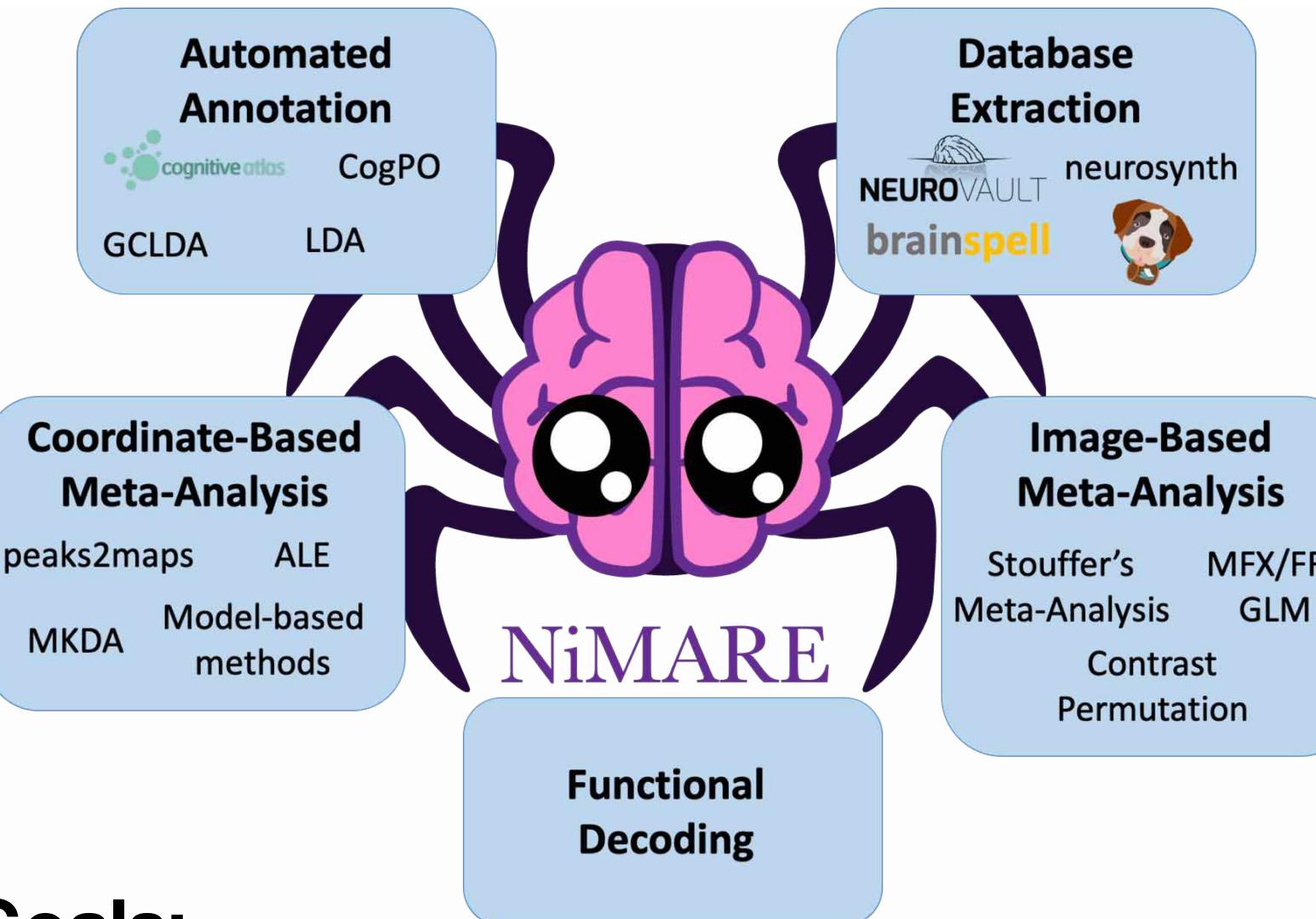
- **Database extraction:** `nimare.extract`
  - NeuroVault<sup>1</sup>
  - Neurosynth<sup>2</sup>
  - Brainspell<sup>3</sup>
- **Text-based annotation:** `nimare.annotate`
  - Tf-idf vectorization
  - Co-occurrence vectorization
- **Ontology extraction:** `nimare.annotate.ontology`
  - Cognitive paradigm ontology<sup>4</sup>
  - Cognitive atlas<sup>5</sup>
- **Topic models:** `nimare.annotate.topic`
  - Latent Dirichlet allocation<sup>6</sup>
  - Generalized correspondence latent Dirichlet allocation<sup>7</sup>
  - Deep Boltzmann machines<sup>8</sup>
- **Vector representation models:** `nimare.annotate.vector`
  - Word2brain<sup>9</sup>
  - Text2brain<sup>10</sup>
- **Meta-analytic algorithms:** `nimare.meta`
  - **Coordinate-based meta-analysis:** `nimare.meta.cbma`
    - Activation likelihood estimation<sup>11</sup>
    - Specific coactivation likelihood estimation<sup>12</sup>
    - Multilevel kernel density analysis<sup>13</sup>
    - Kernel density analysis<sup>14</sup>
    - Bayesian hierarchical cluster process model<sup>15</sup>
    - peaks2maps<sup>16</sup>
  - **Intensity-based meta-analysis:** `nimare.meta.ibma`
    - MFX GLM<sup>17</sup>
    - RFX GLM<sup>17</sup>
    - FFX GLM<sup>17</sup>
    - Contrast permutation<sup>17</sup>
    - Stouffer's meta-analysis<sup>17</sup>
    - Weighted Stouffer's meta-analysis<sup>17</sup>
    - Fisher's meta-analysis<sup>17</sup>
    - Z permutation<sup>17</sup>

### Next Steps

- Recruit contributors!
- Cement interface
- Documentation/code/tests
- Develop standard for metadata representation
- NiDM support with PyNiDM
- Optimization

### References

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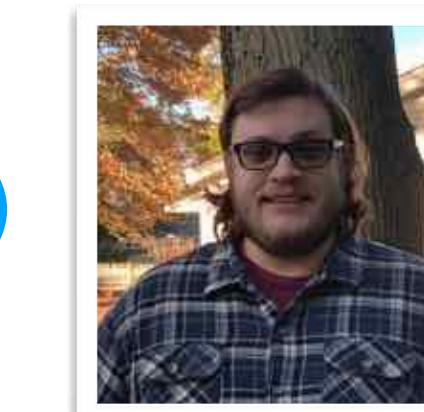


### Goals:

- Implement a common interface across different meta-analysis packages that perform similar tasks
- Facilitate open source community development
- Provide a standard syntax for a variety of different analyses that interact with coordinate and image-based databases (e.g., Neurosynth, Brainspell, NeuroVault)
- Joins the Python neuroimaging ecosystem (along with nipype, nistats, and nilearn)

<https://github.com/neurostuff/NiMARE>

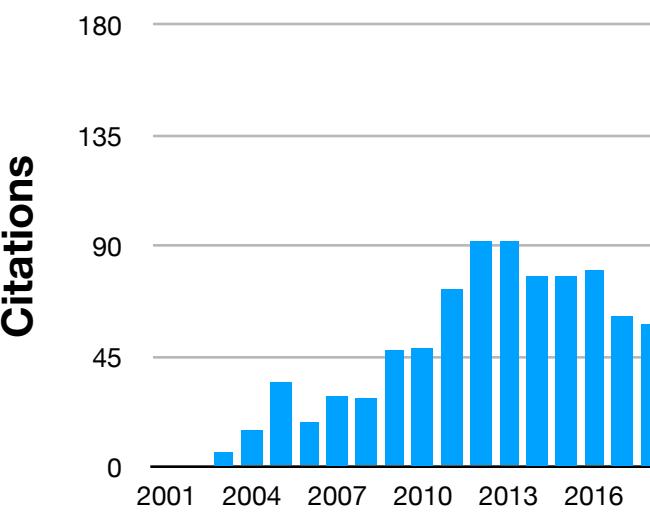
Please contribute!



