

Improving reliability, replicability and interpretability of neuroimaging research – bridging resting state functional neuroimaging and underlying biology

Juergen Dukart

June 25th, 2019

Outline

- ❖ **Why do we need to think more about our methods**
- ❖ **What are the limitations of our tools**
 - What are the analytical and technical limitations
 - Different biological levels need different considerations
- ❖ **How can we do better**
 - New analyses methods
 - Replication is key

WHY DO WE NEED TO THINK MORE ABOUT OUR METHODS?

Why do we need to think more about our methods?

No Support for Historical Candidate Gene or Candidate Gene-by-Interaction Hypotheses for Major Depression Across Multiple Large Samples

Richard Border, M.A., Emma C. Johnson, Ph.D., Luke M. Evans, Ph.D., Andrew Smolen, Ph.D., Noah Berley, Patrick F. Sullivan, M.D., Matthew C. Keller, Ph.D.

Objective: Interest in candidate gene and candidate gene-by-environment interaction hypotheses regarding major depressive disorder remains strong despite controversy surrounding the validity of previous findings. In response to this controversy, the present investigation empirically identified 18 candidate genes for depression that have been studied 10 or more times and examined evidence for their relevance to depression phenotypes.

Methods: Utilizing data from large population-based and case-control samples (Ns ranging from 62,138 to 443,264 across subsamples), the authors conducted a series of pre-registered analyses examining candidate gene polymorphism main effects, polymorphism-by-environment interactions, and gene-level effects across a number of operational definitions of depression (e.g., lifetime diagnosis, current severity, episode recurrence) and environmental moderators (e.g., sexual or physical abuse during childhood, socioeconomic adversity).

Results: No clear evidence was found for any candidate gene polymorphism associations with depression phenotypes or any polymorphism-by-environment moderator effects. As a set, depression candidate genes were no more associated with depression phenotypes than noncandidate genes. The authors demonstrate that phenotypic measurement error is unlikely to account for these null findings.

Conclusions: The study results do not support previous depression candidate gene findings. In which large genetic effects are frequently reported in samples orders of magnitude smaller than those examined here. Instead, the results suggest that early hypotheses about depression candidate genes were incorrect and that the large number of associations reported in the depression candidate gene literature are likely to be false positives.

AJP in Advance (doi: 10.1176/appi.ajp.2018.18070881)

ARTICLES

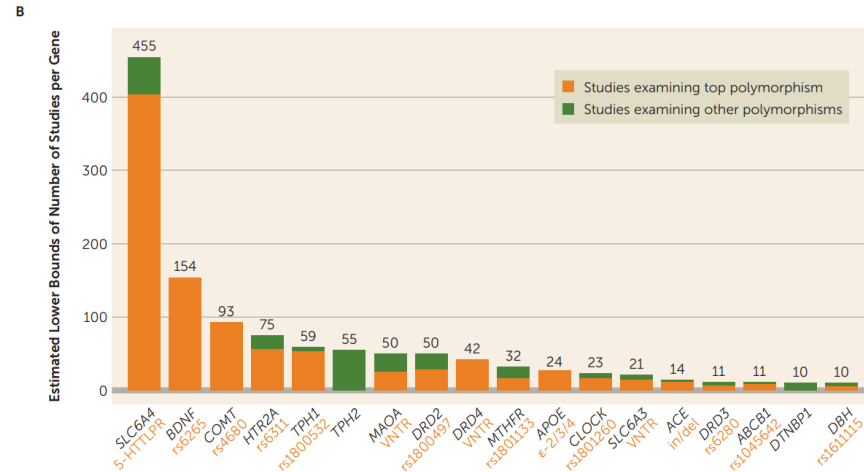
nature
neuroscience

5-HTTLPR polymorphism impacts human cingulate-amygdala interactions: a genetic susceptibility mechanism for depression

Lukas Pezawas^{1,3}, Andreas Meyer-Lindenberg^{1,3}, Emily M. Drabant¹, Beth A. Verchinski¹, Karen E. Munoz¹, Bhaskar S. Kolachana¹, Michael F. Egan¹, Venkata S. Mattay¹, Ahmad R. Hariri² & Daniel R. Weinberger¹

Carriers of the short allele of a functional 5' promoter polymorphism of the serotonin transporter gene have increased anxiety-related temperamental traits, increased amygdala reactivity and elevated risk of depression. Here, we used multimodal neuroimaging in a large sample of healthy human subjects to elucidate neural mechanisms underlying this complex genetic association. Morphometrical analyses showed reduced gray matter volume in short-allele carriers in limbic regions critical for processing of negative emotion, particularly perigenual cingulate and amygdala. Functional analysis of those regions during perceptual processing of fearful stimuli demonstrated tight coupling as a feedback circuit implicated in the extinction of negative affect. Short-allele carriers showed relative uncoupling of this circuit. Furthermore, the magnitude of coupling inversely predicted almost 30% of variation in temperamental anxiety. These genotype-related alterations in anatomy and function of an amygdala-cingulate feedback circuit critical for emotion regulation implicate a developmental, systems-level mechanism underlying normal emotional reactivity and genetic susceptibility for depression.

