



"Opening Up" (Cognitive Neuro)science

Rik Henson

MRC CBU, Cambridge

With thanks to: Rogier Kievit, Niko Kriegeskorte, Dorothy Bishop, Anthony Isles, Amy Orben, Marcus Munafo...

The Problem







Education



Discredited "Mozart Effect" Remains Music to American Ears

Science | Wed Mar 28, 2012 7:09pm BST

In cancer science, many "discoveries" don't hold up

NEW YORK | BY SHARON BEGLEY











53 landmark papers on cancer

47 did not replicate

For a comedian's recent perspective:

In Neuro...





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

Katherine S. Button^{1,2}, John P. A. Ioannidis³, Claire Mokrysz¹, Brian A. Nosek⁴, Jonathan Flint⁵. Emma S. J. Robinson⁶ and Marcus R. Munafò¹

Scanning the horizon: towards transparent and reproducible neuroimaging research

Russell A. Poldrack¹, Chris I. Baker², Joke Durnez^{1,3}, Krzysztof J. Gorgolewski¹, Paul M. Matthews⁴, Marcus R. Mu<u>nafò^{5,6}, Thomas E. Nichols⁷, Jean-Baptiste Poline⁸</u>

Edward Vul⁹ and Tal Yarkoni¹⁰

Article

Reproducible brain-wide association studies require thousands of individuals

https://doi.org/10.1038/s41586-022-04492-9
Received: 19 May 2021
Accepted: 31 January 2022
Published online: 16 March 2022
Open access

Check for updates

Scott Marek^{1,30}, Brenden Tervo-Clemmens^{2,3,30}, Finnegan J. Calabro^{4,5}, David F. Montez⁶, Benjamin P. Kay⁶, Alexander S. Hatoum¹, Meghan Rose Donohue¹, William Foran⁴, Ryland L. Miller^{1,6}, Timothy J. Hendrickson⁷, Stephen M. Malone⁸, Sridhar Kandala¹, Eric Feczko^{1,10}, Oscar Miranda-Dominguez^{1,10}, Alice M. Graham¹, Eric A. Earl^{1,11}, Anders J. Perrone^{2,11}, Michaela Cordova¹¹, Olivia Doyle¹¹, Lucille A. Moore¹¹, Gregory M. Conan^{2,11}, Johnny Uriarte¹¹, Kathy Snider¹¹, Benjamin J. Lynch^{2,12}, James C. Wilgenbusch^{2,12}, Thomas Pengo⁷, Angela Tam^{13,14,15,16}, Jilanzhong Chen^{13,14,15,16}, Dillan J. Newbold⁶, Annie Zheng⁶, Nicole A. Seider⁶, Andrew N. Van^{6,17}, Athanasia Metoki⁶, Roselyne J. Chauvin⁶, Timothy O. Laumann¹, Deanna J. Greene¹⁰, Steven E. Petersen^{6,17,10,20,21}, Hugh Garavan²², Wesley K. Thompson²³, Thomas E. Nichols²⁴, B. T. Thomas Yeo^{13,14,15,10,25,26}, Deanna M. Barch^{1,21}, Beatriz Luna^{3,4}, Damien A. Fair^{21,10,21,21,21}, Richols²⁴, B. I. Thomas Yeo^{13,14,15,10,25,26}, Deanna M. Barch^{1,21}, Beatriz Luna^{3,4}, Damien A. Fair^{21,10,21,21,21}, Richols², Rico U. F. Dosenbach Grizio^{2,0,21}, Deanna M. Barch^{1,21}, Beatriz Luna^{3,4}, Damien A. Fair^{21,10,21,21,21}, Richols², Rico U. F. Dosenbach Grizio^{2,0,21}, Richols^{2,0,21}, Richols^{2,0,21}, Richols^{2,0,21}, Richols^{2,0,21}, Richols^{2,0,21}, Richols^{2,0,21}, Richols^{2,0,21}, Richols^{2,0,21}, Richol

In Neuroimaging...





Scanning the horizon: towards transparent and reproducible neuroimaging research

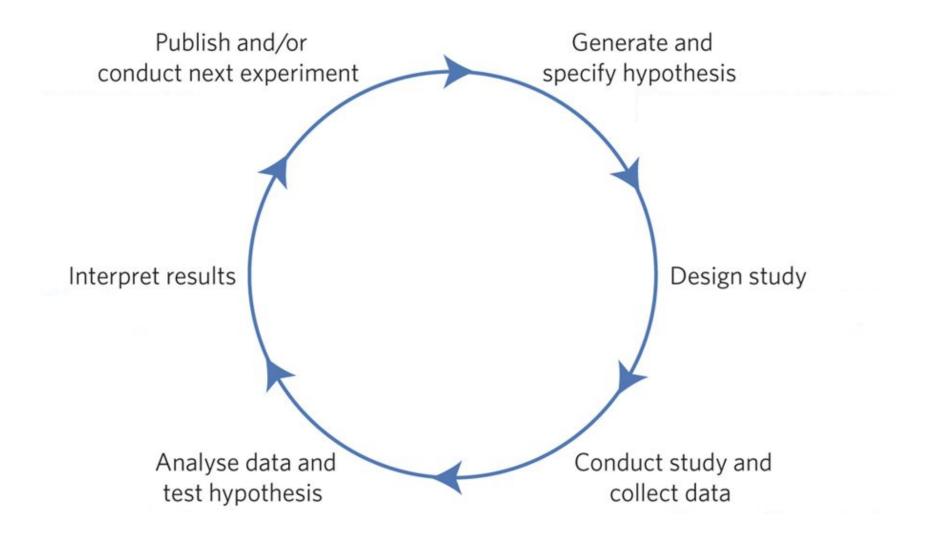
Russell A. Poldrack¹, Chris I. Baker², Joke Durnez^{1,3}, Krzysztof J. Gorgolewski¹, Paul M. Matthews⁴, Marcus R. Munafò^{5,6}, Thomas E. Nichols⁷, Jean-Baptiste Poline⁸, Edward Vul⁹ and Tal Yarkoni¹⁰

"...the high dimensionality of fMRI data, the relatively low power of most fMRI studies and the great amount of flexibility in data analysis contribute to a potentially high degree of false-positive findings."

The Problems







Overview





- Registration
 - Study Registration (eg OSF)
 - Registered Reports
 - Pre-Registration Posters
- Statistical analysis
- Sharing Data and Code
- Publication

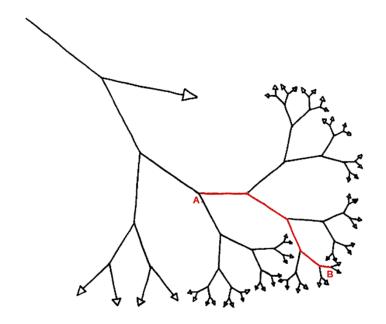
Research Culture

(Un)conscious Bias





The Garden of Forking Paths by Jorge Luis Borges



Particularly likely in neuroimaging, given so many analysis choices...?

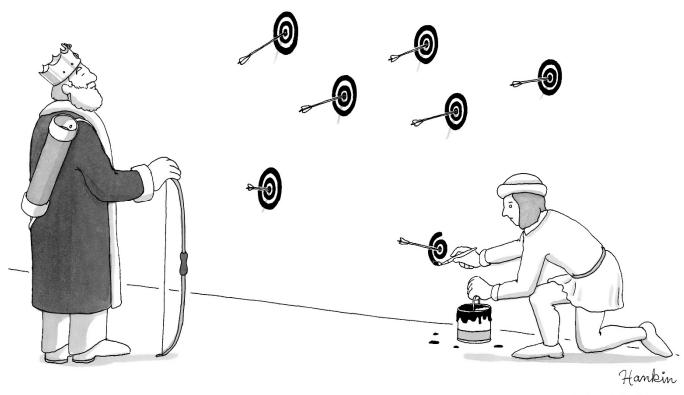
Multiverse analyses?