Slide courtesy of Taylor Salo

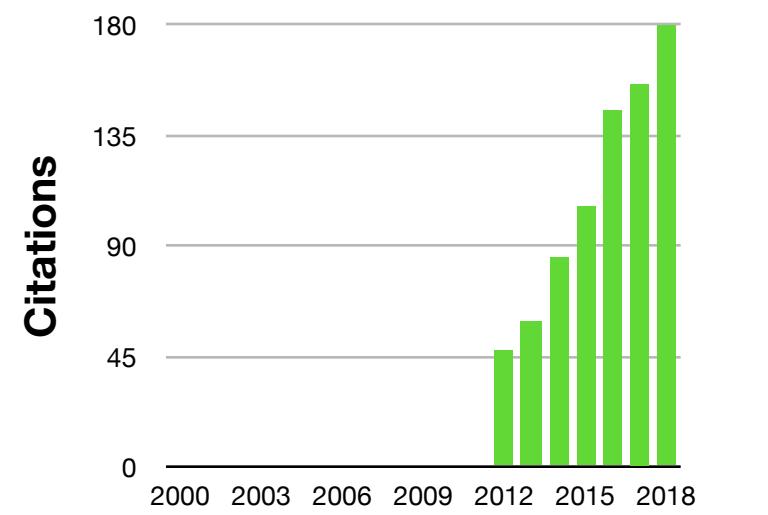
# Examples of coordinate-based neuroimaging meta-analysis