ublishing Group <http://www.nature.com/natureneuroscience>

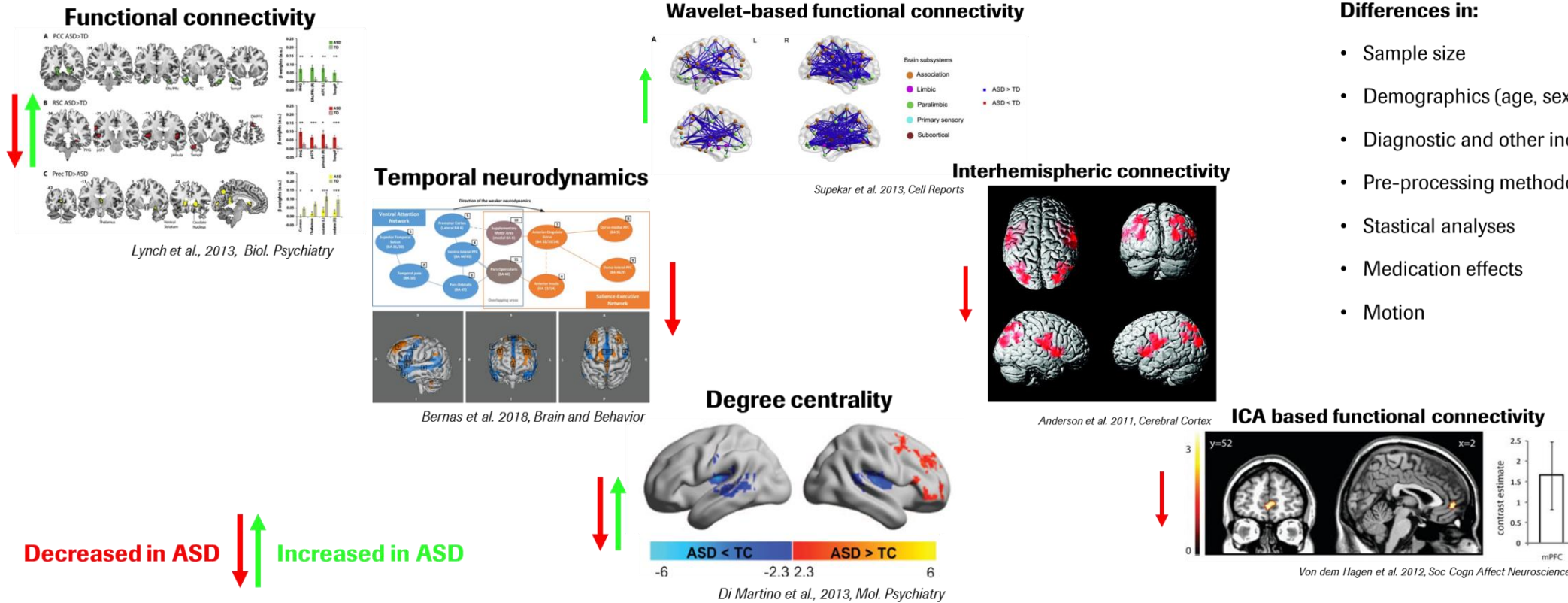


“what bothers me isn’t just that people said 5-HTTLPR mattered and it didn’t. It’s that we built whole imaginary edifices, whole castles in the air on top of this idea of 5-HTTLPR mattering. We “figured out” how 5-HTTLPR exerted its effects, what parts of the brain it was active in, what sorts of things it interacted with, how its effects were enhanced or suppressed by the effects of other imaginary depression genes. This isn’t just an explorer coming back from the Orient and claiming there are unicorns there. It’s the explorer describing the life cycle of unicorns, what unicorns eat, all the different subspecies of unicorn, which cuts of unicorn meat are tastiest, and a blow-by-blow account of a wrestling match between unicorns and Bigfoot.” by Scott Alexander

<https://slatestarcodex.com/2019/05/07/5-httlpr-a-pointed-review/>

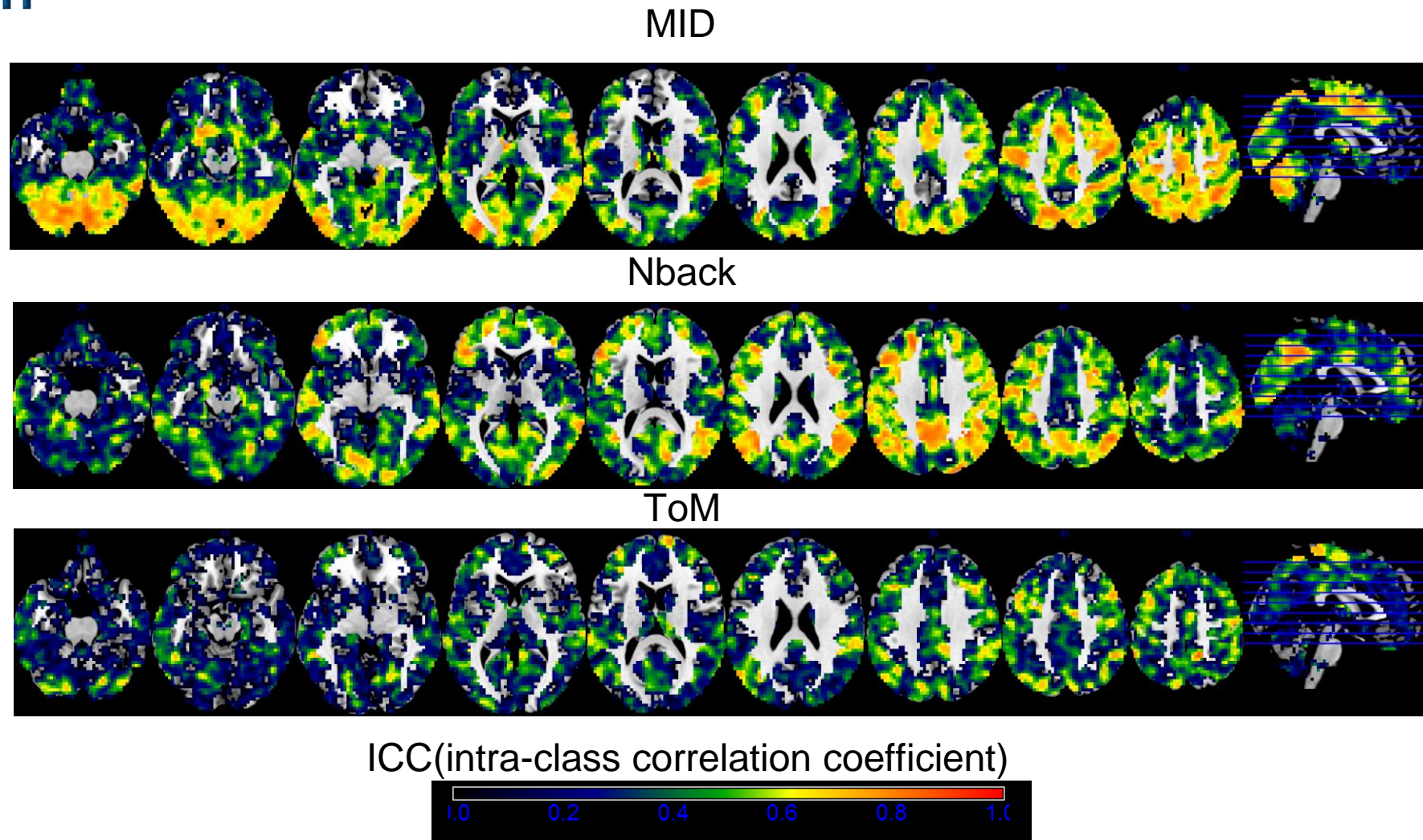
Why do we need to think more about our methods?

Increases, decreases and a mixture of both is reported in the literature



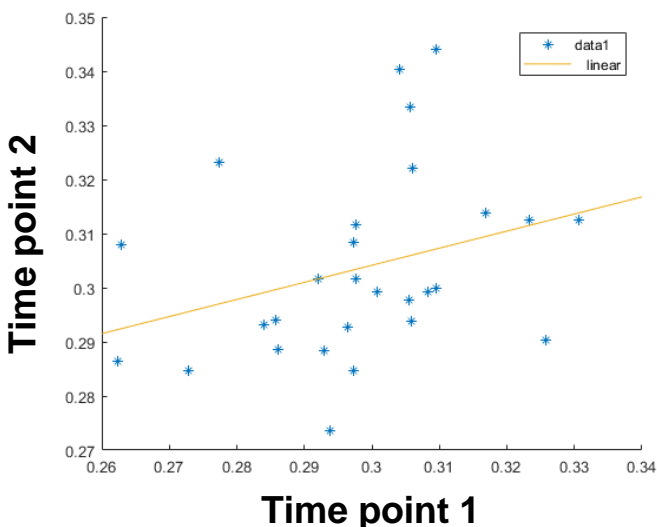
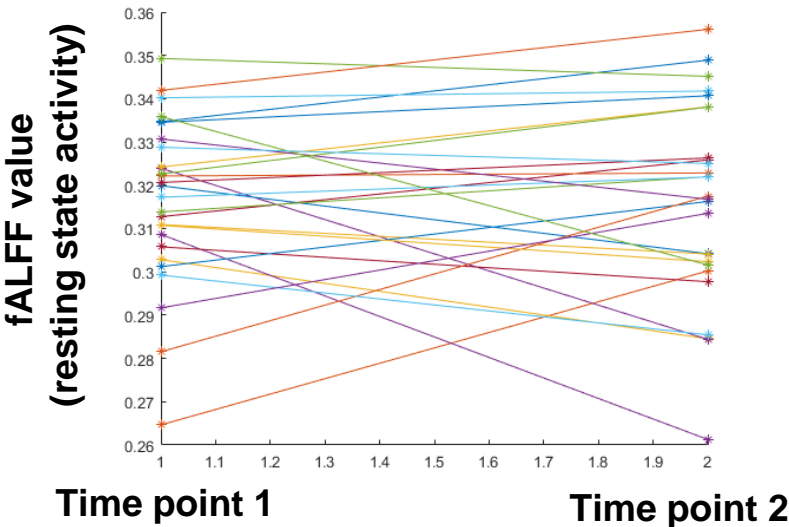
WHAT ARE THE LIMITATIONS OF OUR TOOLS