HARKing





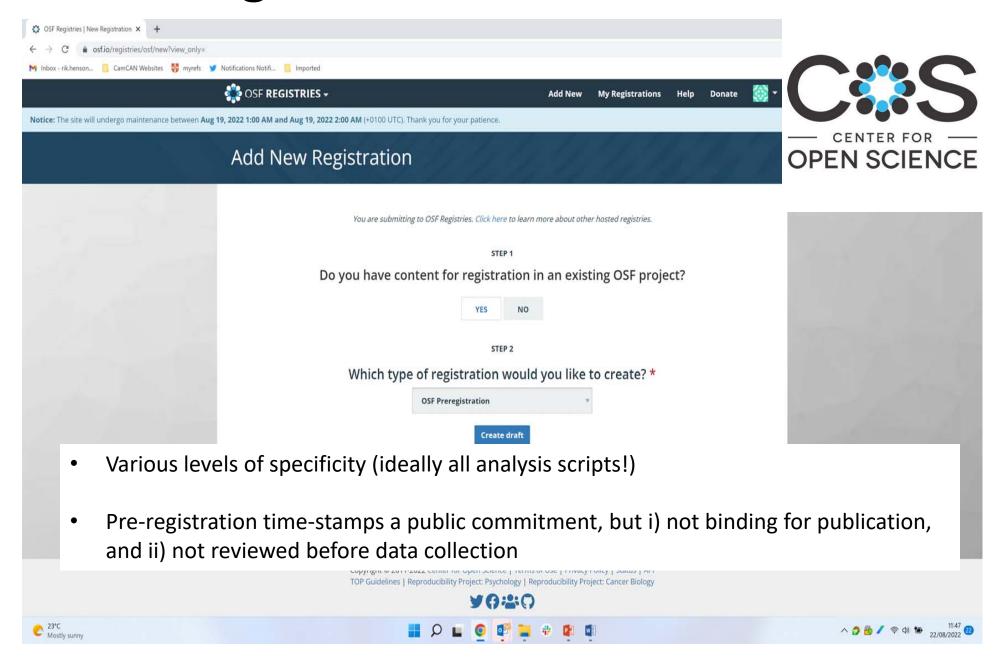
HARK = "Hypothesising After the Results are Known"



OSF Registration







Registered Reports





- Peer Review before data collection/analysis
- Guaranteed Publication regardless of results

Filing Drawer problem



Registered Reports





- Peer Review before data collection/analysis
- Guaranteed Publication regardless of results



- Can report non-registered findings, but clear division between "confirmatory" and "exploratory" results
- Some of many Cognitive Neuroscience journals allowing RRs:
 Cortex, Frontiers, Journal of Cognitive Neuroscience, Nature Human Behaviour,
 Psychological Science, Quarterly Journal of Experimental Psychology, Brain

 Neuroscience Advances...
- (not currently: Nature, Science, J. Neuroscience, Neuroimage, APA journals... 😊)

Pre-Reg Posters





Trends in Cognitive Sciences

Home / News / Preregistration posters: early findings about presenting research early

Scientific Life

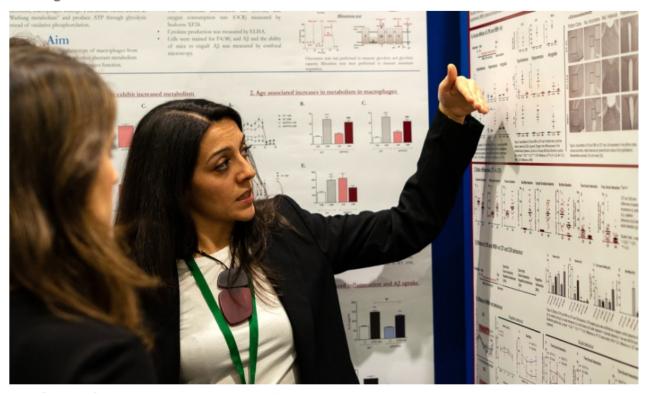
Title TBA: Revising the Abstract Submission Process

Roni Tibon,^{1,*} CBU Open Science Committee,¹ and Richard Henson¹

Academic conferences are among the most prolific scientific activities, yet the current abstract submission and review process has serious limitations. We propose a revised process that would address these limitations, achieve some of the aims of Open Science, and stimulate discussion throughout the entire lifecycle of the scientific work.

PREREGISTRATION POSTERS: EARLY FINDINGS ABOUT PRESENTING RESEARCH EARLY

21st Aug 2019



• Chance to get feedback (eg, "Is hypothesis interesting? Sufficient controls? Appropriate analysis?") before submitting a website registration or RR...

Overview





- Registration
 - Study Registration (eg OSF)
 - Registered Reports
 - Pre-Registration Posters
- Statistical analysis
 - Power and PPV
 - Bayesian Statistics
 - Sequential Designs
- Sharing Data and Code
- Publication

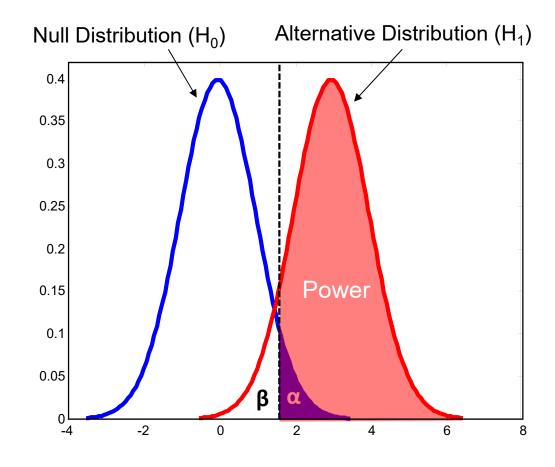
Research Culture

Power





- Power = probability of rejecting H₀
 when H₁ is true
- Must specify:
 - Sample size *n*
 - Level α
 (allowed false positive rate)
 - Standard deviation σ (population variability)
 - Effect magnitude Δ
- Last two can be replaced with
 - Effect size: $\delta = \Delta/\sigma$
 - E.g, according to Cohen: δ =0.8 is a large effect size δ =0.5 is a medium effect size δ =0.2 is a small effect size



Power Curves

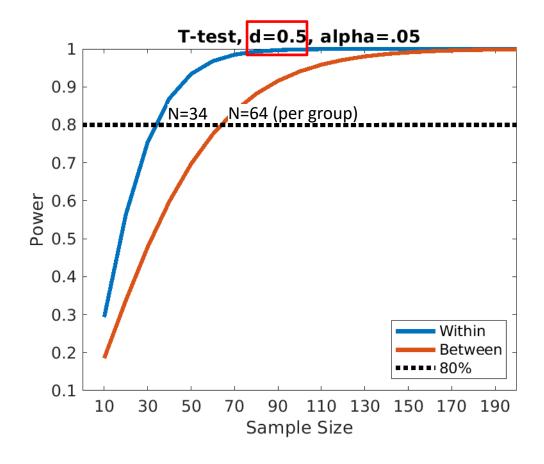




- Assuming medium effect size (d=0.5) for a (two-tailed) frequentist T-test:
- Within-participant (repeated measures) tests more powerful than between-participant tests (latter need N~128 participants total for >80% power)

G*Power:

 https://www.psychologie.hhu.de/a
 rbeitsgruppen/allgemeine psychologie-und arbeitspsychologie/gpower



In Neuro...