## Introduction of ALE Approach



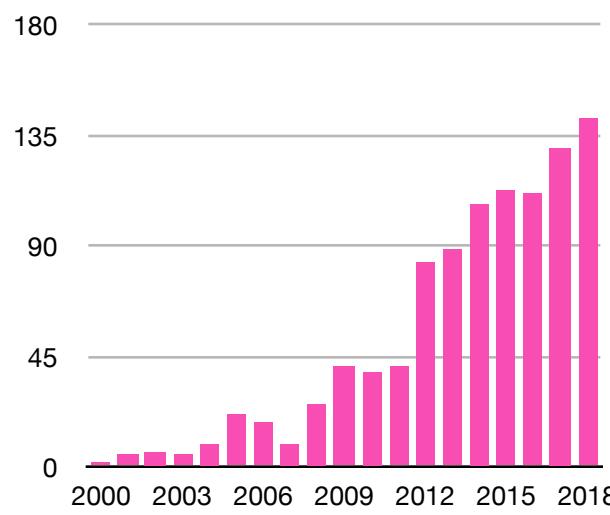
Turkeltaub et al., Neuroimage, 2002

## Introduction of Neurosynth

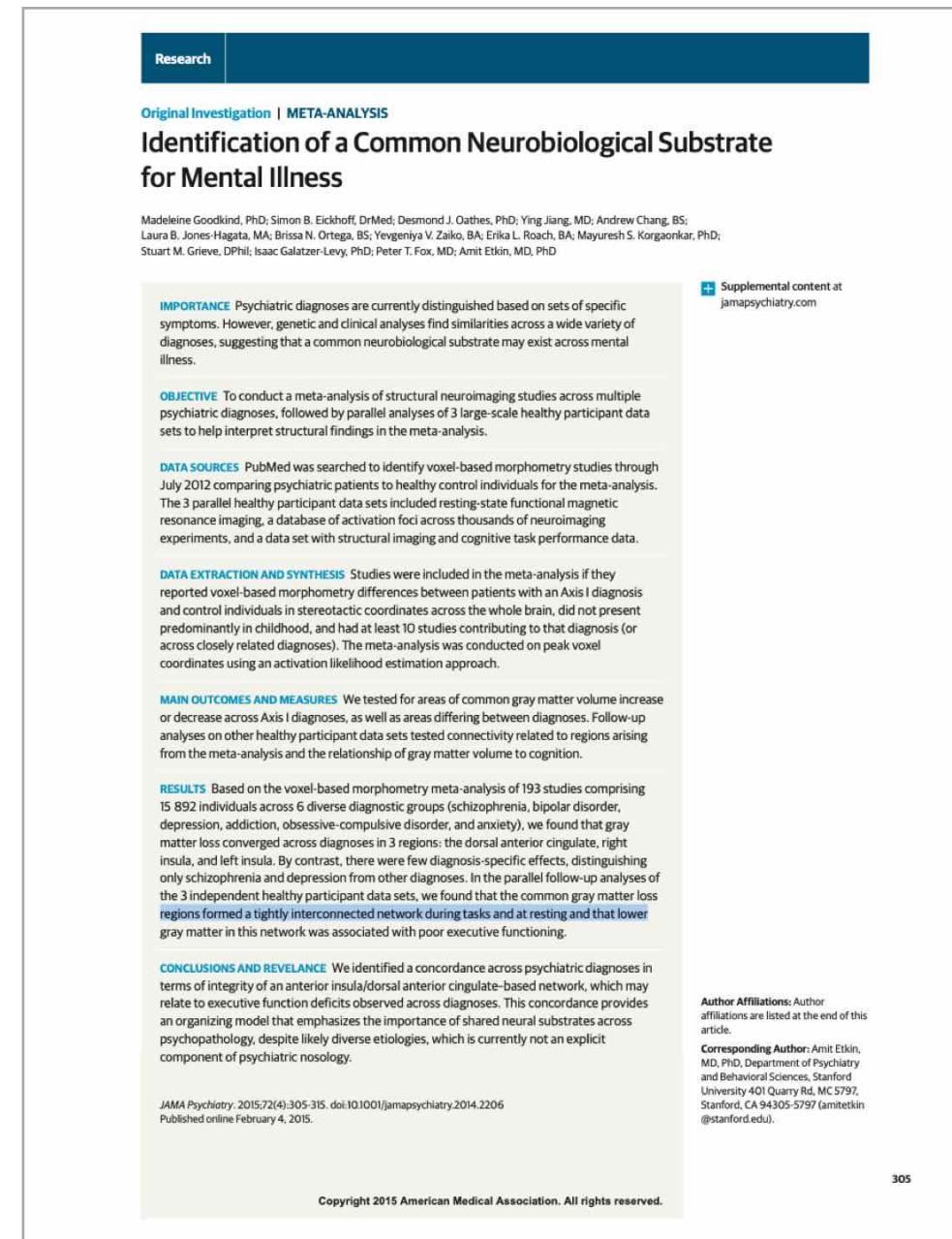


Yarkoni et al., Nat Methods, 2011

## fMRI + Meta-Analysis

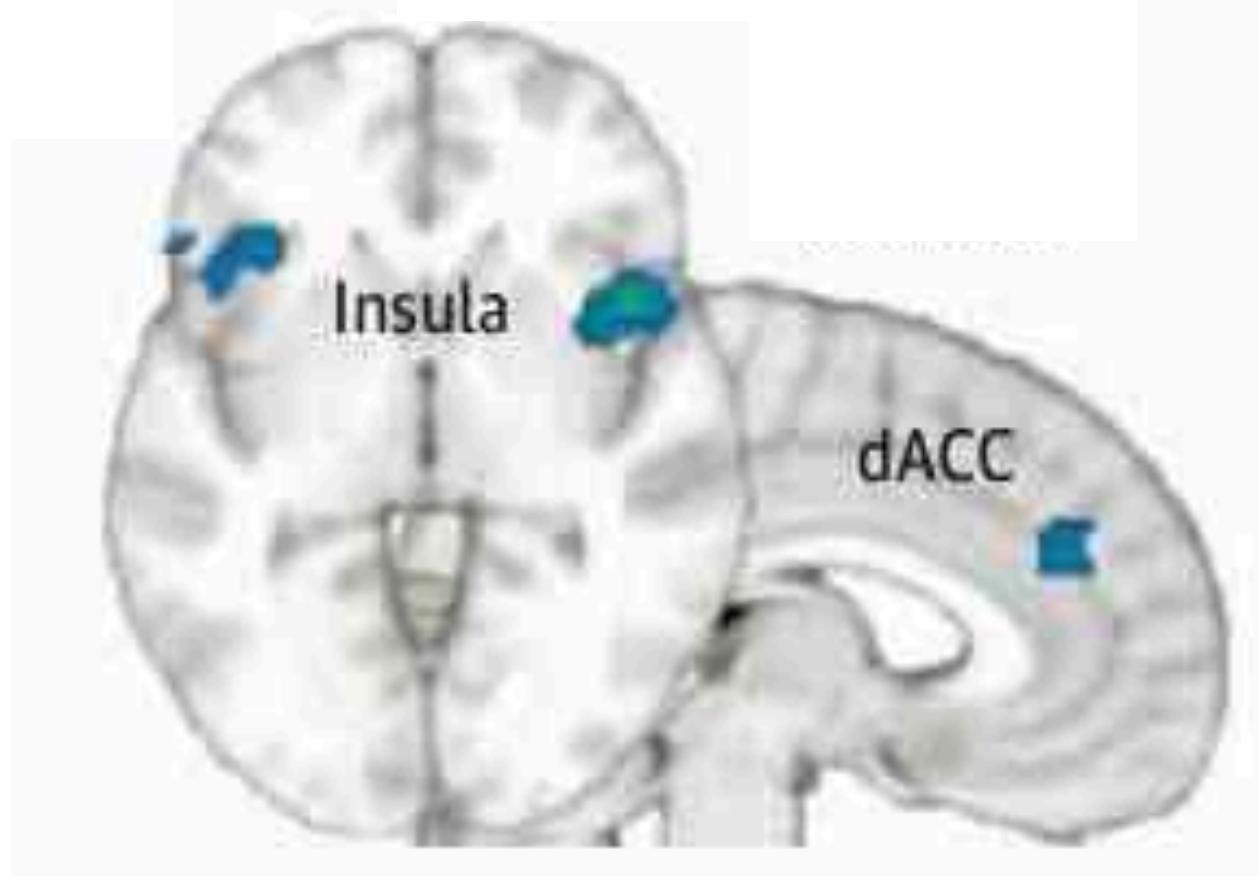


Yarkoni et al., Nat Methods, 2011

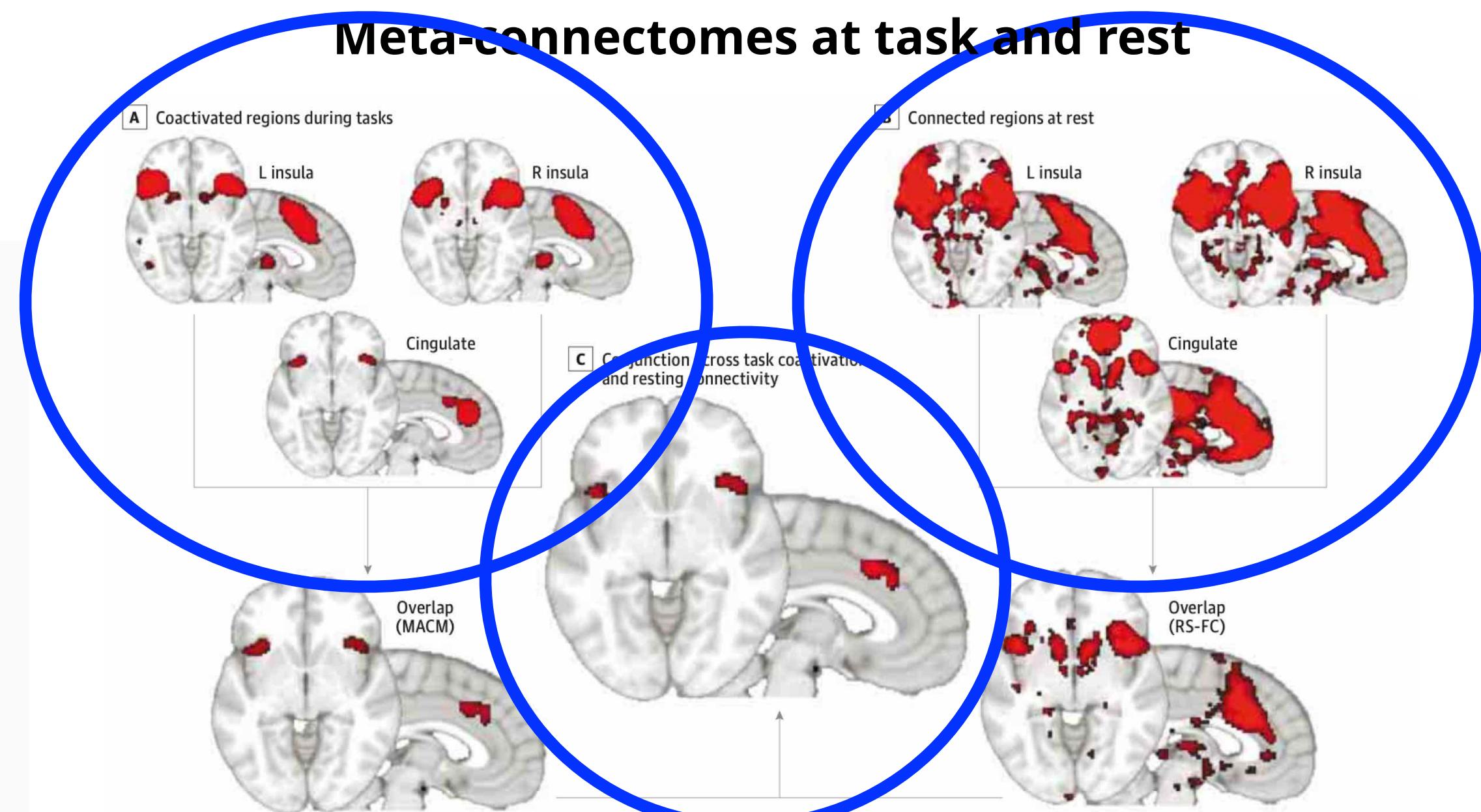


## VBM meta-analysis

schizophrenia, bipolar disorder, depression, addiction, obsessive-compulsive disorder, anxiety  
193 papers: 7,381 patients and 8,511 controls

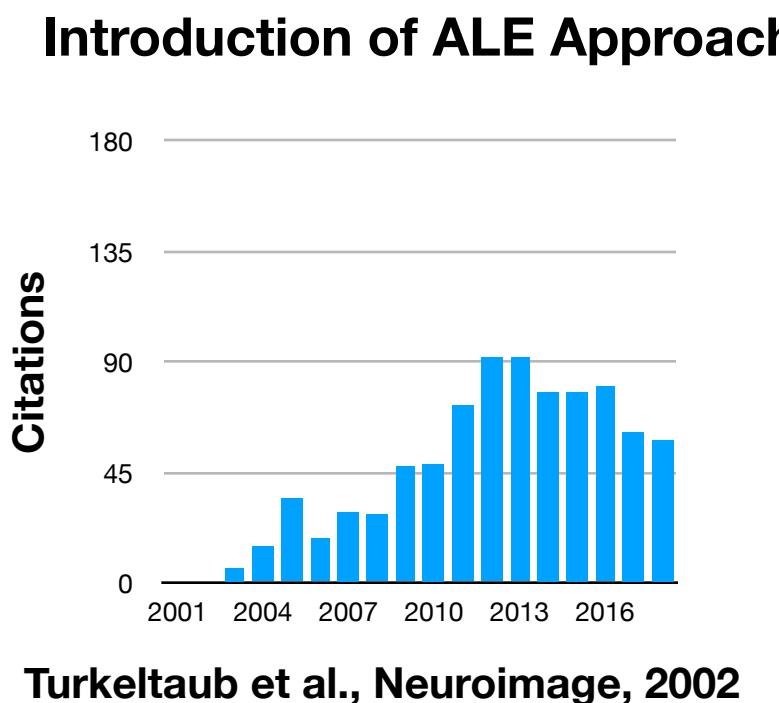


But what about functional associations?

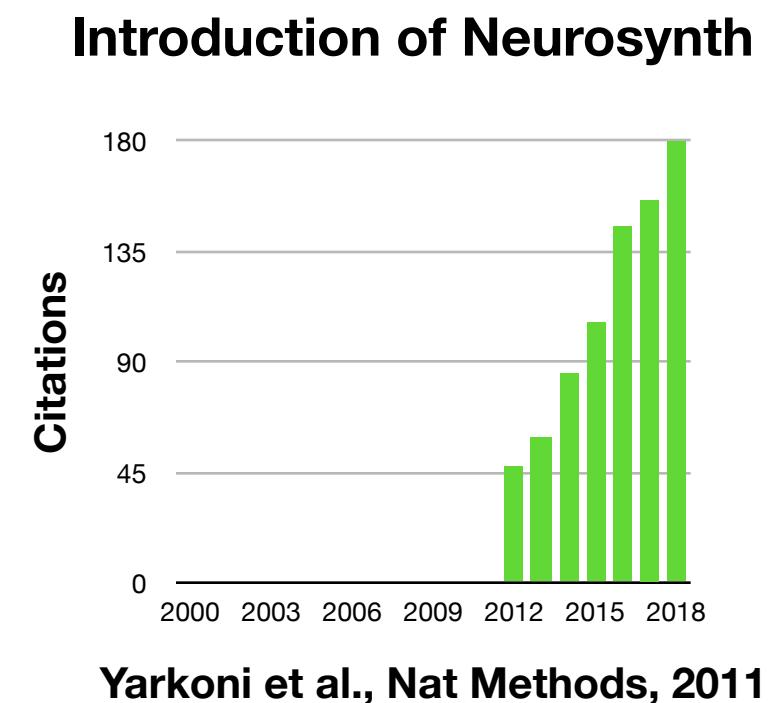


Conjunction of task-based coactivation and task-free resting state connectivity results

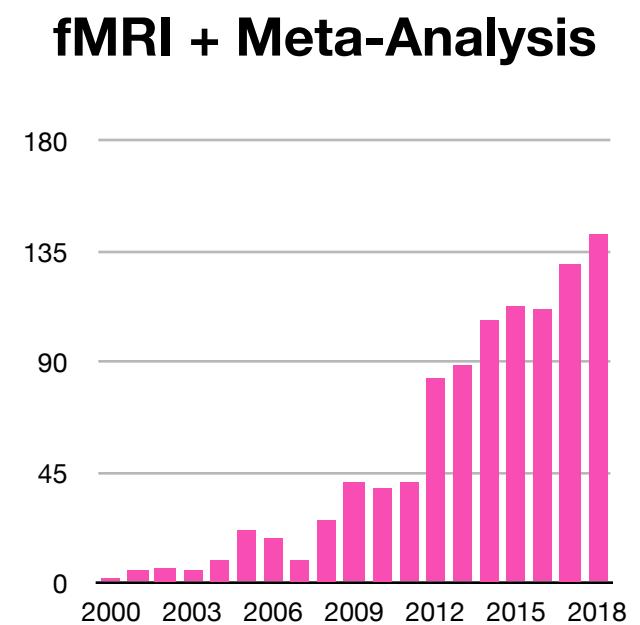
# Examples of coordinate-based neuroimaging meta-analysis