Reliability of fMRI is strongly dependent on the task and spatial location



Generally rather low to fair reliability of region- and voxel-wise fMRI and rsfMRI analyses

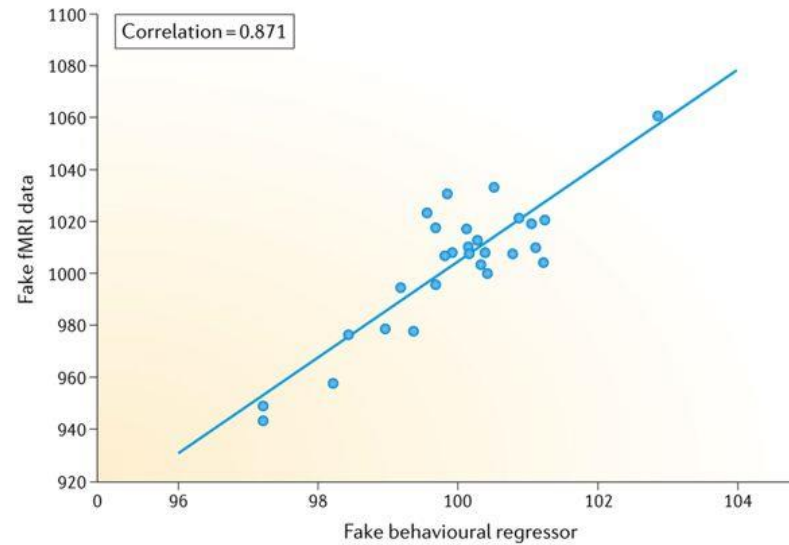
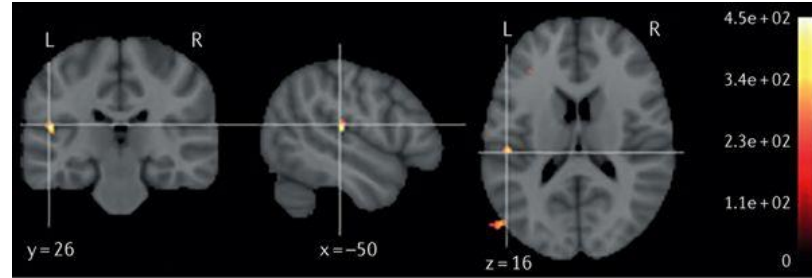
Exemplary atlas region: ICC(reliability)=0.31



| Domain | Measure | Region-wise ICC |
|---------|-------------|--|
| | | Visit 1 to visit 2 median [P_5 – P_{95}] |
| tb-fMRI | MID | 0.70 [–0.00–0.88] |
| | N-back | 0.38 [–0.09–0.68] |
| | ToM | 0.42 [–0.09–0.69] |
| | FM | 0.38 [–0.15–0.71] |
| | Encoding | 0.30 [–0.19–0.58] |
| | Recall | 0.23 [–0.84–0.77] |
| | Recognition | 0.48 [0.03–0.72] |
| | Go/no-go | –0.16 [–0.74–0.36] |
| rs-fMRI | ALFF | 0.72 [0.27–0.86] |
| | fALFF | 0.57 [0.17–0.75] |
| | ReHo | 0.58 [0.21–0.78] |
| | DC | 0.44 [–0.04–0.71] |
| | EC | 0.36 [–0.15–0.67] |
| | Hurst | 0.45 [0.18–0.64] |
| ASL | CBF | 0.83 [0.42–0.91] |

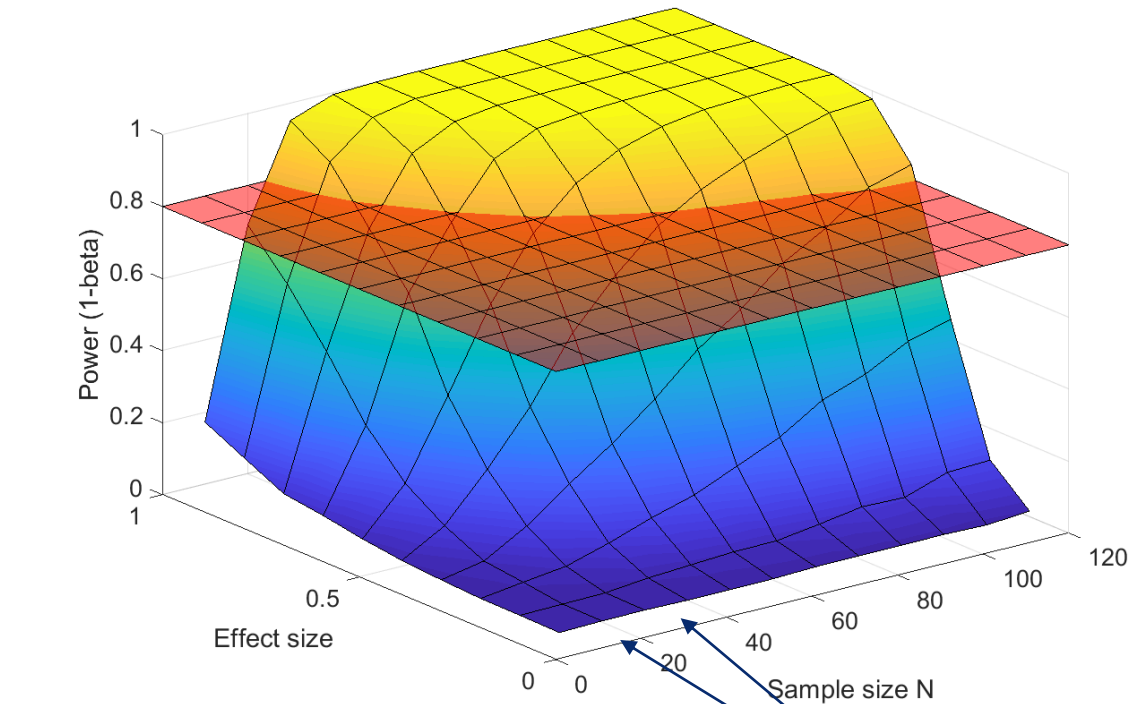
ICC criteria (Cicchetti, Domenic V. 1994):
 Less than 0.40—poor.
 Between 0.40 and 0.59—fair.
 Between 0.60 and 0.74—good.
 Between 0.75 and 1.00—excellent.
 ICC – Intra-class correlation coefficient

