Reproducible Research through Open Science

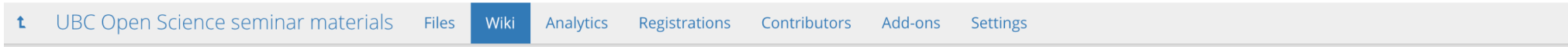
October 24, 2019

Supporting materials at
https://osf.io/vgjpq/

Jason Pither (UBC Okanagan, Biology) & Mathew Vis-Dunbar (UBC SMP Librarian)

With additional materials from the Open Science Ambassadors Program
at the Center for Open Science

CENTER FOR OPEN SCIENCE



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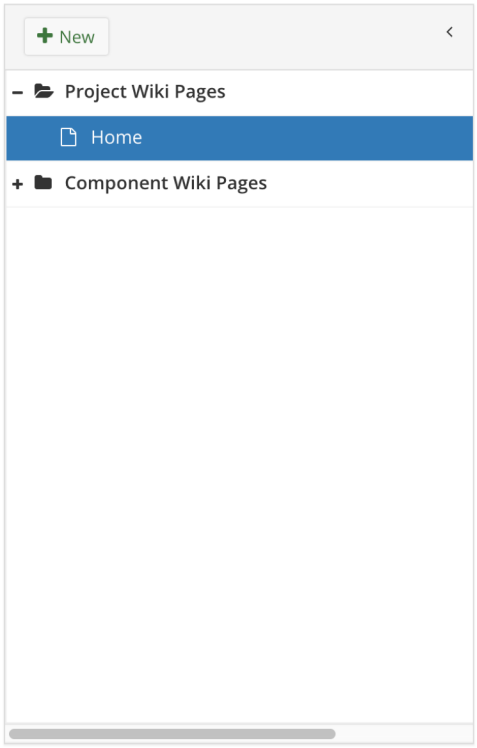

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UBC Open Science

This OSF component links to resources referred to in Open Science seminars and workshops delivered at the University of British Columbia.

Presentations

- Presentations delivered at UBC are available here.

Articles openly available as PDFs

- Some OS-related resources are provided as PDF documents, which are available for download from the files page, and links to others are provided below.

Articles open online

Smaldino, P.E. and McElreath, R. 2016. The natural selection of bad science. Royal Society Open Science.

Ali-Khan, S.E., Jean, A., and Gold, R.E. 2018. Identifying the challenges in implementing Open Science. MNI Open Research.

Campbell et al. 2019. Early career researchers embrace data sharing. Trends Ecol. Evol. 24:95-98.

Nelson et al. 2018. Psychology's renaissance. Ann. Rev. Psych. 69:511-534.

Nosek et al. 2017. The pregistration revolution. PNAS.

Nosek et al. 2015. Estimating the reproducibility of psychological science. Science, 349.

Simmons et al. 2011. False-positive psychology: undisclosed flexibility in data collection and analysis allows presenting anything as significant. Psych. Sci. 22(11):1359-1366.

Plesser. 2018. Reproducibility vs. Replicability: a brief history of a confused terminology. Frontiers in Neuroinformatics. 11:1-4.

*Lazic et al. 2018. What exactly is "n" in cell culture and animal experiments? *please be sure to read the commentary that corrects serious flaws with the Lazic et al. article

Reproducibility bibliography

- Librarians at the University of Minnesota maintain excellent discipline-specific bibliographies pertaining to reproducibility.

General OS resources

- Transparency and Openness Promotion Guidelines

Background

Problem

- Irreproducible research
- Sources of the problem

Solutions

- Practices that improve reproducibility – Open Science
- Other benefits of Open Science best practices
- Tools that facilitate Open Science best practices

Open Science initiatives at UBC

- Excellence fund strategic initiative
- Okanagan pilot project

Discussion / Q&A

Terminology

Computational Reproducibility:

If we took your data and code/analysis scripts and reran it, we can reproduce the numbers/graphs in your paper

Methods Reproducibility:

We have enough information to rerun the experiment or survey the way it was originally conducted

Results Reproducibility/Replicability:

We reproduce the methods (as above), collect new data, and get the same statistical conclusion

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Foundational to science

Terminology

One of many possible definitions of **Open Science:**

Scientific research conducted and communicated in an honest, accessible, and transparent way, such that independent researchers can reproduce the results