Turkeltaub et al., Neuroimage, 2002



**Yarkoni et al., Nat Methods, 2011**



**Goodkind et al., 2015**

Figure 5. Common Gray Matter Loss Regions From the Voxel-Based Morphometry Meta-analysis Are Part of an Interconnected Brain Network

A. Coactivated regions during tasks

B. Conjunction across all MACMs and RS-FC map

C. Conjunction across task coactivation and resting connectivity

D. Conjunction across all of the MACMs and RS-FC map

E. Group (BS+FC)

L insula, R insula, Cingulate, Overlap (MA & RS), Group (BS+FC)

Revealed insula and ACC as highly connected brain regions that are linked to shared structural alterations across transdiagnostic psychopathological disorders

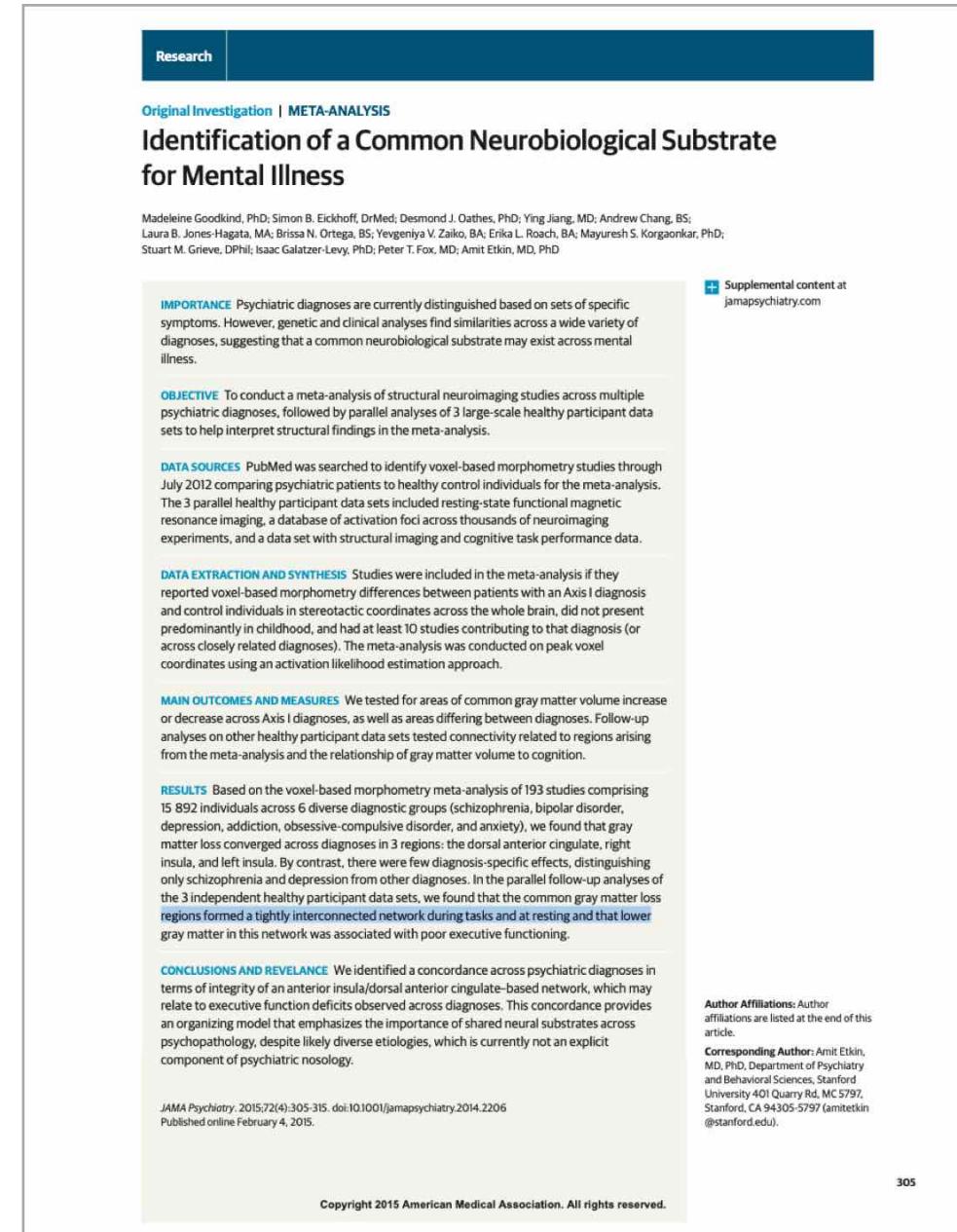
# Task-based meta-analysis

aberrant fMRI brain activations during cognitive and emotional processing in patients with **unipolar depression**  
99 experiments: 1,058 patients  
34 cognitive processing; 65 emotional processing

# **Meta-analysis was adequately powered.**

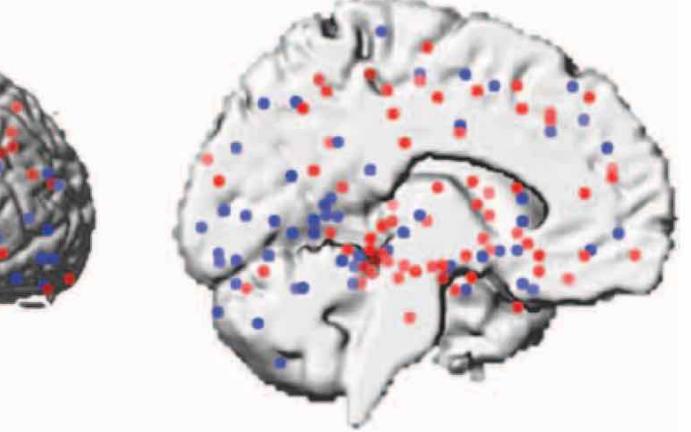
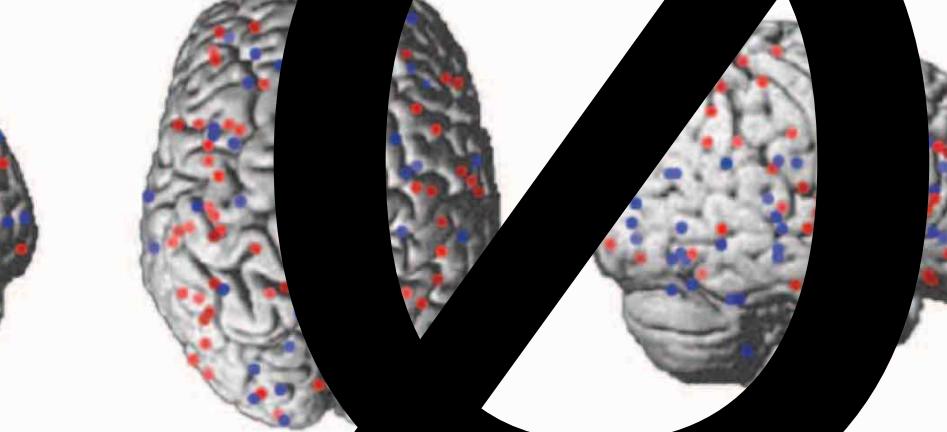
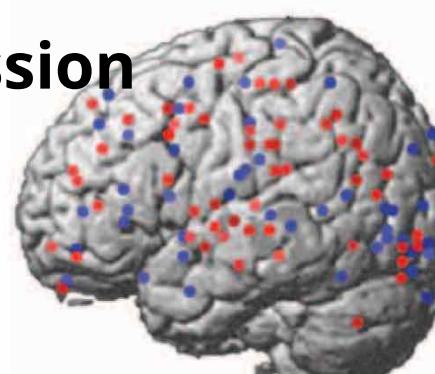
**Null results likely reflect high degrees of experimental flexibility (experimental design and analytic procedures).**