Uncorrected statistics and circularity can produce misleading effect sizes



Why large sample sizes are needed

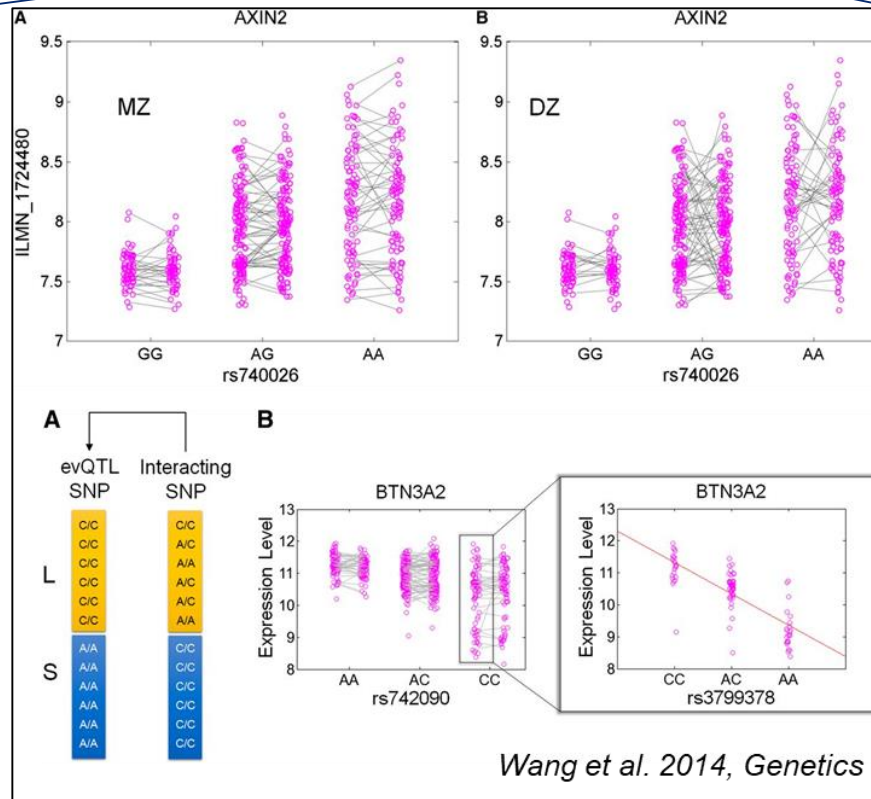
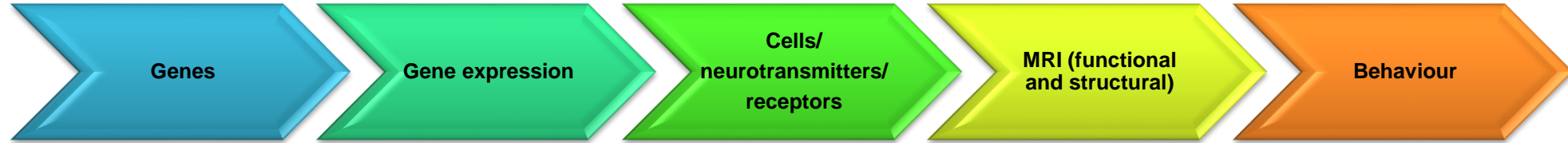
“Typical” size neuroimaging studies can only detect extremely large effects



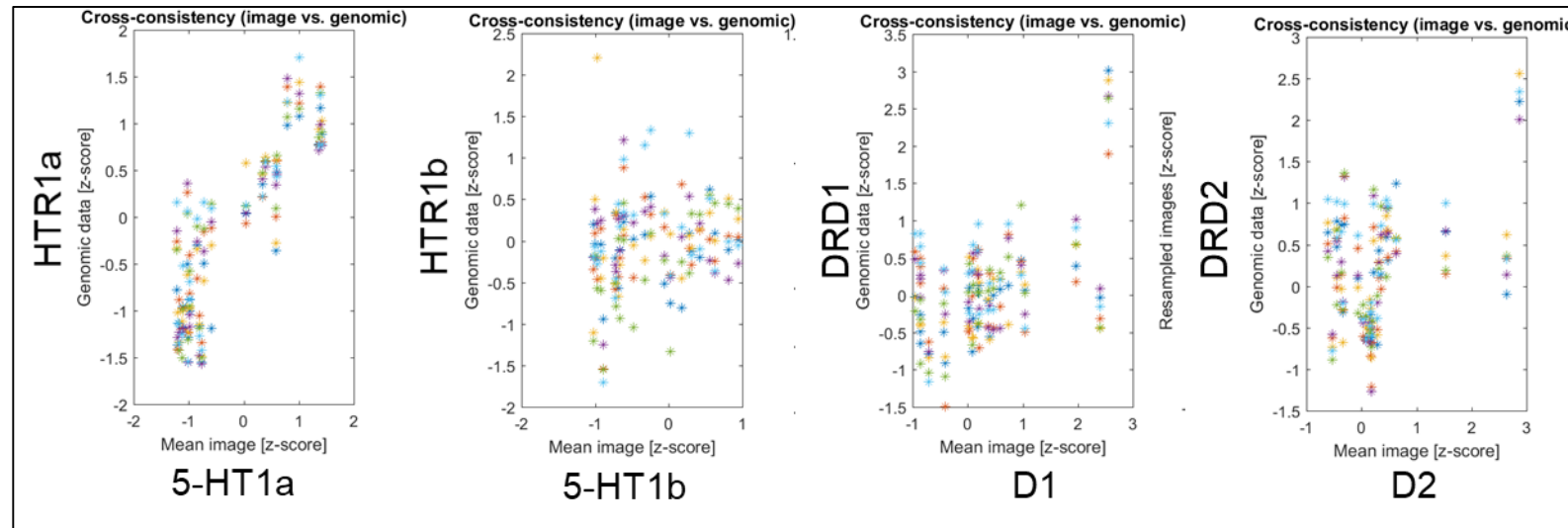
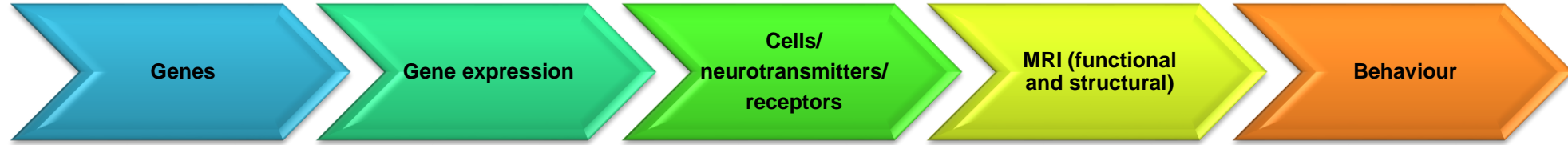
Power at $p < .001$ uncorrected

Typical fMRI study has about 15-30 participants

We need to better understand sources of biological variability



We need to better understand sources of biological variability



Correlations between Allen Brain Atlas and group-average in vivo PET receptor maps, unpublished data

Correlations between gene expression and imaging: 0 and 0.7

Genetic auto-correlation:

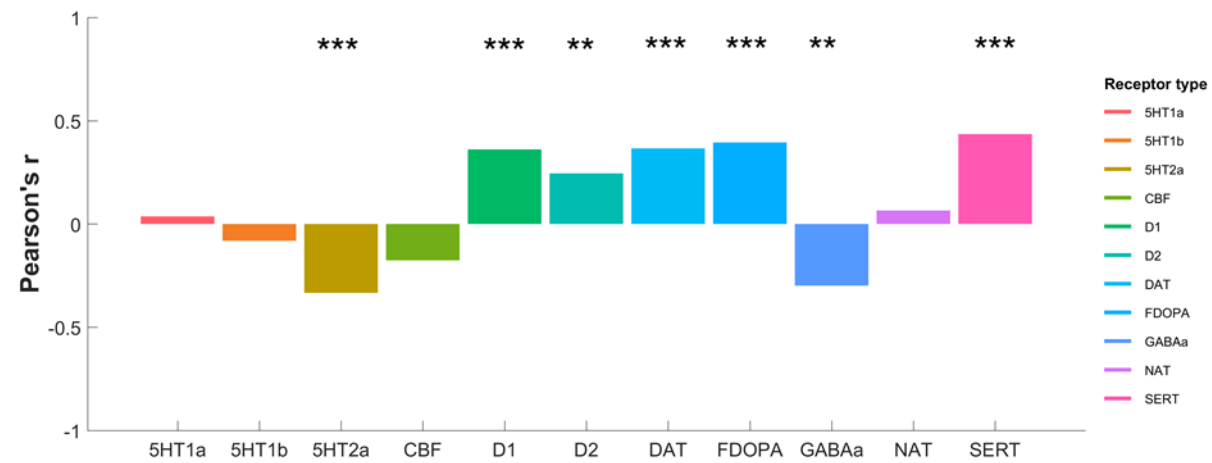
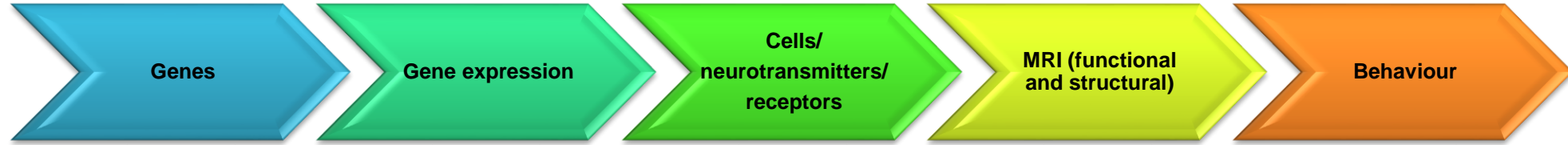
HTR1a: $r=0.88$

HTR1b: $r=0.16$

D1: $r=0.54$

D2: $r=0.71$

We need to better understand sources of biological variability

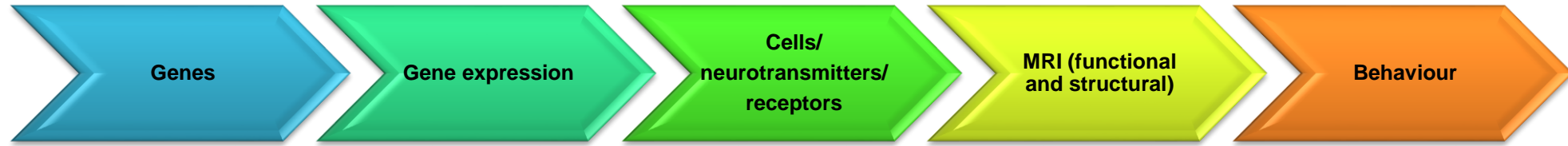


*** $p < 0.001$

** $p < 0.01$

Correlation between PET derived receptor maps and risperidone induced blood flow changes

We need to better understand sources of biological variability



Limitations

A lot of variance in transcription is explained by environment or by gene/gene interactions

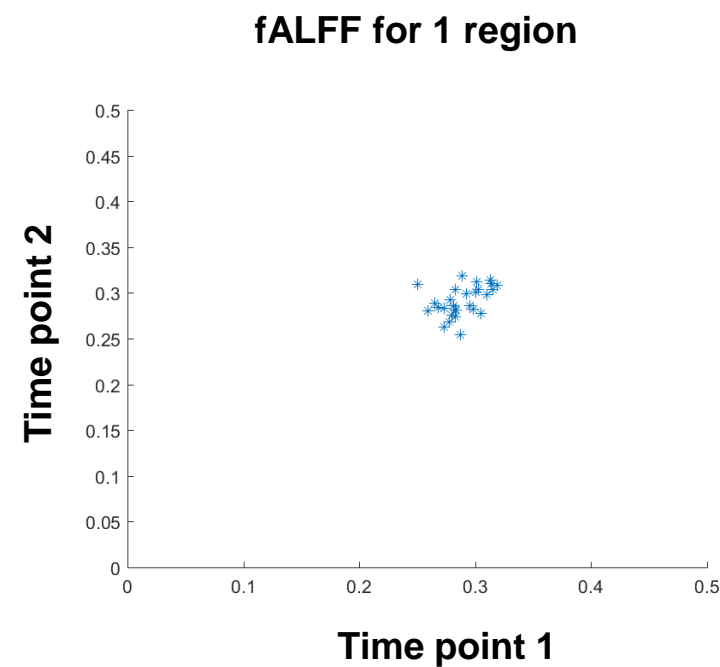
- a) mRNA expression often poorly correlates with respective receptor expression
- b) Large variability in gene expression is observed for some genes across individuals

- a) Functional MRI measures are only sensitive to some aspects of underlying activity
- b) Some neurotransmitter changes do not result in changes in functional activity

Low reliability of regional functional MRI measures adds a lot of noise to the data

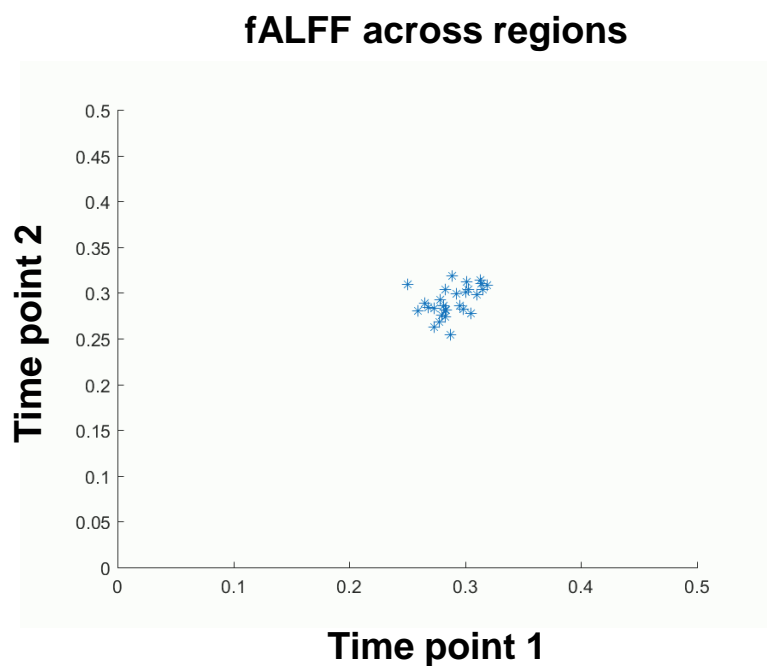
HOW CAN WE ADDRESS THOSE LIMITATIONS

Within region reliability is rather moderate for most functional MRI measures



| Domain | Measure | Between ICC |
|---------|-------------|---|
| | | Visit 1 to visit 2 median [P_5 - P_{95}] |
| tb-fMRI | MID | 0.70 [-0.00-0.88] |
| | N-back | 0.38 [-0.09-0.68] |
| | ToM | 0.42 [-0.09-0.69] |
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| | DC | 0.44 [-0.04-0.71] |
| ASL | EC | 0.36 [-0.15-0.67] |
| | Hurst | 0.45 [0.18-0.64] |
| | CBF | 0.83 [0.42-0.91] |