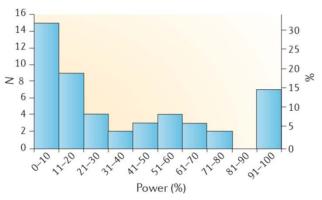


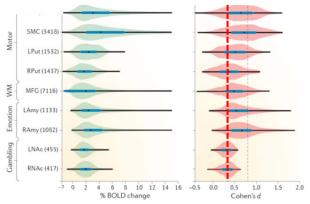
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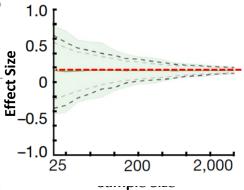
Article

Reproducible brain-wide association studies require thousands of individuals

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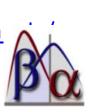


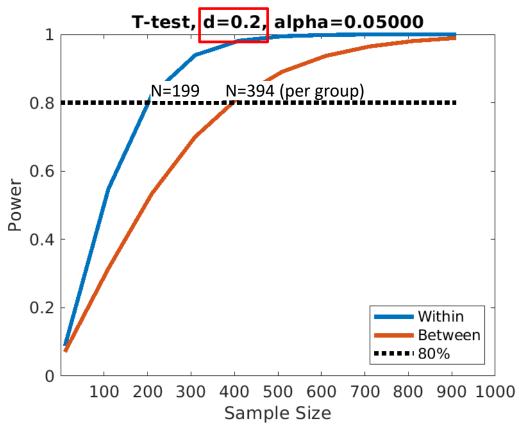
Power Curves





- Assuming medium effect size (d=0.5) for a (two-tailed) frequentist T-test:
- Within-participant (repeated measures) tests more powerful than between-participant tests (latter need N~128 participants total for >80% power)
- With small effect size d=0.2, approaching total of N~o(10³) for between-participant test
- G*Power:
 https://www.psychologie.hh
 rbeitsgruppen/allgemeine psychologie-und arbeitspsychologie/gpower

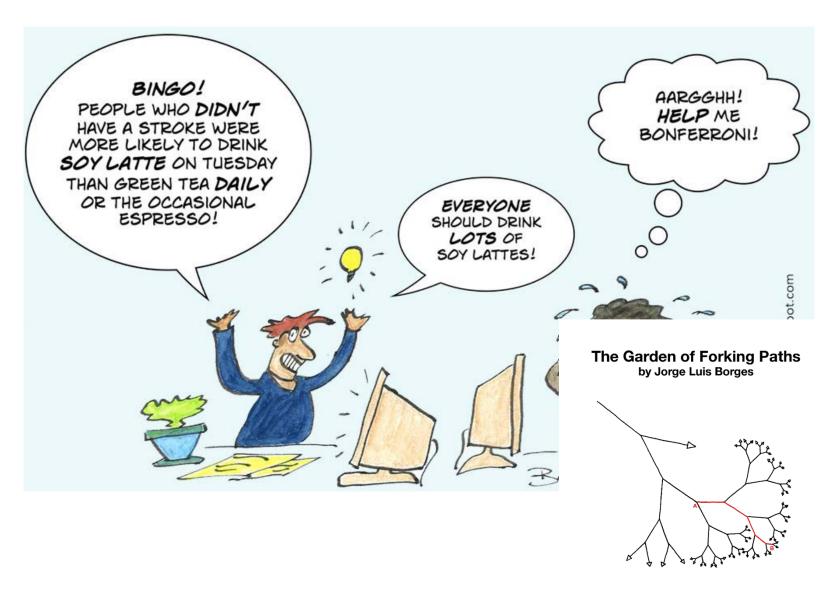




Multiple Comparisons K





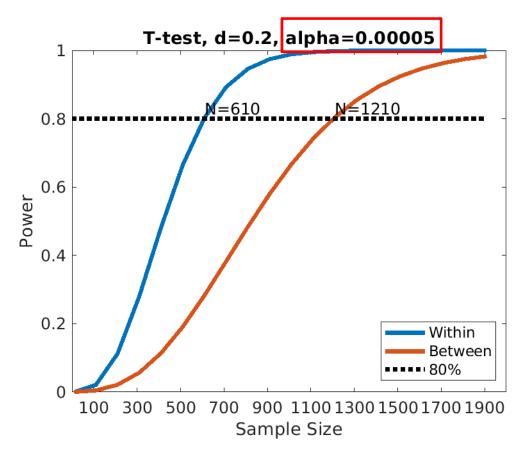


Power Curves





- Assuming medium effect size (d=0.5) for a (two-tailed) frequentist T-test:
- Within-participant (repeated measures) tests more powerful than between-participant tests (latter need ~128 participants total for >80% power)
- With small effect size d=0.2, correction for 1000 tests ("resels") approaches total of N~2500 for between-participant test



More sophisticated treatment of multiple comparisons, within- and between-participant variance (e.g, #trials and #participants):

fMRIpower: http://fmripower.org

PowerMap: http://sourceforge.net/projects/powermap
NeuroPower: http://neuropower.shinyapps.io/neuropower

Positive Predictive Value (PPV)





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. Simulations 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

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 articles

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

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 – β (one minus the Type II error rate). The probability of claiming a relationship when none truly exists reflects the Type I error rate, α . Assuming that ϵ relationships are being probed in the field, the expected values of the 2×2 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.





	Hypothesis True (H+)	Hypothesis False (H-)
Positive Finding D+	P(D+ H+) ("hit", "sensitivity") <i>Power</i> 1-β	P(D+ H-) ("false alarm", "Type I error") <i>FPR</i> α
Negative Finding D-	P(D- H+) ("miss", "Type II error")	P(D- H-) ("correct rejection", "specificity")





	Hypothesis True (H+)	Hypothesis False (H-)
Positive Finding D+	P(D+ H+) ("hit", "sensitivity") <i>Power</i> 1-β	P(D+ H-) ("false alarm", "Type I error") FPR α
Negative Finding D-	P(D- H+) ("miss", "Type II error")	P(D- H-) ("correct rejection", "specificity")
(Prior)	P(H+)	P(H-)

$$PPV = P(H+|D+)$$

$$= p(D+|H+) \times p(H+) / p(D+)$$
 Bayes Rule

$$p(D+) = p(D+|H+) \times p(H+) + p(D+|H-) \times p(H-)$$
 Summation Rule

PPV =
$$p(D+|H+) \times p(H+) / (p(D+|H+) \times p(H+) + p(D+|H-) \times p(H-))$$

$$R = p(H+)/p(H-)$$
 (a priori) Odds Ratio of Hypothesis being true

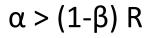
PPV =
$$(1-β) x R / ((1-β) x R) + α)$$



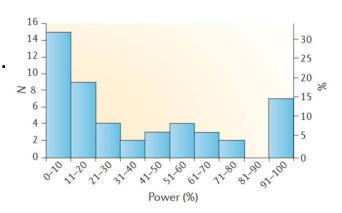


• Why most studies false, ie PPV < ½?

$$0.5 > PPV = \frac{(1-\beta) R}{(1-\beta) R + \alpha}$$



- Assume power 20%, ie (1-β) = 0.2 (and α =0.05)...
- $-0.05 > 0.20 R \rightarrow R < 0.05/0.20$
- So PPV < 0.5 if H1:H0 < 1:4; discovery science ?</p>
- Worse once consider bias...