**This works points to an urgent need for replication analyses, particularly in clinical neuroimaging.**

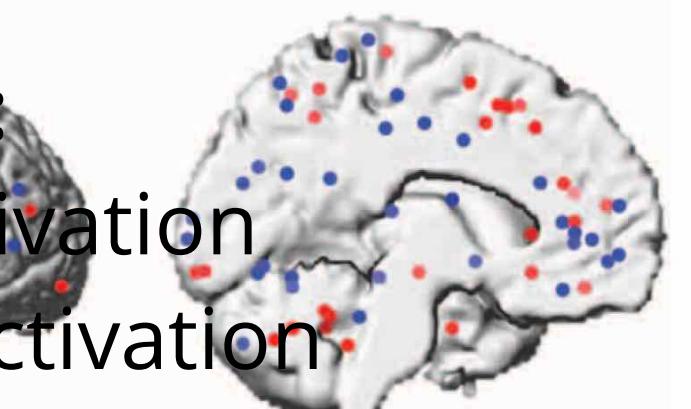
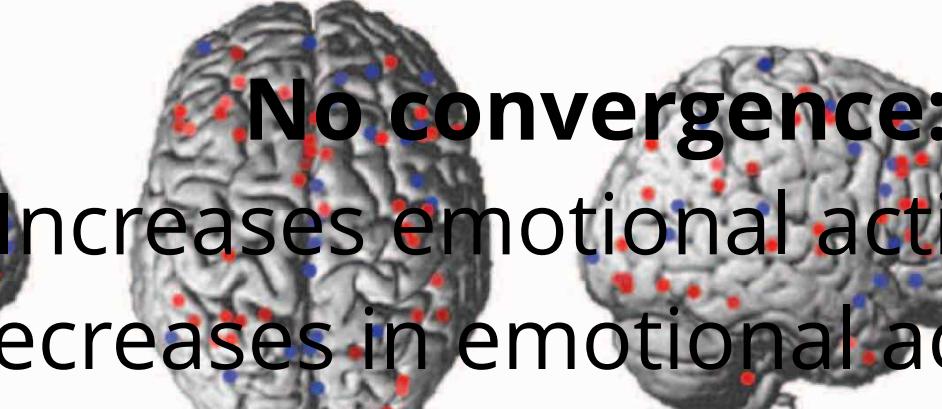
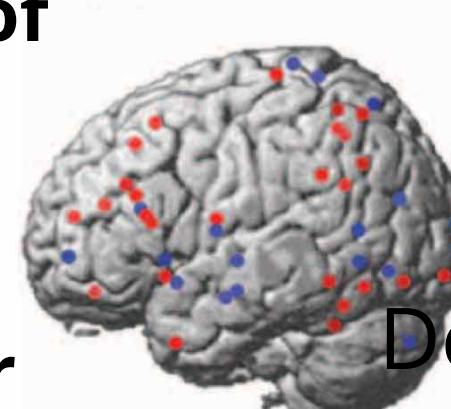


**Figure 4.** Render of the Distribution of Coordinates Included in the Analysis

## A Coordinates included in the emotional meta-analyses



## B Coordinates included in the cognitive meta-analyses



**No convergence:**

- Increases emotional activation
- Decreases in emotional activation
- Increases in cognitive activation
- Decreases in cognitive activation

Activation in unipolar depression (UD), whereas blue shows all foci reported as decreased activity in UD. Color related to the cortical surface.

# The three reproducibility opportunities

Open access, freely available online

**Essay**

# Why Most Published Research Findings Are False

John P. A. Ioannidis

**Summary**

There is increasing concern that most current published research findings are false. The probability that a research claim is true may depend on study power and bias, the number of other studies on the same question, and, importantly, the ratio of true to no relationships among the relationships probed in each scientific field. In this framework, a research finding is less likely to be true when the studies conducted in a field are smaller; when effect sizes are smaller; when there is a greater number and lesser preselection of tested relationships; where there is greater flexibility in designs, definitions, outcomes, and analytical modes; when there is greater financial and other interest and prejudice; and when more teams are involved in a scientific field in chase of statistical significance. Simulation show that for most study designs and settings, it is more likely for a research claim to be false than true. Moreover, for many current scientific fields, claimed research findings may often be simply accurate measures of the prevailing bias. In this essay, I discuss the implications of these problems for the conduct and interpretation of research.

Published research findings are sometimes refuted by subsequent evidence, with ensuing confusion and disappointment. Refutation and controversy is seen across the range of research designs, from clinical trials and traditional epidemiological studies [1–3] to the most modern molecular research [4,5]. There is increasing concern that in modern research, false findings may be the majority or even the vast majority of published research claims [6–8]. However, this should not be surprising. It can be proven that most claimed research findings are false. Here I will examine the key

factors that influence this problem and some corollaries thereof.

## Modeling the Framework for False Positive Findings

Several methodologists have pointed out [9–11] that the high rate of nonreplication (lack of confirmation) of research discoveries is a consequence of the convenient, yet ill-founded strategy of claiming conclusive research findings solely on the basis of a single study assessed by formal statistical significance, typically for a  $p$ -value less than 0.05. Research is not most appropriately represented and summarized by  $p$ -values, but, unfortunately, there is a widespread notion that medical research article

## It can be proven that most claimed research findings are false.

should be interpreted based only on  $p$ -values. Research findings are defined here as any relationship reaching formal statistical significance, e.g., effective interventions, informative predictors, risk factors, or associations. “Negative” research is also very useful. “Negative” is actually a misnomer, and the misinterpretation is widespread. However, here we will target relationships that investigators claim exist, rather than null findings.

As has been shown previously, the probability that a research finding is indeed true depends on the prior probability of it being true (before doing the study), the statistical power of the study, and the level of statistical significance [10,11]. Consider a  $2 \times 2$  table in which research findings are compared against the gold standard of true relationships in a scientific field. In a research field both true and false hypotheses can be made about the presence of relationships. Let  $R$  be the ratio of the number of “true relationships” to “no relationships” among those tested in the field.  $R$

is characteristic of the field and can vary a lot depending on whether the field targets highly likely relationships or searches for only one or a few true relationships among thousands and millions of hypotheses that may be postulated. Let us also consider, for computational simplicity, circumscribed fields where either there is only one true relationship (among many that can be hypothesized) or the power is similar to find any of the several existing true relationships. The pre-study probability of a relationship being true is  $R/(R+1)$ . The probability of a study finding a true relationship reflects the power  $1 - \beta$  ( $\alpha$  minus the Type II error rate). The probability of claiming a relationship when none truly exists reflects the Type I error rate,  $\alpha$ . Assuming that  $\alpha$  relationships are being probed in the field, the expected values of the  $2 \times 2$  table are given in Table 1. After a research finding has been claimed based on achieving formal statistical significance, the post-study probability that it is true is the positive predictive value, PPV. The PPV is also the complementary probability of what Wacholder et al. have called the false positive report probability [10]. According to the  $2 \times 2$  table, one gets  $PPV = (1 - \beta)/R/(R + \betaR + \alpha)$ . A research finding is thus

**Citation:** Ioannidis JPA (2005) Why most published research findings are false. *PLoS Med* 2(8):e128.

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### Abbreviations:

PPV, positive predictive value  
 John P. A. Ioannidis, Department of Biostatistics and Epidemiology, University of California School of Medicine, Ira M. Lerner Institute, and Institute for Clinical Research and Health Policy Study, Department of Medicine, Tufts New England Medical Center, Tufts University School of Medicine, Boston, Massachusetts, United States of America. Email: joannidis@tufts.edu

**Competing interests:** The author has declared that no competing interests exist.

**DOI:** [10.1371/journal.pmed.0020124](https://doi.org/10.1371/journal.pmed.0020124)

The Essay section contains opinion pieces on topics of broad interest to a general medical audience.

PLOS Medicine | www.plosmedicine.org

0696

August 2005 | Volume 2 | Issue 8 | e124

# ANALYSIS

## Power failure: why small sample size undermines the reliability of neuroscience

Katherine S. Button<sup>1,2</sup>, John P. A. Ioannidis<sup>3</sup>, Claire Mokrysz<sup>4</sup>, Brian A. Nosek<sup>4</sup>, Jonathan Flint<sup>5</sup>, Emma S. J. Robinson<sup>6</sup> and Marcus R. Munafò<sup>1</sup>

**Abstract** | A study with low statistical power has a reduced chance of detecting a true effect, but it is less well appreciated that low power also reduces the likelihood that a statistically significant result reflects a true effect. Here, we show that the average statistical power of studies in the neurosciences is very low. The consequences of this include overestimates of effect size and low reproducibility of results. There are also ethical dimensions to this problem, as unreliable research is inefficient and wasteful. Improving reproducibility in neuroscience is a key priority and requires attention to well-established but often ignored methodological principles.

It has been claimed and demonstrated that many (and probably most) of the conclusions drawn from biomedical research are probably false.<sup>1</sup> A central cause for this important problem is that researchers must publish in order to succeed, and publishing is a highly competitive enterprise, with certain kinds of findings more likely to be published than others. Research that produces novel results, statistically significant results (that is, typically  $p < 0.05$ ) and seemingly 'clean' results is more likely to be published<sup>2–4</sup>. As a consequence, researchers have strong incentives to engage in research practices that make their findings publishable quickly, even if those practices reduce the likelihood that the findings reflect a true (that is, non-null) effect.<sup>5</sup> Such practices include using flexible study designs and flexible statistical analyses and running small studies with low statistical power.<sup>5,6</sup> A simulation of genetic association studies showed that a typical dataset would generate at least one false-positive result almost 97% of the time<sup>7</sup>, and two efforts to replicate promising findings in biomedicine reveal replication rates of 25% or less<sup>8,9</sup>. Given that these publishing biases are pervasive across scientific practice, it is possible that false positives heavily contaminate the neuroscience literature as well, and this problem may affect at least as much, if not even more so, the most prominent journals<sup>10</sup>.