Spatial reliability across regions is consistently higher than the reliability within each region for task-based fMRI and rsfMRI



| Domain | Measure | Between | Within |
|---------|-------------|---|---|
| | | ICC | ICC |
| | | Visit 1 to visit 2 median [P_5 - P_{95}] | Visit 1 to visit 2 median [P_5 - P_{95}] |
| tb-fMRI | MID | 0.70 [-0.00-0.88] | 0.79 [-0.32-0.93] |
| | N-back | 0.38 [-0.09-0.68] | 0.81 [0.61-0.94] |
| | ToM | 0.42 [-0.09-0.69] | 0.58 [-0.10-0.83] |
| | FM | 0.38 [-0.15-0.71] | 0.80 [0.63-0.93] |
| | Encoding | 0.30 [-0.19-0.58] | 0.73 [0.47-0.94] |
| | Recall | 0.23 [-0.84-0.77] | 0.72 [0.25-0.89] |
| rs-fMRI | Recognition | 0.48 [0.03-0.72] | 0.72 [0.48-0.86] |
| | Go/no-go | -0.16 [-0.74-0.36] | 0.24 [-1.11-0.66] |
| | ALFF | 0.72 [0.27-0.86] | 0.96 [0.73-0.98] |
| | fALFF | 0.57 [0.17-0.75] | 0.98 [0.95-0.99] |
| | ReHo | 0.58 [0.21-0.78] | 0.96 [0.86-0.98] |
| | DC | 0.44 [-0.04-0.71] | 0.89 [0.62-0.95] |
| ASL | EC | 0.36 [-0.15-0.67] | 0.65 [0.19-0.92] |
| | Hurst | 0.45 [0.18-0.64] | 0.92 [0.77-0.96] |
| | CBF | 0.83 [0.42-0.91] | 0.96 [0.91-0.98] |

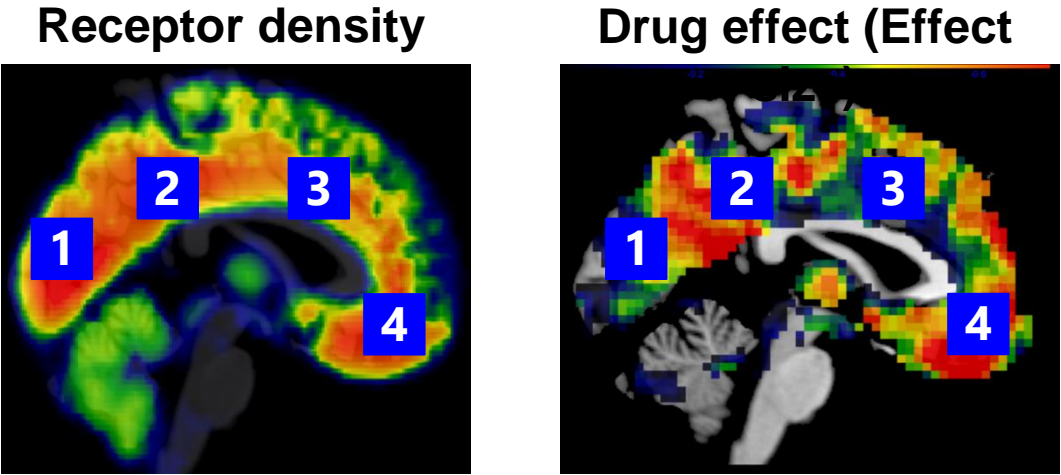
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Between 0.75 and 1.00—excellent.
ICC – Intra-class correlation coefficient

Pharmacodynamic mapping of drug receptor profiles using Cerebral Blood Flow – Illustration of the concept

Correlating spatial profiles of receptor densities and drug effects

| 13 Ex vivo receptor density estimates | In vivo receptor estimates |
|---------------------------------------|----------------------------|
| | GABAA |
| | DAT |
| AMPA | |
| NMDA | |
| Kainate | |
| GABAA | |
| m1 | |
| m2 | |
| Nicotinic $\alpha 2 \beta 4$ | |
| $\alpha 1$ | |
| $\alpha 2$ | |
| 5-HT 1a | |
| 5-HT 2 | |
| D1 | |
| D2 | |

Palomero-Gallagher et al. 2015, in Brain Mapping: An Encyclopedic Reference



Cerebral Blood Flow (CBF, using Arterial Spin Labeling) for:

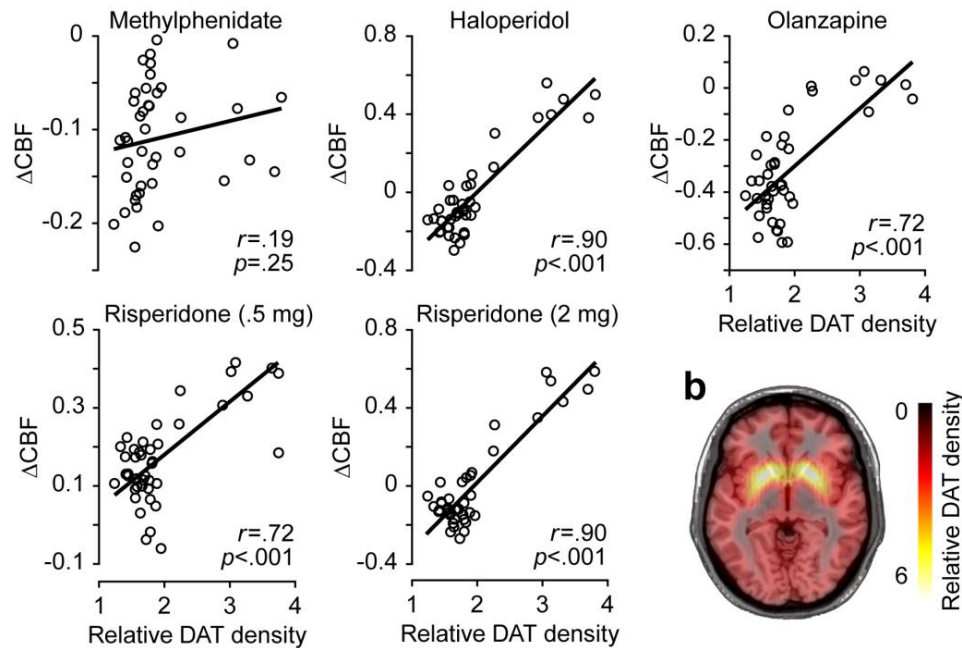
- Risperidone
- Olanzapine
- Haloperidol
- Methylphenidate
- Escitalopram
- Ketamine
- Midazolam

Always vs placebo

Correlations

Spatial patterns of CBF alterations are predictive of the underlying mechanism of action of respective compounds

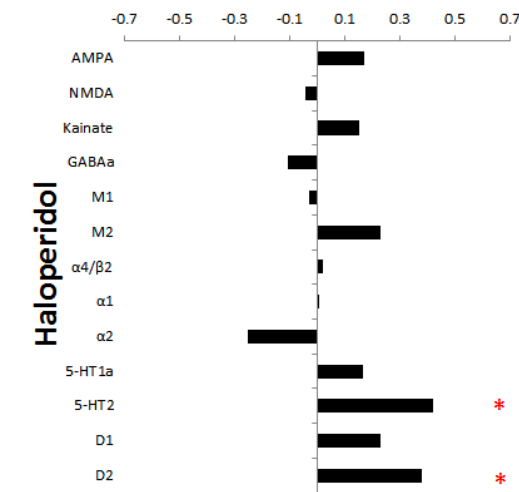
Correlations with in vivo receptor density estimates (dopaminegic compounds)



Further potential applications:

- Profiling of new drugs (hypothesis generation)
- Disease patterns
- Individual symptom prediction/treatment response

Correlational profiles with ex vivo receptor density estimates



* $p < .05$

These profiles align well with underlying affinity to the respective receptor systems (highest affinity to D2, 5-HT₂)

Making use of novel tools and resources

Gene expression

Genetics and traits



Gene Atlas is a large database of associations between hundreds of traits and millions of variants using the UK Biobank cohort.