OPEN LETTER

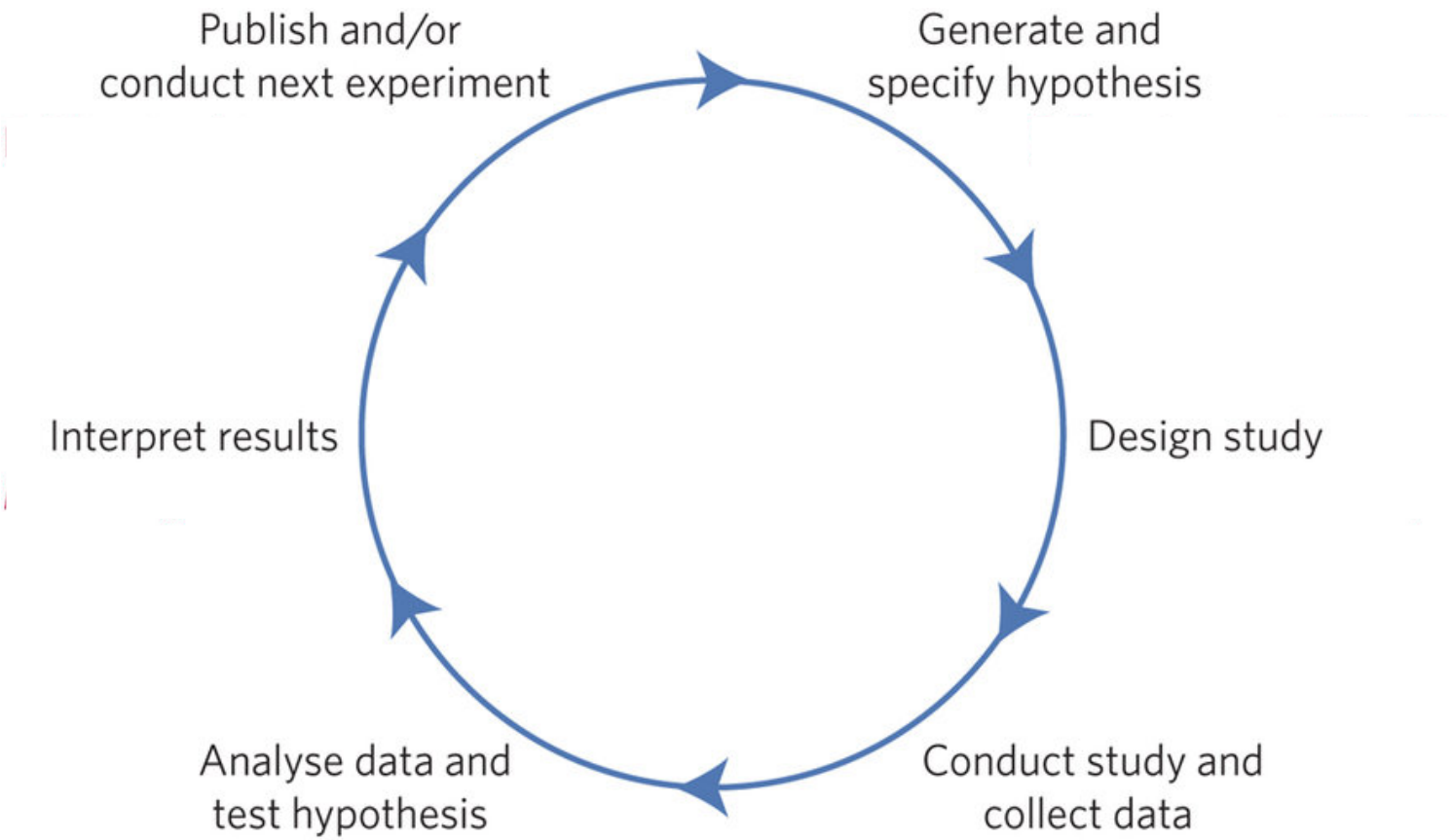
Identifying the challenges in implementing open science [version 1; referees: 2 approved]

Sarah E. Ali-Khan [1,2], Antoine Jean[1], E. Richard Gold [1,3]