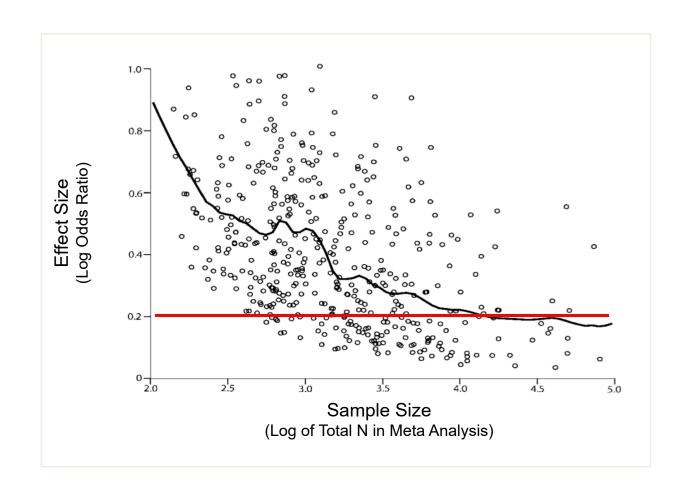
• PPV highly dependent on Power (since α small)

$$PPV = (1-\beta) \frac{R}{R + \alpha/(1-\beta)} \approx (1-\beta)$$

Additional Bias (u)







Filing Drawer problem



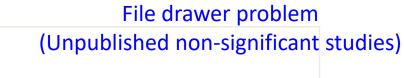


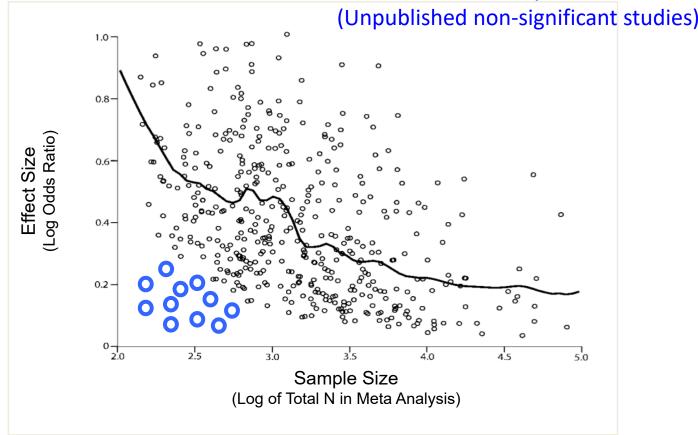


Additional Bias (u)





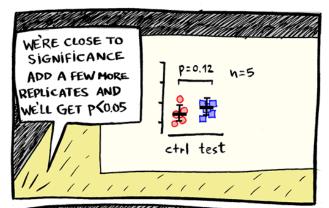


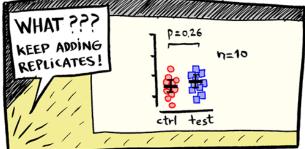


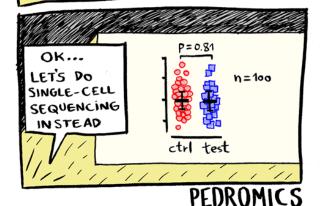
P-Hacking





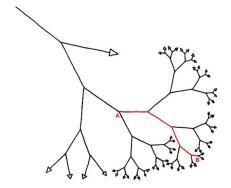






- Different statistical tests
- Different covariate adjustment
- Removal of outliers
- Peeking & +/- n = numbers

The Garden of Forking Paths by Jorge Luis Borges



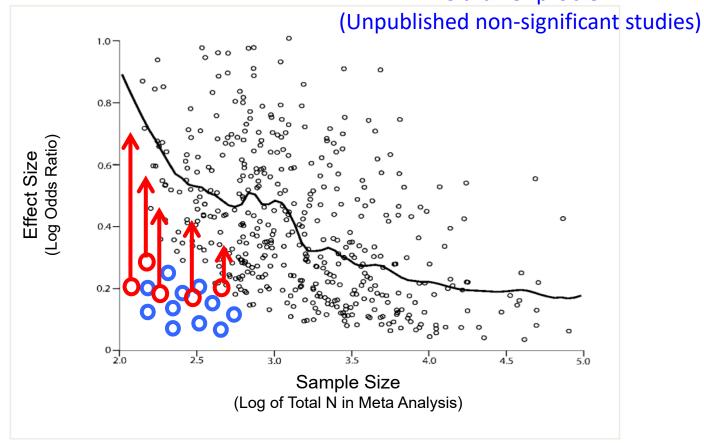
Additional Bias (u)





P-hacking (Fishing or Vibration Effects)

File drawer problem







Adding bias of u:

$$PPV = \frac{(1-\beta)R + u\beta R}{(1-\beta)R + u\beta R + \alpha + u(1-\alpha)}$$

of True to Not-True Relationships (R), and Bias (u)					
1 – β	R	и	Practical Example	PPV	
0.80	1:1	0.10	Adequately powered RCT with little bias and 1:1 pre-study odds	0.85	
0.95	2:1	0.30	Confirmatory meta-analysis of good- quality RCTs	0.85	
0.80	1:3	0.40	Meta-analysis of small inconclusive studies	0.41	
0.20	1:5	0.20	Underpowered, but well-performed phase I/II RCT	0.23	
0.20	1:5	0.80	Underpowered, poorly performed phase I/II RCT	0.17	
0.80	1:10	0.30	Adequately powered exploratory epidemiological study	0.20	
0.20	1:10	0.30	Underpowered exploratory epidemiological study	0.12	
0.20	1:1,000	0.80	Discovery-oriented exploratory research with massive testing	0.0010	

Piloting





- Where obtain effect size for new study?
 - From literature? But publication bias (over-estimated)...
 - From pilot experiment? But then need large sample...
 - A priori (e.g, medium effect)? But will reviewers agree... (register!)



Classical (Frequentist) vs Bayesian Inference





• Classical "p-value" is *likelihood* of getting a statistic (derived from the data, D), given Null Hypothesis (H0) is true, i.e, that effect size is exactly zero:

$$p(D|H_0)$$

• Bayes Factor (BF) is the *relative evidence* for H1 vs H0 (or vice versa):

$$BF_{10} = \frac{p(D/H_1)}{p(D/H_0)}$$

- ...though requires you to specify some priors on H1, H0 parameters...
 - "Subjective Bayesians" specify priors based on theory/data (register!)
 - "Objective Bayesians" specify priors as minimal (default) assumptions...

Bayes Factors





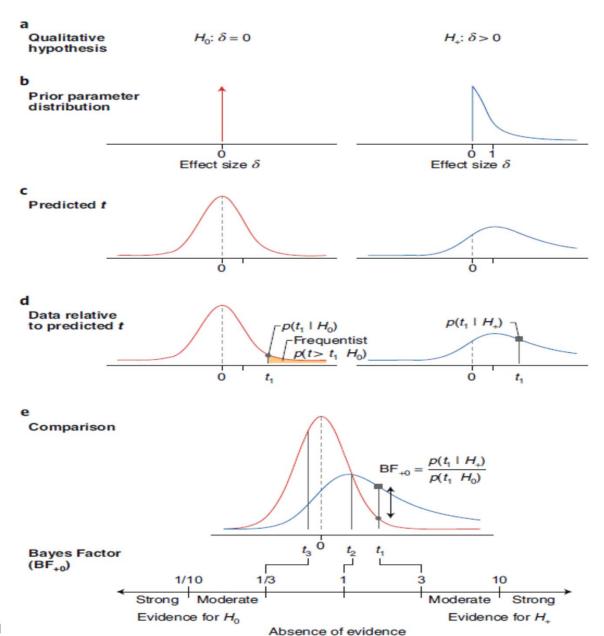
BF ₁₀	Evidence
> 100	Extreme evidence for H_1
30 – 100	Very strong evidence for H_1
10 – 30	Strong evidence for H_1
3 – 10	Moderate evidence for H_1
1-3	Anecdotal evidence for H_1
1	No evidence
1-1/3	Anecdotal evidence for H_0
1/10 – 1/30	Strong evidence for H_0
1/30 – 1/100	Very strong evidence for H_0
< 1/100	Extreme evidence for H_0

- Most journals either require BF of 6 or 10 for registered reports
- We often take $BF_{10} > 10$ and $BF_{10} < 1/6$ as sufficient

Bayes Factors







Keysers et al. (2020). Nat. Neurosci.

Classical (Frequentist) vs Bayesian Inference





Problems of Classical Inference (or advantages of "going Bayesian"):

• A "non-significant" p-value (e.g, p>.05) does not mean there is no effect ("absence of evidence is not evidence of absence")...