Here, we focus on one major aspect of the problem: low statistical power. The relationship between study power and the veracity of the resulting finding is under-appreciated. Low statistical power (because of

low sample size of studies, small effects or both) negatively affects the likelihood that a nominally statistically significant finding actually reflects a true effect. We discuss the problems that arise when low-powered research designs are pervasive. In general, these problems can be divided into two categories. The first concerns problems that are mathematically expected to arise even if the research conducted is otherwise perfect; in other words, when there are no biases that tend to create statistically significant (that is, 'positive') results that are spurious. The second category concerns problems that reflect biases that tend to co-occur with studies of low power or that become worse in small, underpowered studies. We next empirically show that statistical power is typically low in the field of neuroscience by using evidence from a range of subfields within the neuroscience literature. We illustrate that low statistical power is an endemic problem in neuroscience and discuss the implications of this for interpreting the results of individual studies.

### Low power in the absence of other biases

Three main problems contribute to producing unreliable findings in studies with low power, even when all other research practices are ideal. They are the low probability of finding true effects; the low positive predictive value (PPV; see Box 1) for definitions of key statistical terms) when an effect is claimed; and an exaggerated estimate of the magnitude of the effect when a true effect is discovered. Here, we discuss these problems in more detail.

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VOLUME 14 | MAY 2013 | 365

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Magazine

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Christopher Lane Ph.D.  
Side Effects

# Neuroscience Research Faulted for Widespread Inaccuracies

Selective reporting and inflated effect sizes mar even high-impact studies

Posted September 9, 2016

Source: Shutterstock

We've all seen the headlines: "This Is Your Brain on Politics"; "This Is Your Brain after a Breakup"; "Neural Correlate" for Religion, Greed, or Narcissism "Found."

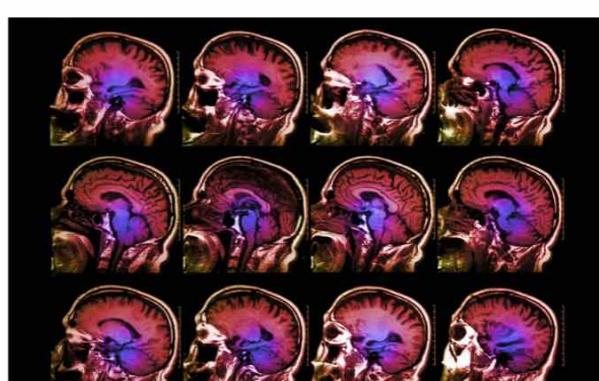
Much of the authority tied to such enticing but dubious claims rests

with fMRI scans of the brain (short for "functional magnetic resonance imaging"), which depict areas of the organ as receiving more oxygen due to heightened activity—images that are then interpreted by software and again by researchers, often from painfully small sample sizes, as giving us credible insights into behavior X or emotion Y. The misleading newspaper headline "**Hate Circuit Found in Brain**" stemmed for instance from a 2008 study, "**Neural Correlates of Hate**," which involved brain scans of a small sample of people shown photos of their exes, colleagues, and controversial politicians. According to *PubMed*, more than 40,000 scholarly articles published in the last twenty years draw assumptions and inferences about the brain from such scans. But how reliable are their conclusions? And how good is the software that reads and interprets them?

EMILY REYNOLDS SCIENCE 06.07.2016 10:58 AM

# Bug in fMRI software calls 15 years of research into question

Popular pieces of software for fMRI were found to have false positive rates up to 70%



ISTOCK

A bug in the software used by researchers to interpret fMRI data could invalidate fifteen years worth of [neuroscientific](#) research, a [paper](#) claims.

Three of the most popular pieces of software for fMRI – SPM, FSL and AFNI – were all found to have false positive rates of up to 70 per cent. These findings could invalidate "up to 40,000 papers", researchers claim.



DISCOVER HOW THE ROLEX AWARDS LAUREATES HELP CREATE A PERPETUAL PLANET

ROLEX

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## Most Popular



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BY MATT REYNOLDS



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All the Things That Drain Your EV Battery

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An NFT Bubble Is Taking Over the Gig Economy

BY CHRIS STOKEL-WALKER

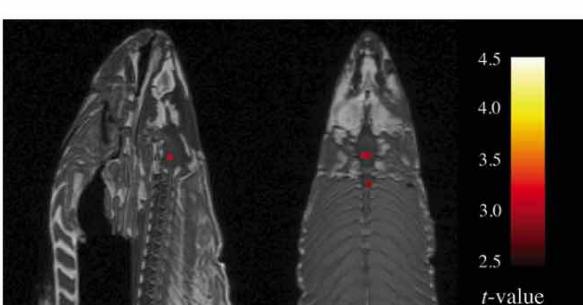
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# Scanning Dead Salmon in fMRI Machine Highlights Risk of Red Herrings

Scientist Craig Bennett purchased a whole Atlantic salmon, took it to a lab at Dartmouth, and put it into an fMRI machine used to study the brain. The fish was to be the lab's test object as they worked out some new methods. So, as the fish sat in the scanner, they showed it [...]



Neuroscientist Craig Bennett purchased a whole Atlantic salmon, took it to a lab at Dartmouth, and put it into an fMRI machine used to study the brain. The beautiful fish was to be the lab's test object as they worked out some new methods.

So, as the fish sat in the scanner, they showed it "a series of photographs depicting human individuals in social situations." To maintain the rigor of the protocol (and perhaps because it was hilarious), the salmon, just like a human test subject, "was asked to determine what emotion the individual in the photo must have been experiencing."

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For me, Twirla is a weekly birth control patch that fits my life.

Important Safety Information about the TWIRLA® (levonorgestrel and ethynodiol dihydrogesterone) transdermal system

- Do not use TWIRLA if you smoke cigarettes and are over 35 years old. This increases your risk of serious cardiovascular side effects from combined hormonal

Full Prescribing Information, including BOXED WARNING

 Matt Wall       
@m\_wall ...  
**Me when I see that bloody dead salmon brought up AGAIN.**