MNI Open Research 2018, 2:5 Last updated: 04 FEB 2019

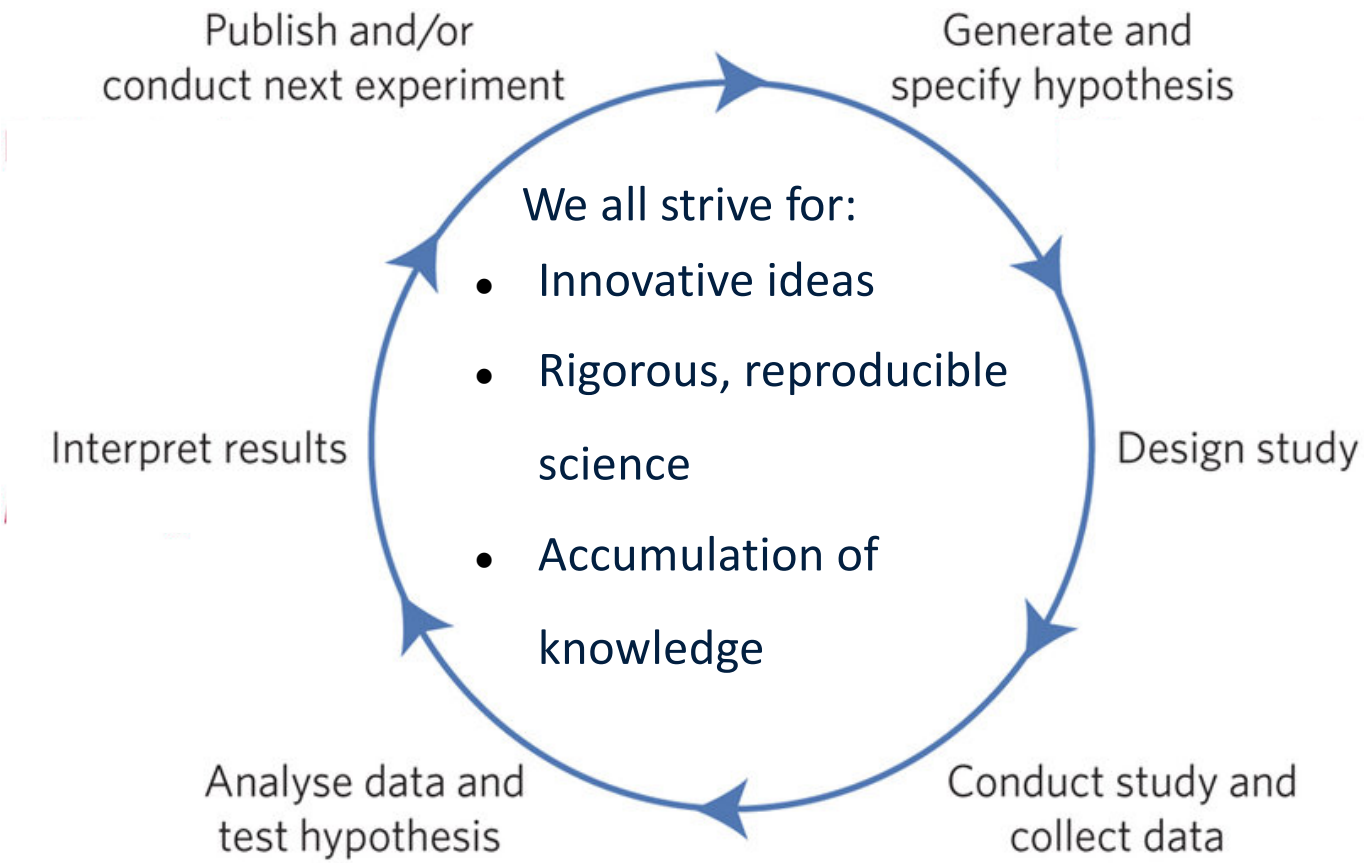
Open science (OS) comprises a set of institutional policies, infrastructure and relationships related to open access publication, open data and scientific resources, and lack of restrictive intellectual and other proprietary rights with the goal of increasing the quality and credibility of scientific outputs, increasing efficiency, and spurring both discovery and innovation.

Hypothetico-Deductive Model of the Scientific Method



Note distinction between Confirmatory studies vs Exploratory studies

Hypothetico-Deductive Model of the Scientific Method



The problem

Questionable methods infiltrate the research workflow at various stages (typically unwittingly!), ultimately yielding **irreproducible** research.

Science is broken?

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

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

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.

Believe it or not: how much can we rely on published data on potential drug targets?

NATURE REVIEWS | DRUG DISCOVERY

Florian Prinz, Thomas Schlange and Khusru Asadullah

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 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.