...BFs can quantify evidence for Null (BF01=1/BF10)

A "significant" p-value can be found for unrealistic/trivial effect sizes...

...BFs make reference to likely effect sizes...

• The more tests performed, the more likely a "Type I" error (when *p*<.05 but H0 is true)...

...BFs can be combined across data (or prior adjusted)

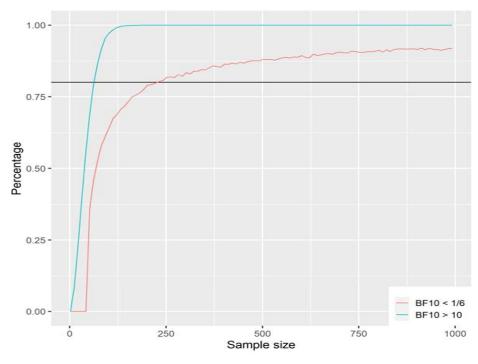
• You should specify sample size (stopping rule) in advance (you cannot "top-up" observations just to try to get p < .05)...

...BFs reflect belief-updating, and allow Sequential Designs

"Fixed N" design





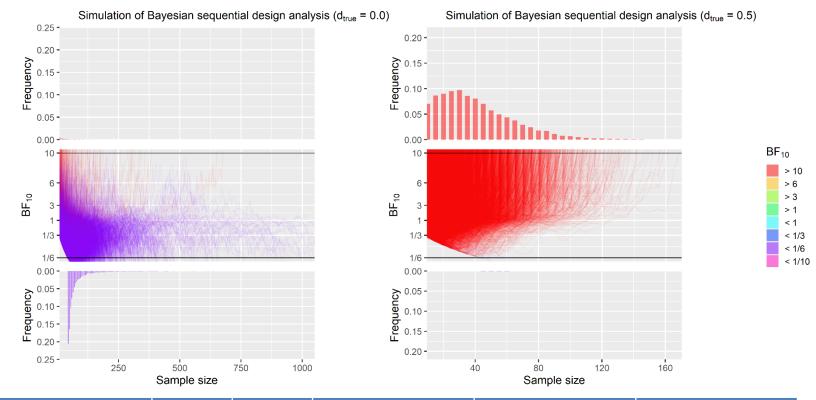


Effect size	Fix N	Misleading evidence	Strong evidence	Costs fMRI experiment
0.5	72	0.0003 %	80 %	£ 39,600
0.0	232	0.0011 %	80 %	£ 127,600

Sequential design





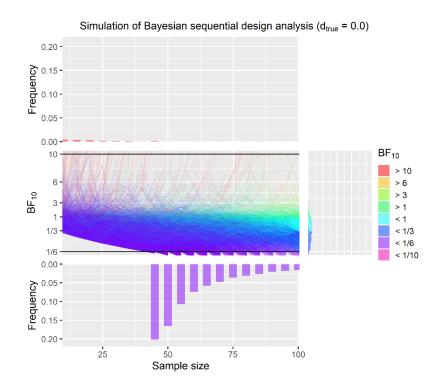


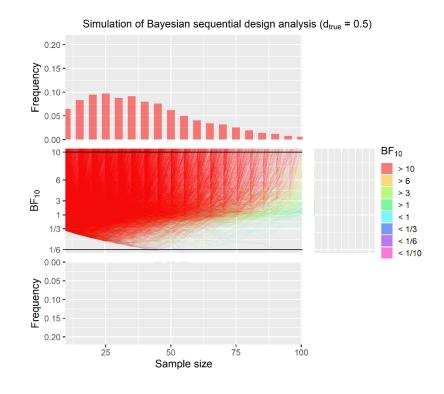
Effect size	Max N	Mean N	Misleading evidence	Strong evidence	Costs fMRI experiment
0.5	170	41	0.13 %	100 %	£ 22,550
0.0	2765	83	2.95 %	100 %	£ 45,650

"Max N" Sequential design









Effect size	Max N	Mean N	Misleading evidence	Strong evidence	Costs fMRI experiment
0.5	100	39	0.12 %	98 %	£ 21,450
0.0	100	58	2.31 %	80 %	£ 44,138

Comparison





Fixed-N Design

Effect size	Max N	Misleading evidence	Strong evidence	Costs fMRI experiment
0.5	72	0.0003 %	80 %	£ 39,600
0.0	232	0.0011 %	80 %	£ 127,600

Sequential design

Effect size	Max N	Mean N	Misleading evidence	Strong evidence	Costs fMRI experiment
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Sequential, Max-N design

Effect size	Max N	Mean N	Misleading evidence	Strong evidence	Costs fMRI experiment
0.5	100	39	0.12 %	98 %	£ 21,450
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Overview





Registration

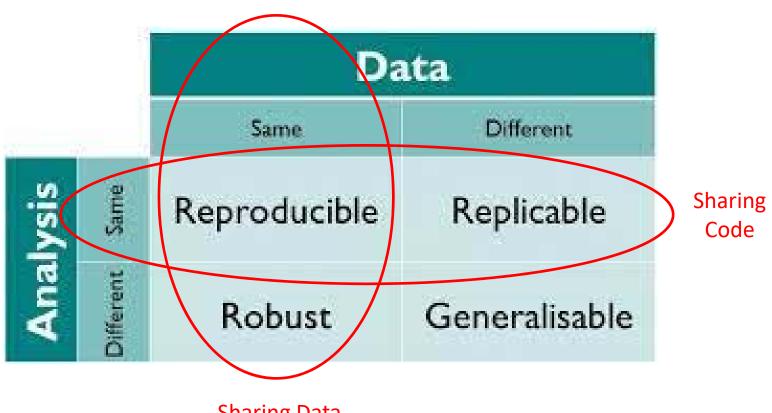
- Statistical analysis
 - Power and PPV
 - Bayesian Statistics
 - Sequential Designs
- Sharing Data and Code
 - FAIR principles
 - Incentivising
 - GDPR
- Publication

Research Culture

Definitions





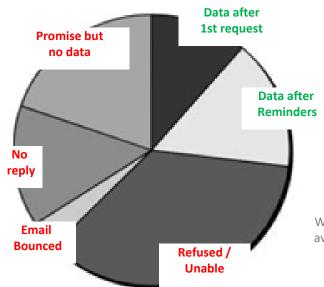


Sharing Data

Sharing Data







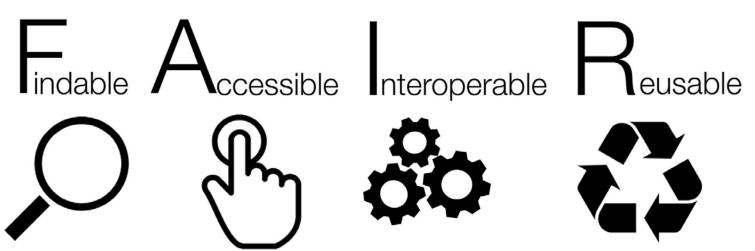
Wicherts, Borsboom, Kats & Molenaar (2006). The poor availability of psychological research data for reanalysis. *American Psychologist*, *61*(7), 726.

- What to share?
- Where to share?
- How to share?
- When to share?

What to Share?







By SangyaPundir - Treball propi, CC BY-SA 4.0, https://commons.wikimedia.org/w/index.php?curid=53414062



Committee on Best Practice in Data Analysis and Sharing (COBIDAS) https://www.humanbrainmapping.org/i4a/pages/index.cfm?pageID=3728

What to Share?





- Sufficient for someone to reproduce your results
- Minimal: raw data and analysis scripts to results in paper
- Non-proprietary formats
- Conventional data formats, eg BIDS for neuroimaging
- Sufficient documentation (data paper?)



Where to Share?