# Resources for Reliable, Reproducible, and Replicable Data Analyses

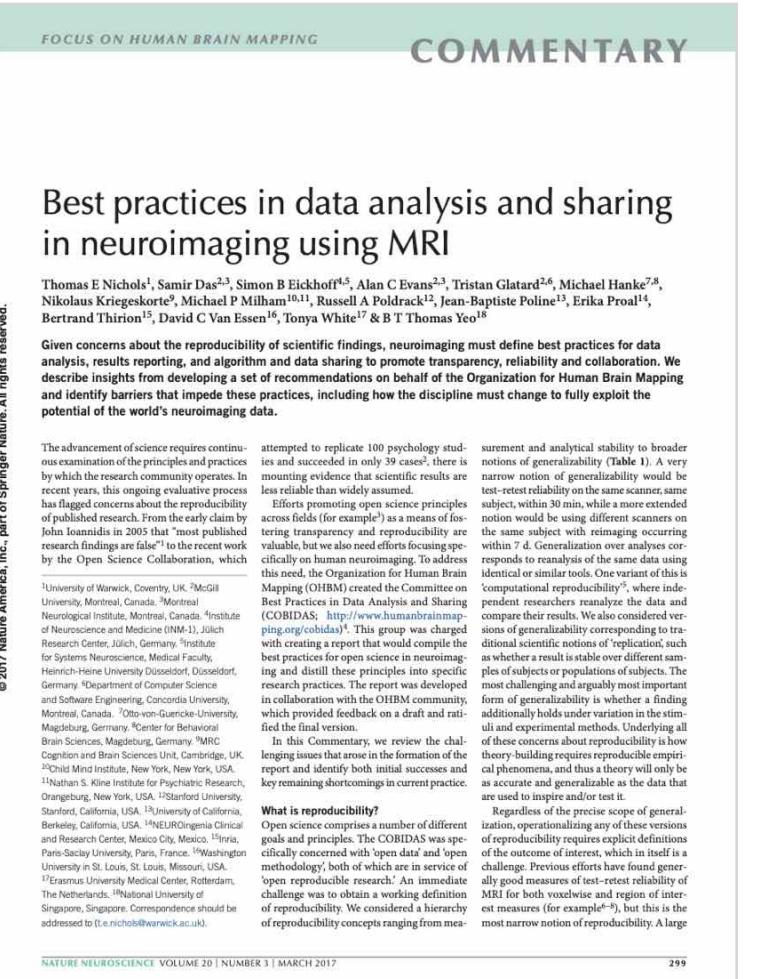
# **. Guidelines and Recommendations**



Nichols et al., Nat  
Neurosci. 2017



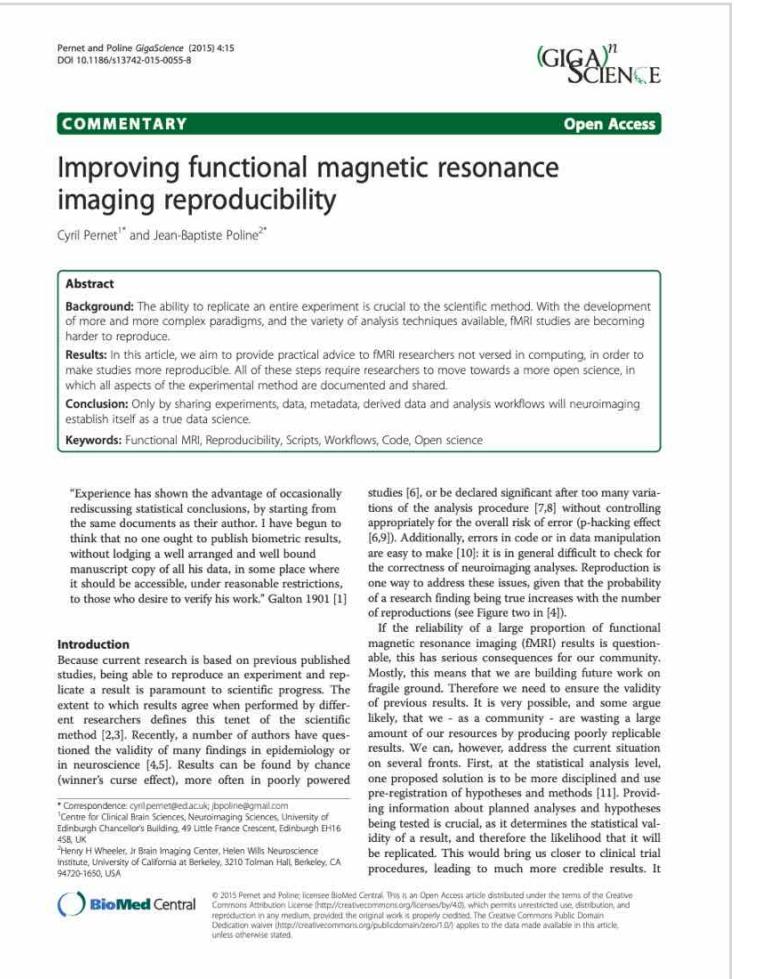
Horien et al., Nat Hum  
Behav, 2021



# Gorgolewski and Poldrack, PLoS Biol. 2016



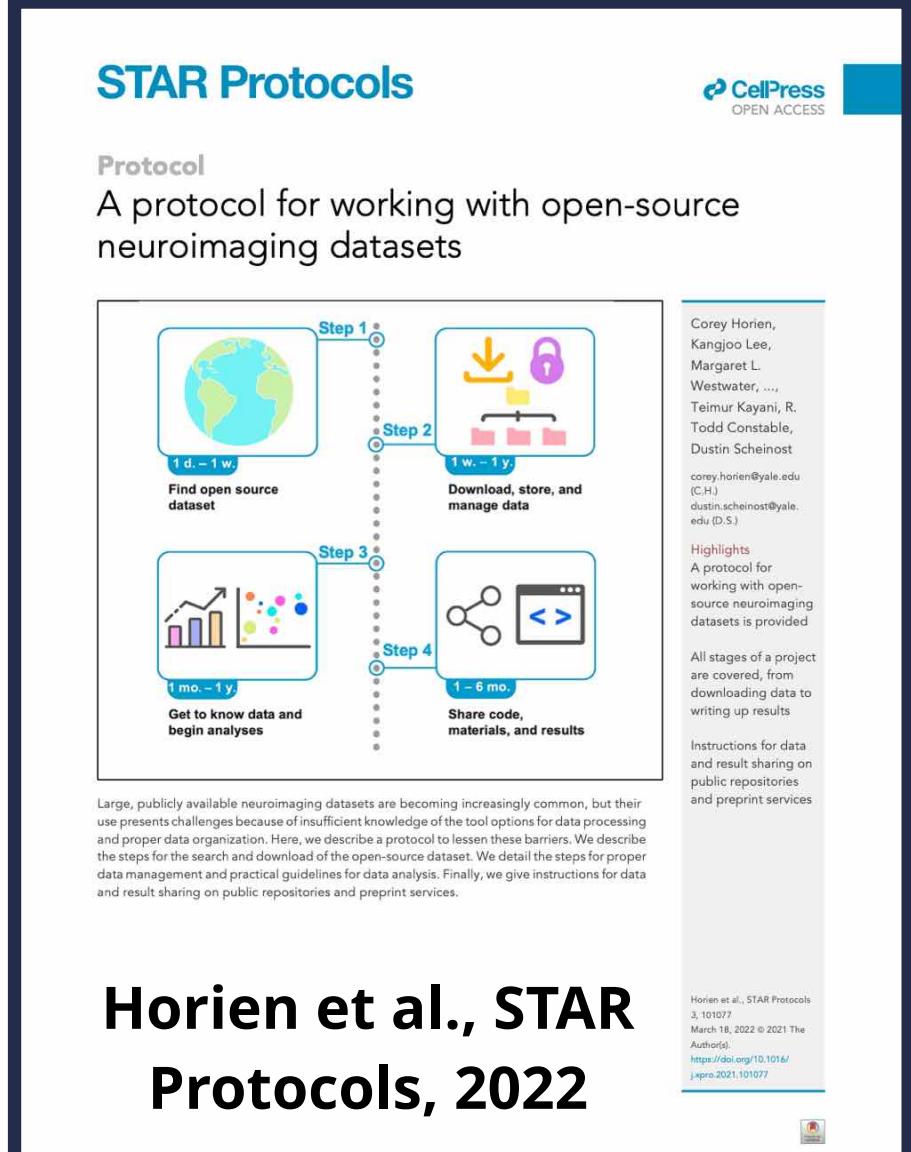
# Saragosa-Harris et al., PsyArXiv, 2021



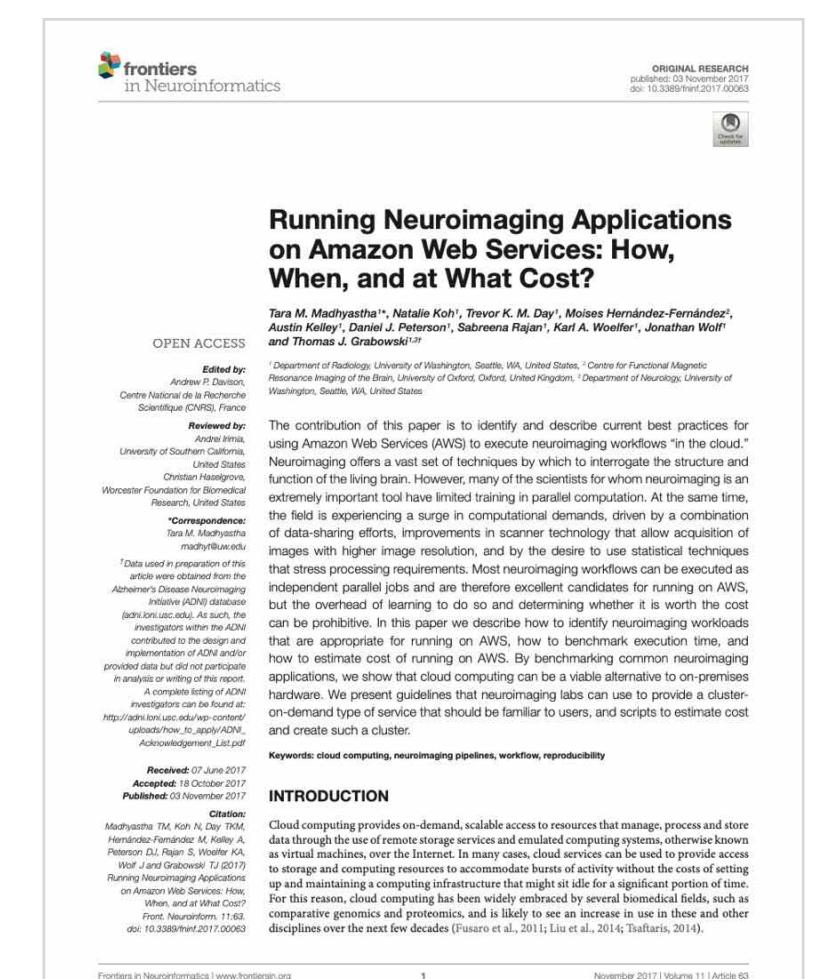
# Pernet and Poline, GigaScience, 2015



Kiar et al.,  
GigaScience 2017



Horien et al., STAR  
Protocols, 2022



Madhyastha et al., Front Neuroinform. 2017

# Resources for Reliable, Reproducible, and Replicable Data Analyses



## 2. Standards, Software, and Data Management

### Standards

#### Image Formats

NIfTI (vol), GIFTI (surf),  
CIFTI (conn)