The associations have been computed using 452,264 UK Biobank White British individuals. To avoid having to remove the large amount of related individuals present on the study, the associations have been computed using Mixed Linear Models in a large supercomputer using DISSECT. The objective of the current database is to benefit the research community by making a searchable atlas of genetic associations that help researchers to query associations results in an easy way, without the need to incur in the high computational costs required to analyze the UK Biobank large cohort.

452264
Individuals

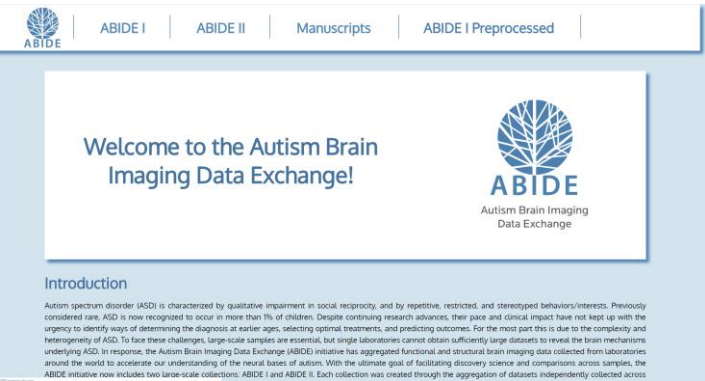
778
Traits

30
Million Variants

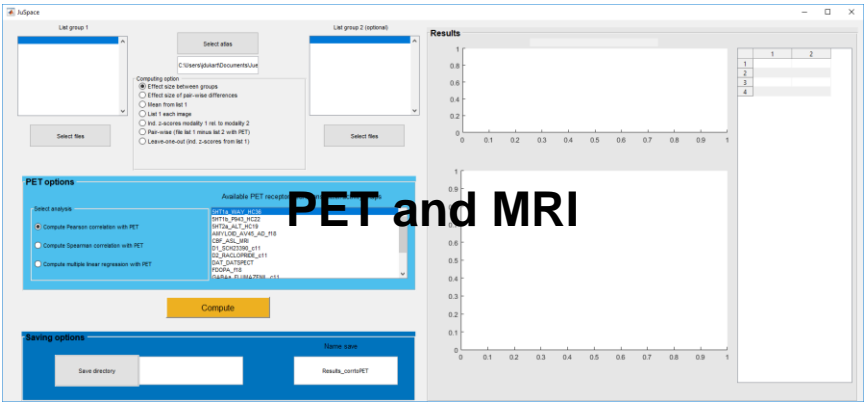
This work has been done at the Roslin Institute and MRC-HGU within the Albert Tenesa's group with the contributions of Oriol Canela-Xandri and Konrad Rawlik.



Public neuroimaging databases



Tools for cross-modal spatial correlations



Dukart et al., in preparation

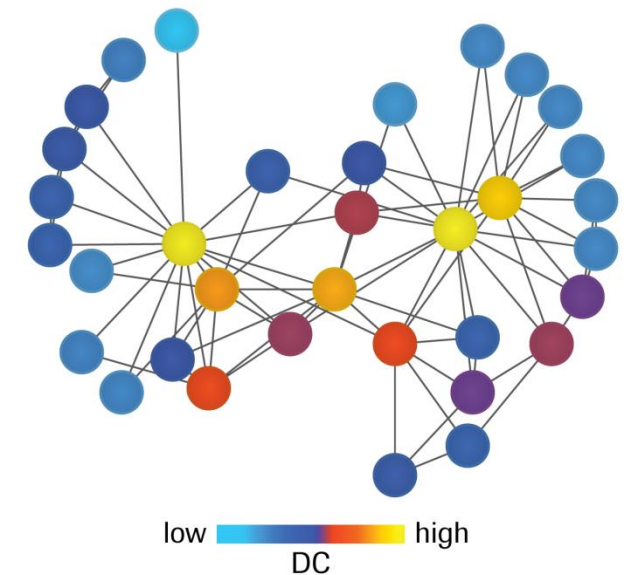
Objective: to test for replicability of ASD resting state connectivity alterations across several cohorts using the same methodology

| | Exploration dataset | | | Validation datasets | | | | | | | | |
|--|---------------------|----------|---------------------------------|---------------------|-------------|---------------------------------|--------------|-------------|---------------------------------|------------|------------|---------------------------------|
| | EU-AIMS LEAP | | | ABIDE I | | | ABIDE II | | | InFoR | | |
| | ASD | TD | Stats (test value, df, p-value) | ASD | TD | Stats (test value, df, p-value) | ASD | TD | Stats (test value, df, p-value) | ASD | TD | Stats (test value, df, p-value) |
| N | 202 | 192 | - | 299 | 376 | - | 306 | 391 | - | 34 | 25 | - |
| Male/female | 142/60 | 124/68 | 1.5, 1, 26 | 268/31 | 313/63 | 5.7, 1, 0.17 | 262/44 | 263/127 | 30.4, 1, <.001 | 26/8 | 19/6 | 0.0, 1, 967 |
| Age±SD | 17.5±5.3 | 17.4±5.7 | 0.1, 392, .915 | 17.5±7.7 | 17.7±7.8 | 3.673, .776 | 14.0±6.8 | 13.6±6.2 | 8.695, .428 | 29.5±8.9 | 30.6±8.3 | 5.57, .638 |
| Child/Adol/Adult | 35/76/91 | 43/71/78 | 1.7, 2, 434 | 69/118/112 | 85/147/144 | 1.2, .974 | 147/85/74 | 234/77/80 | 10.3, 2, .006 | 0/0/34 | 0/0/25 | - |
| IQ (mean±SD, N) | 106±14.9 | 109±12.6 | 2.1, 392, .033 | 106.3±16.0 | 112.0±12.1 | 5.3, 673, <.001 | 107.0±16.0 | 115.7±12.5 | 8.0, 695, <.001 | 104.3±18.7 | 108.6±17.5 | 9.54, .392 |
| DSM IV diag (none/ ASD/ Asperger/ PDD-NOS) | - | - | - | 16/204/60/16 | - | - | 121/55/78/52 | - | - | - | - | - |
| On medication (N) | 54 | 2 | - | 61 | 1 | - | 81 | 17 | - | - | - | - |
| ADOS total (mean±SD, N) | 10.1±4.9, 170 | - | - | 11.9±3.7, 259 | 1.3±1.4, 30 | 15.4, 287, <.001 | 10±3.7, 167 | 1.8±1.7, 38 | 13.4, 203, <.001 | - | - | - |

TD: typically developing healthy controls

Holiga S, Hipp JF, Chatham CH, ... & Dukart J. (2019). Patients with autism spectrum disorders display reproducible functional connectivity alterations. *Science Translational Medicine*

Same pre-processing and analysis pipeline for all data



Degree centrality = Sum($r > \text{prespecified threshold}^*$)