- Small, non-personal or consented (GDPR) data:
 - open on personal website (but DOI?), university repository, OSF...
 - http://neurovault.org for imaging effect size maps
- Large, non-personal or consented data:
 - Public websites like https://openneuro.org/ for neuroimaging
- Personal data with limited consent
 - managed access, electronic Data Usage Agreements (DUAs)
- Personal, unconsented data
 - only by ethical approval / collaboration agreement / DTA / re-consent
- Synthetic data with same statistical properties anywhere!

When to Share?





- As soon as possible, even pre-publication!
 - Unwarranted fear of scooping?

The Open Scoop Challenge

Posted 2014-02-25 by Greg Wilson in Community, Open Science.

- During review (but reviewer anonymity?)
- Mandatory on publication!?
 - (In principle) reproducibility is a cornerstone of Science...

Incentivising Sharing?



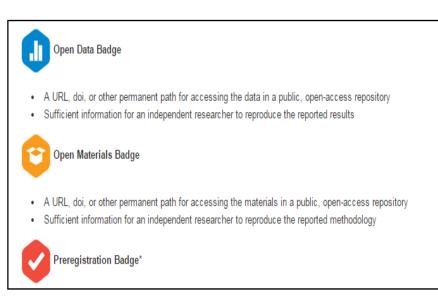


Data Papers

Kite Marking

 Reproduction Papers (citation inheritance)?

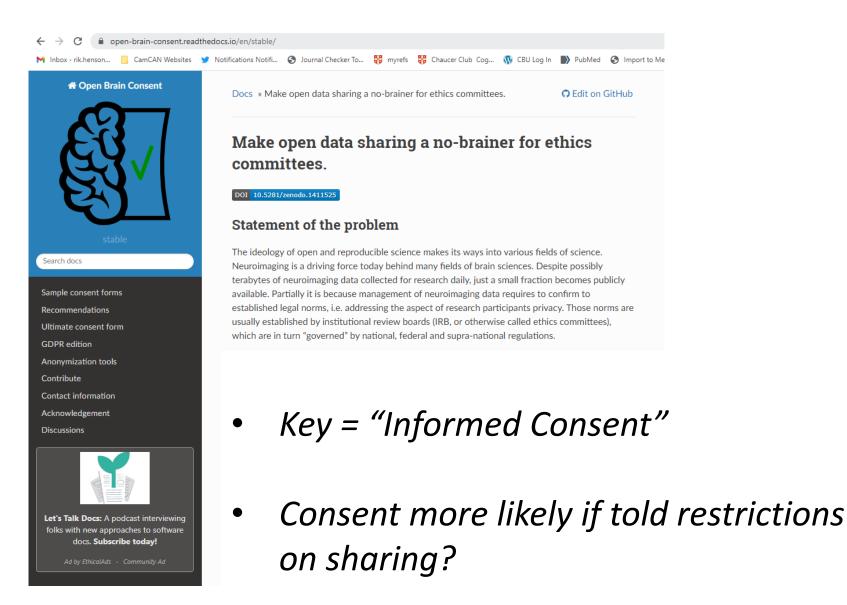




GDPR



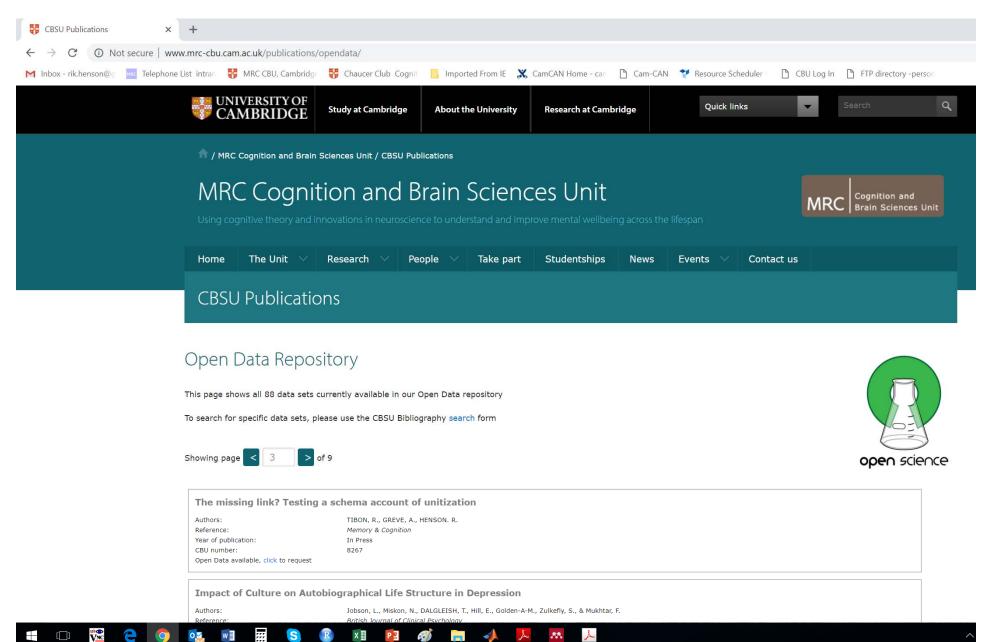




Managed Access







Managed Access



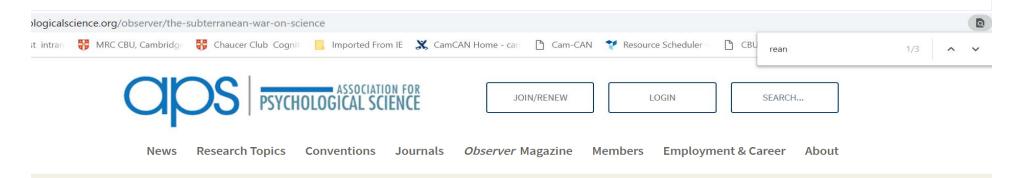


- I will receive access to de-identified data and will not attempt to establish the identity of, or attempt to contact any of the participants.
- I will not publish or disclose any information in a way that would allow the identity of any individual participants to become known.
- I will only use the data for the purposes of non-commercial, ethically approved research or teaching as specified above. I will seek approval from the MRC CBU if I wish to use the data for any other purpose.
- I agree to store the data securely.
- I will not disclose the data to any third parties beyond my immediate research team
- I will require any members of my team with whom I do share the data to comply with these terms and conditions
- I will comply with any rules and regulations imposed by my institution and its institutional review board when requesting and using the data.
- I understand that determining whether ethical approval is needed for the use of the data and gaining that approval is my responsibility.
- I understand that the CBU cannot guarantee exclusive use of these data or police potential overlaps of interest between researchers who request the data.
- I understand that it is my responsibility to check the data for errors, and that the MRC CBU is not responsible for any consequences of unreported errors in the data.
- I agree to make any errors that I discover in this data known to MRC CBU as soon as possible.
- I agree to acknowledge the MRC CBU in any output arising from the use of the data.
- I agree to make any publications that arise from use of the data open-access.
- I agree that should any data I derive from this data set appear in a publication, I will make that derived data, as well as any processing scripts used to produce that derived data, available on a suitable open-access data repository. I will also notify the MRC CBU where the data has been made available.

(Dangers of Open Data?)







Observer > 2013 > November > The Subterranean War on Science

The Subterranean War on Science

STEPHAN LEWANDOWSKY, MICHAEL E. MANN, LINDA BAULD, GERARD HASTINGS, AND ELIZABETH F. LOFTUS

TAGS: COGNITIVE PSYCHOLOGY EXPERIMENTAL PSYCHOLOGY FALSE MEMORY PREJUDICE

Science denial kills. More than 300,000 South Africans died needlessly in the early 2000s because the government of President Mbeki preferred to treat AIDS with garlic and beetroot rather than antiretroviral drugs (Chigwedere, Seage, Gruskin, Lee, & Essex,2008). The premature death toll from tobacco is staggering and historians have shown how it was needlessly inflated by industry-sponsored denial of robust medical evidence (Proctor, 2011). The US now faces the largest outbreak of whooping cough in decades, in part because of widespread denial of the benefits of vaccinations (Rosenau, 2012). According to the World Health Organization, climate change is already claiming more than 150,000 lives annually (Patz, Campbell-Lendrum, Holloway, & Foley, 2005), and estimates of future migrations triggered by unmitigated global warming run as high as 187 million refugees (Nicholls et al., 2011). A common current attribute of denial is that it side-steps the peer-reviewed literature and relies on platforms such as internet blogs or tabloid newspapers to disseminate its dissent from the scientific mainstream. In contrast, the publication of dissenting views in the peer-reviewed literature does not constitute denial.