#### Data Organization

Brain Imaging Data  
Structure (BIDS)

#### Data Specification

Neuroimaging Data  
Model (NIDM)

### Software

#### BIDS Apps

MRIQC, fMRIPrep

### Data Management

#### Joint Management of Analysis Code and Data

DataLad

### Other Tools

#### Text & Code

Rmarkdown, Jupyter  
Notebooks

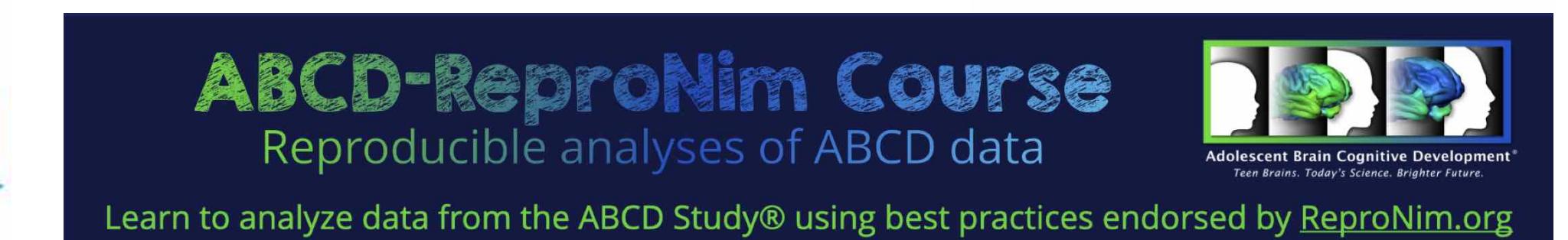
#### Data Visualization

Dash

#### Project Management

Open Science  
Framework, GitHub

## 3. Training and Education







## Inclusivity Among Participants

Western  
Educated  
Industrialized  
Rich  
Democratic

# WEIRD

## “CONVENIENCE SAMPLES”

American or European  
University Students  
Affluent  
White  
Cisgender  
Right-Handed  
“Healthy”



# Inclusivity Among Participants



**Inclusion of racially, ethnically, geographically, and socioeconomically diverse samples will likely result in a more comprehensive understanding of brain-behavior mechanisms, particularly through the lens of cross-cultural, global mental health.**

# Responsible Data Use of Large-Scale Neuroimaging Data

## Responsible Conduct of Research

Data Management  
Data Sharing and Ownership  
Scientific Rigor and Reproducibility  
Responsible Authorship and Publication

## Large, Open Datasets

Participant Identity →  
Learning About the Data  
Designing the Research Question

Consent Forms  
Data Use Agreements

**Pause. Think. Then Analyze.**

# Preventing Stigmatizing Research

Prior to any data analysis or interpretation, researchers must engage responsibly and fully consider the psychological, social, economic, and any other potentially harmful impacts their research could have on individuals, communities, and society.

→ Responsible use of variables related to **race, ethnicity, gender, and sex**

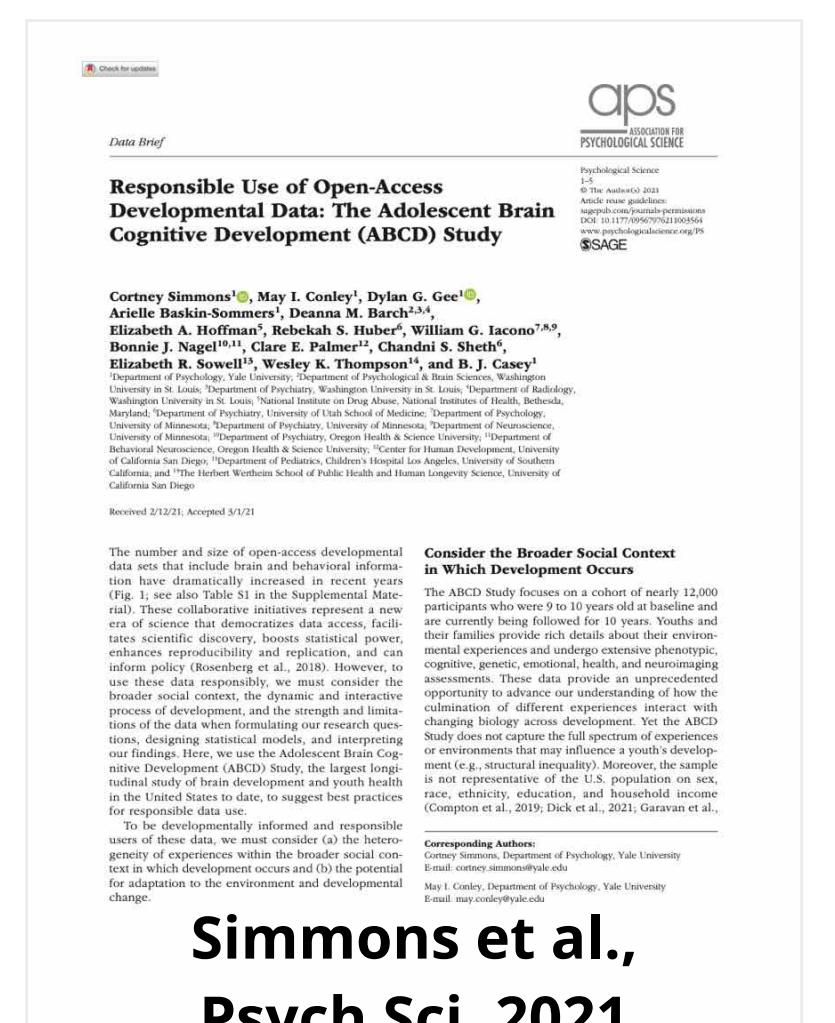
Ethical conduct in research includes ensuring that analyses prevent further stigmatization, marginalization, and injustice toward individuals because of racial, ethnic, or gender status.

## Factors that may contribute to stigma in research:

- A lack of cultural sensitivity, awareness, or competence in study design
- Insufficient understanding of the limitations of techniques, instruments, or methods
- Improper scope
- Inadequate context
- Overstating the significance of findings

## Prevent Stigmatization

- Consider study inclusion criteria carefully and be as expansive as possible
- Respect the people whose lives form the basis of your research data
- Understand and appropriately implement your analytical tools
- Use precise language to describe your findings
- Consider how your research might be misinterpreted to the detriment of others
- Consider the full range of factors that may be related and contextualize your results



# Social Determinants of Health



Health Topics Countries Newsroom Emergencies Data About WHO

Home / Health topics / Social determinants of health

Credits +

## Social determinants of health

Overview In practice Health equity

**Non-medical factors that influence health outcomes...**

The social determinants of health (SDH) are the non-medical factors that influence health outcomes. They are the conditions in which people are born, grown, work, live and age. The SDH have an important influence on health status seen within and between populations. The social gradient: the lower the socioeconomic position, the worse the health.

**... conditions in which people are born, grown, work, live and age**

**... an important influence on health inequities**

The following list provides examples of the social determinants of health that contribute to health inequities in positive and negative ways:

- Income and social protection
- Education
- Unemployment and job insecurity
- Working life conditions
- Food insecurity
- Housing, basic amenities and the environment
- Early childhood development
- Social inclusion and non-discrimination
- Structural conflict
- Access to affordable health services of decent quality.

Statistical models that appropriately contextualize findings through consideration of the social determinants of health are not possible unless studies are **designed to acquire relevant measures of interest**.

- Education, employment, income

housing & food insecurity, access to healthcare

- Neighborhood safety and crime

- Family and school environment

- Racial & ethnic identity

- Acculturation and cultural stress

More comprehensive measures of that assess the **social determinants of health** are likely to help us understand how **adverse and protective factors** impact individuals because of biological, cultural, and environmental factors at **individual, community, and societal levels**.

An assessment of flexibility in the measurement of socioeconomic status

Contributors Hu Chuan-Peng, Yaqing Cai, Eiko I. Fried, and Patrick S. Froscher

Description See the attached document for details of our protocol and PRISMA-P style registration note that here.

Registration type Open-Ended Registration

Date registered November 3, 2020

Date created November 3, 2020

Associated project osf.io/b64nx

Internet Archive link https://archive.org/details/osf-10.17025.OSF.IO/HWTQ

Category Methods and measures

Registration DOI 10.17025/OSF.IO/HWTQ

Subjects Psychology Social and Behavioral Sciences Neuroscience and Neurobiology Child Psychology Life Sciences Developmental Psychology Cognitive Neuroscience

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Tags Measurement Meta-research SES Socioeconomic Status

Chuan-Peng et al., OSF, 2020

**COLLABORATION ALERT!**

# Thank You!



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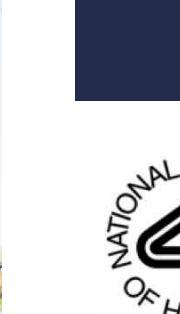
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U01 DA041156  
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R25 DA051675

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