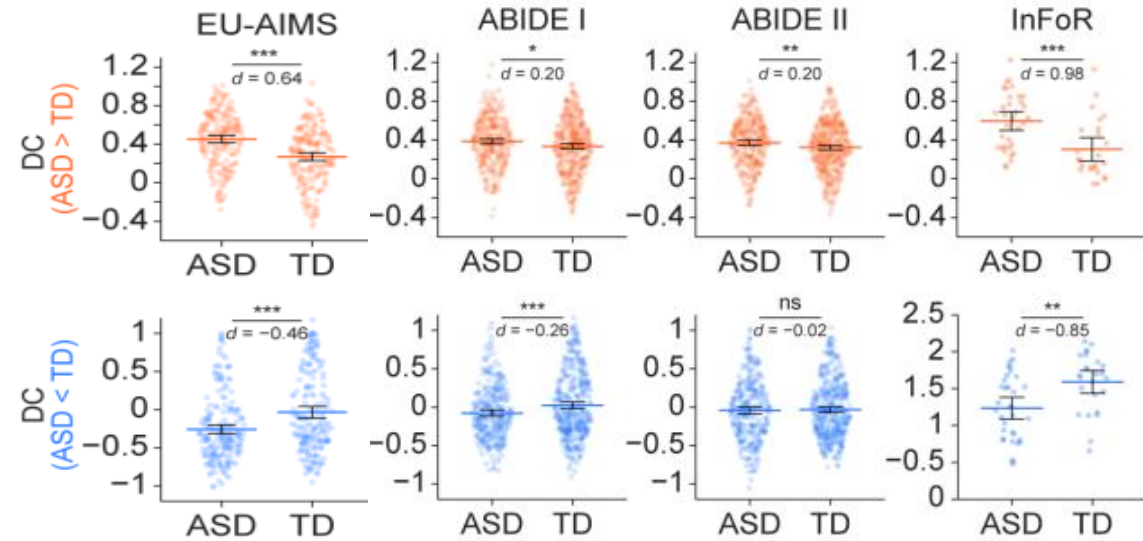
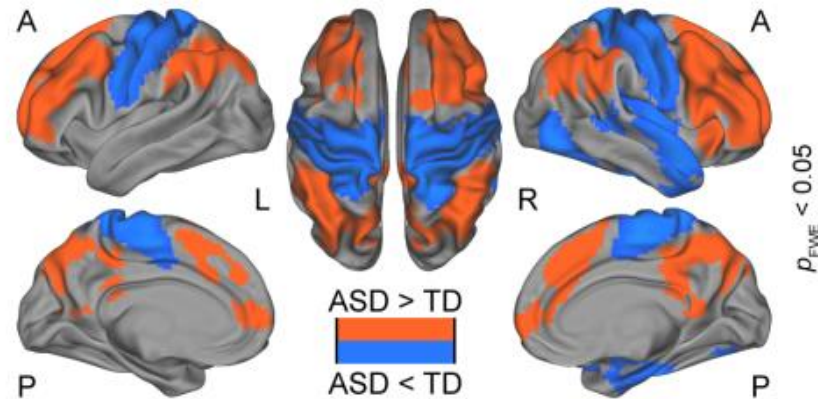
* $r > 0.25$ based on previous literature for degree centrality

Computed using the REST toolbox

Outcomes of the degree centrality analysis

Increases are replicated in all four cohorts and decreases in three out of four

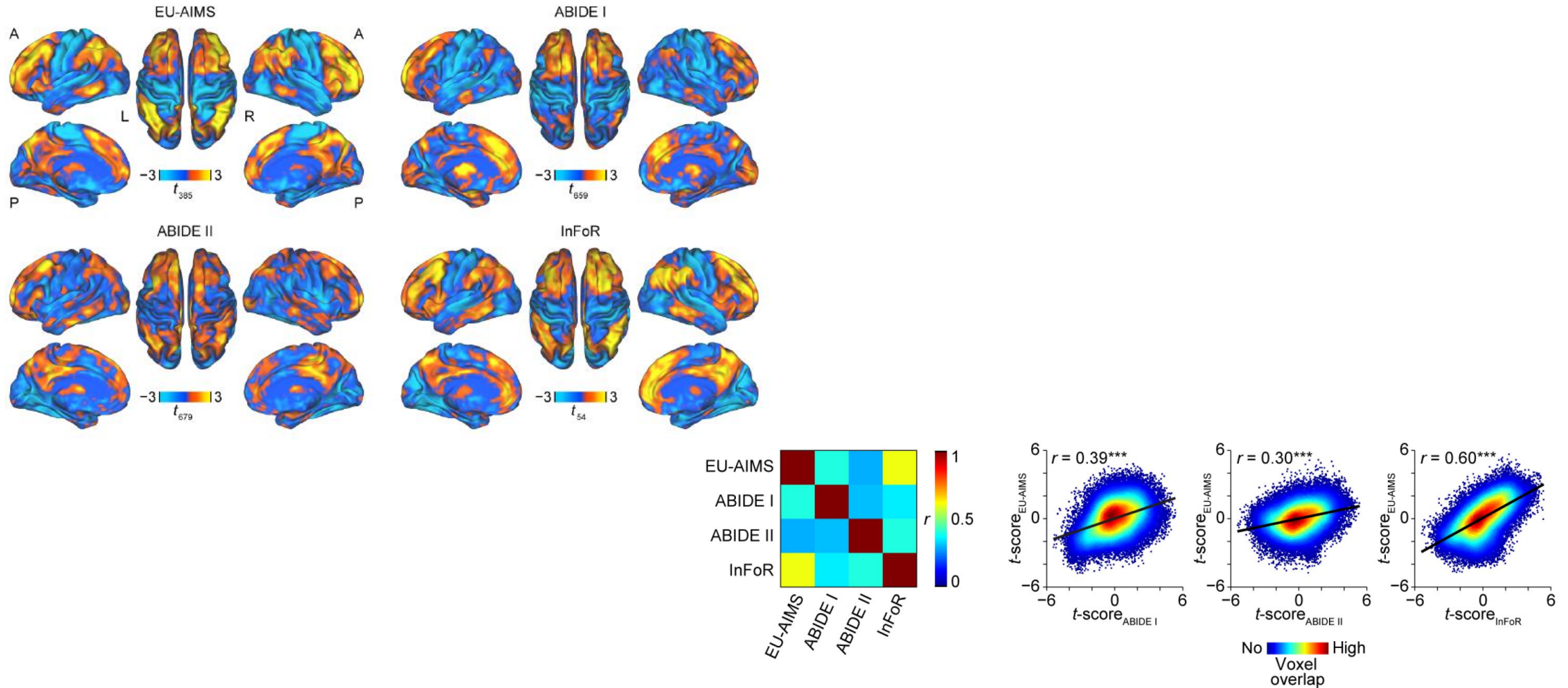
Significant DC alteration in EU-AIMS



* $p < .05$, ** $p < .01$, *** $p < .001$

Outcomes of the degree centrality analysis

Consistent spatial alteration patterns are observed across all four cohorts



Conclusions

- Replication in independent datasets is an important first step for increasing replicability of neuroimaging research
- Spatial profile analyses and correlations with PET, gene expression data may provide a way forward to increase reliability of neuroimaging tools
- Novel tools allow to answer all of the necessary questions to establish more reliable, interpretable and replicable links between genetics, imaging and behaviour



THANK YOU FOR YOUR ATTENTION!

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