The tragic track record of denial has stimulated research into its political, sociological, and psychological underpinnings (Dunlap, 2013; Jacobson, Targonski, & Poland, 2007;



About the Authors

Stephan Lewandowsky is with the Department of Psychology at the University of Bristol, UK, and University of Western Australia; Michael E. Mann is with the Departments of Meteorology & Geosciences at Penn State University; Linda Bauld and Gerard Hastings are with the Centre for Tobacco Control Research at the University of Stirling, UK; and Elizabeth F. Loftus is with the Department of Psychology and Social Behavior at the University of California, Irvine.

Related



MYTH: EYEWITNESS TESTIMONY IS THE BEST KIND OF EVIDENCE

Activities in this unit reveal how eyewitness testimony is subject to unconscious memory distortions and biases even

among the most confident of witnesses. ... More



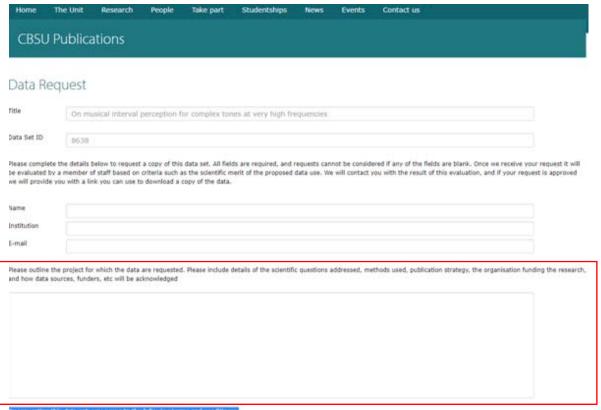
MYTH: TRAUMATIC MEMORIES ARE OFTEN REPRESSED AND LATER RECOVERED

This provides students with an opportunity to see that, often, analyses may lead to conclusions.

Data Usage Agreement (DUA)







by requesting this data set, you agree to the following terms and condition

- . I will receive access to de-identified data and will not attempt to establish the identity of, or attempt to contact any of the participants.
- . I will not publish or disclose any information in a way that would allow the identity of any individual participants to become known.
- I will only use the data for the purposes of non-commercial, ethically approved research or teaching as specified above. I will seek approval from the MRC CBSU if I wish to use the data for any other purpose.
- . I agree to store the data securely.
- . I will not disclose the data to any third parties beyond my immediate research team
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 a suitable open-access data repository. I will also notify the MRC CBSU where the data has been made available.

Data Usage Agreement (DUA)





Please outline the project for which the data are requested. Please include details of the scientific questions addressed, methods used, publication strategy, the organisation funding the research, and how data sources, funders, etc will be acknowledged

Open Code







Free Version Control Multiple Users (or GitLab)

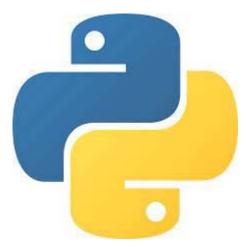


https://software-carpentry.org/

R (for statistics)



Python (for anything!)



Overview





- Registration
- Statistical analysis

- Sharing Data and Code
 - FAIR principles
 - Incentivising
 - GDPR
- Publication
 - Open Access
 - Preprints
 - Open Review
- Research Culture



Trailers Our Team Interviews Photo Gallery News Screenings Contact





























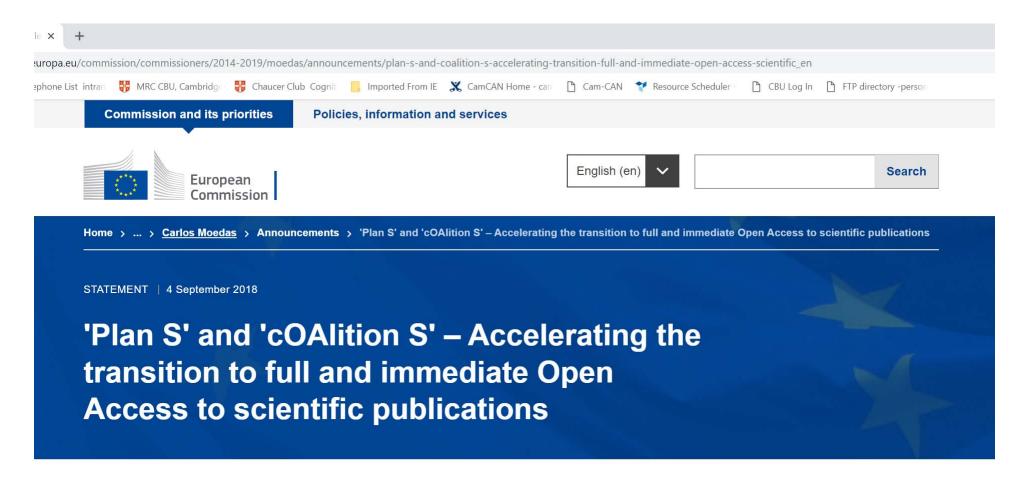












With the increasing pace of scientific discovery and growing public demand for reliable information, there has never been a greater need for immediate, universal, access to the latest research findings. But with many scientific journals behind paywalls not everyone can get hold of this knowledge. 'Knowledge is power' and I firmly believe that free access to all scientific publications from publicly funded research is a moral right of citizens. Two years ago, on 27 May 2016, all Member States of the European Union committed to achieve this goal by 2020. It is one of the most important political commitments on science of recent times and puts Europe at the forefront of the global transition to open nissioners/2014-2019/moedas_en

- **UKRI** adopted April 2022
- Similar initiative in US



























Open Publication





- Open Access (OA): Public-funded (tax payer) money!
- Gold OA but minimal Author Processing Charge (APC)?
- Free journals (funded by government eg UKRI)?
- More radical solutions, eg Octopus, https://www.octopus.ac/

frontiers in COMPUTATIONAL NEUROSCIENCE



An emerging consensus for open evaluation: 18 visions for the future of scientific publishing

Nikolaus Kriegeskorte^{1*}, Alexander Walther¹ and Diana Deca²

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Preprints







https://www.biorxiv.org/

Pros and Cons of peer-review as gateway to publication

Pro: Publication Bias (like FDA asking Pfizer to review AZ's paper!?)

Con: COVID examples

Open Review

Double-blind Reviews





- Post-publication of Reviews (eg PubMed Commons, F1000)...
- ...continuing dialogue linked to original paper ("conversation")



PubMed Commons is a system that enables researchers to share their opinions about scientific publications. Researchers can comment on any publication indexed by PubMed, and read the comments of others. PubMed Commons is a forum for open and constructive criticism and discussion of scientific issues. It will thrive with high quality interchange from the scientific community. PubMed Commons is currently in a closed pilot testing phase, which means that only invited participants can add and view comments in PubMed.

Adding comments Usage guidelines Invite an

How do I join? FAQ

- ...or even identified Reviewers (or unique ID within system?)
- Publish reviews



https://asapbio.org/publishyourreviews

Quality of Reviews – overworked, incentivize (£, or CVs, eg Publons)

Kite Marking Again





Transparency and Openness Promotion (TOP) guidelines

https://www.cos.io/initiatives/top-guidelines



↓ HARKing ↓ P-hacking
+ Feedback

Null results



Materials; Code

↑ Reliability
↓ Variability



Re-analysis + pooling data

Quality control

Overview





- Registration
- Statistical analysis
- Sharing Data and Code

- Publication
 - Open Access
 - Preprints
 - Open Review
- Research Culture
 - DORA
 - CRediT
 - Narrative CVs

Publish or Perish





19th century scientist

I must find the explanation for this phenomenon in order to truly understand Nature...



21st century scientist

I must get the result that fits my narrative so I can get my paper into Nature..

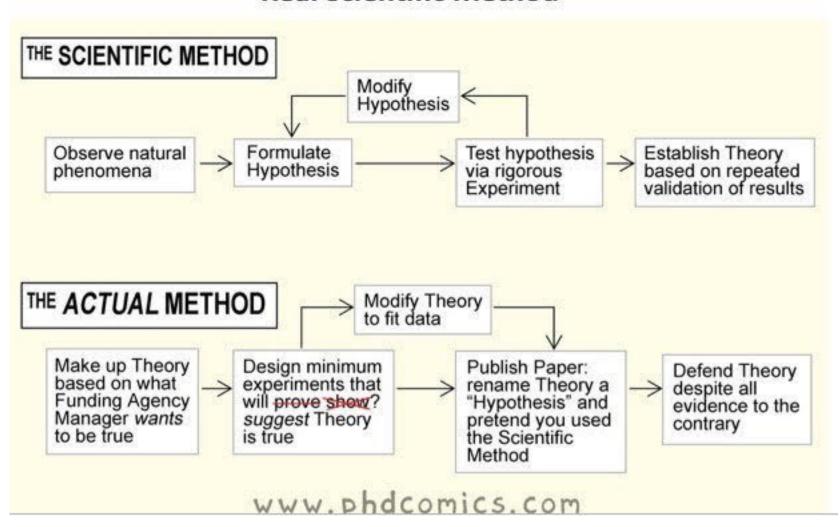


facebook.com/pedromics





Real Scientific Method



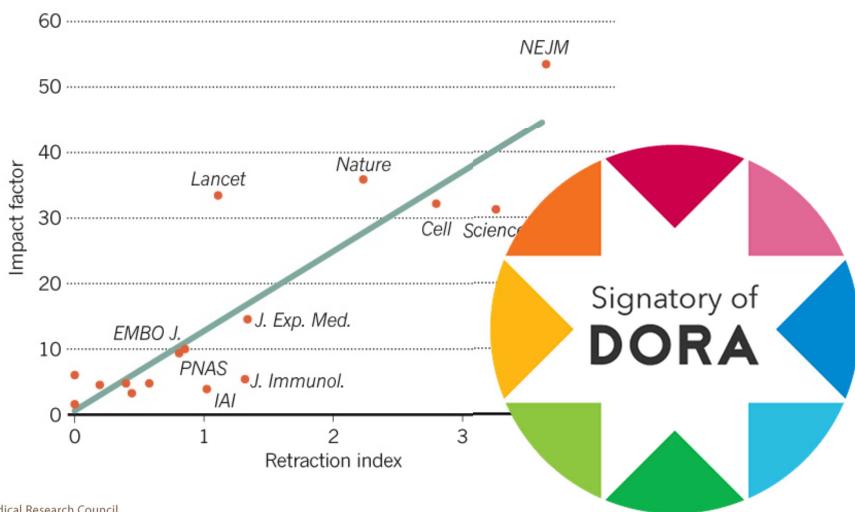
Impact Factor





RETRACTION RELATION

Journals with higher impact factors also have a higher rate of retractions.



Other Issues

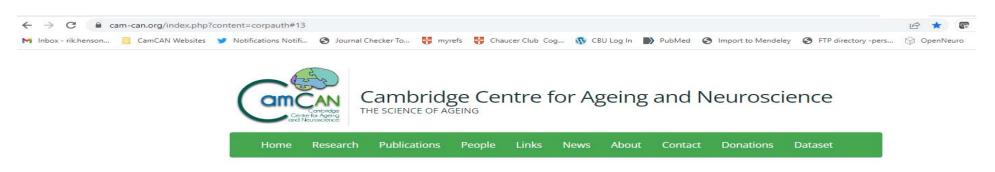




CRediT (Contributor Roles Taxonomy):

Eg: "Zhang San: Conceptualization, Methodology, Software Priya Singh.: Data curation, Writing- Original draft preparation. Wang Wu: Visualization, Investigation. Jan Jansen: Supervision.: Ajay Kumar: Software, Validation.: Sun Qi: Writing-Reviewing and Editing"

Reward «team science», eg corporate authorship



Cam-CAN Corporate Authorship Membership

14. Project principal personnel: Lorraine K Tyler, Carol Brayne, Edward T Bullmore, Andrew C Calder, Rhodri Cusack, Tim Dalgleish, John Duncan, Richard N Henson, Fiona E Matthews, William D Marslen-Wilson, James B Rowe, Meredith A Shafto; Research Associates: Karen Campbell, Teresa Cheung, Simon Davis, Linda Geerligs, Rogier Kievit, Anna McCarrey, Abdur Mustafa, Darren Price, David Samu, Jason R Taylor, Matthias Treder, Kamen A Tsvetanov, Janna van Belle, Nitin Williams, Daniel Mitchell, Simon Fisher, Else Eising, Ethan Knights; Research Assistants: Lauren Bates, Tina Emery, Sharon Erzinçlioglu, Andrew Gadle, Sofia Gerbase, Stanimira Georgieva, Claire Hanley, Beth Parkin, David Troy; Affiliated Personnel: Tibor Auer, Marta Correla, Lu Gao, Emma Green, Rafael Henriques; Research Interviewers: Jodie Allen, Gillian Amery, Liana Amunts, Anne Barcroft, Amanda Castle, Cheryl Dias, Jonathan Dowrick, Melissa Fair, Hayley Fisher, Anna Goulding, Adarsh Grewal, Geoff Hale, Andrew Hilton, Frances Johnson, Patricia Johnston, Thea Kavanagh-Williamson, Magdalena Kwasniewska, Alison McMinn, Kim Norman, Jessica Penrose, Fiona Roby, Diane Rowland, John Sargeant, Maggie Squire, Beth Stevens, Aldabra Stoddart, Cheryl Stone, Tracy Thompson, Ozlem Yazlik; and administrative staff: Dan Barnes, Marie Dixon, Jaya Hillman, Joanne Mitchell, Laura Villis.

13. Project principal personnel: Lorraine K Tyler, Carol Brayne, Edward T Bullmore, Andrew C Calder, Rhodri Cusack, Tim Dalgleish, John Duncan, Richard N Henson, Fiona E Matthews, William D Marslen-Wilson, James B Rowe, Meredith A

Alternative CVs





Narrative CVs

- Royal Society's "Resume for Researchers" (R4R)
 - How have you contributed to: 1) knowledge, 2) develop individuals, 3) research community, 4) society?
- Description of best work; no Impact Factors!

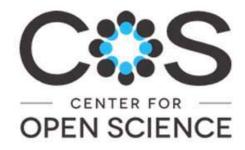
Employers:

- Read papers rather than note journal
- Recruitment & Promotion: seek evidence of commitment to Open Practices
- Reward team/community/support work "scientific citizenship"

Guidance/Hope







https://osf.io/



https://www.ukrn.org/



https://reproducibilitea.org/





https://www.bnacredibility.org.uk/

Overview





- Registration
 - Study Registration (eg OSF)
 - Registered Reports
 - Pre-Registration Posters
- Statistical analysis
 - Power and PPV
 - Bayesian Statistics
 - Sequential Designs
- Sharing Data and Code
 - FAIR principles
 - Incentivising
 - GDPR
- Publication
 - Open Access
 - Preprints
 - Open Review
- Research Culture
 - DORA
 - CRediT
 - Narrative CVs