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

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 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 × 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 $1 - \beta$ (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 c 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. The PPV is also the complementary probability of what Wacholder et al. have called the false positive report probability [10]. According to the 2 × 2 table, one gets $PPV = (1 - \beta)R/(R - \beta R + \alpha)$. A research finding is thus

Citation: Ioannidis JPA (2005) Why most published research findings are false. PLoS Med 2(8): e124.

Abbreviation: PPV, positive predictive value

John P. A. Ioannidis is in the Department of Hygiene and Epidemiology, University of Ioannina School of Medicine, Ioannina, Greece, and Institute for Clinical Research and Health Policy Studies, Department of Medicine, Tufts-New England Medical Center, Tufts University School of Medicine, Boston, Massachusetts, United States of America. E-mail: jioannid@cc.uoi.gr

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

DOI: 10.1371/journal.pmed.0020124

Science is broken?

Unreliable research

Trouble at the lab

The Economist

Scientists like to think of science as self-correcting. To an alarming degree, it is not

THE WEEK

Big Science is broken

Pascal-Emmanuel Gobry

https://theweek.com/articles/618141/big-science-broken

SCIENCE

Science Is Broken. How Much Should We Fix It?

More rigor in research could stamp out false positive results. It might also do more harm than good.

By DANIEL ENGBER

SLATE
THE WORKIEST WORKISTS OF ALL

MAY 05, 2017 • 5:56 AM

Reproducibility is not the norm

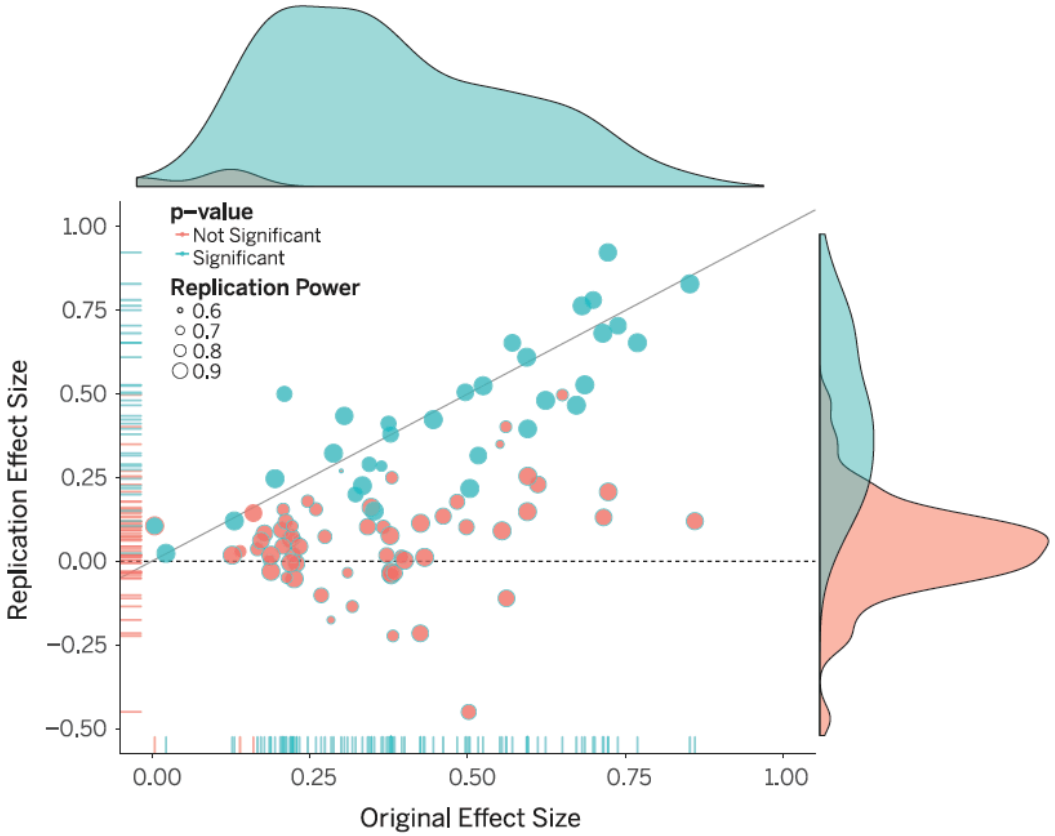
RESEARCH ARTICLE SUMMARY

PSYCHOLOGY

Estimating the reproducibility of psychological science (2015)

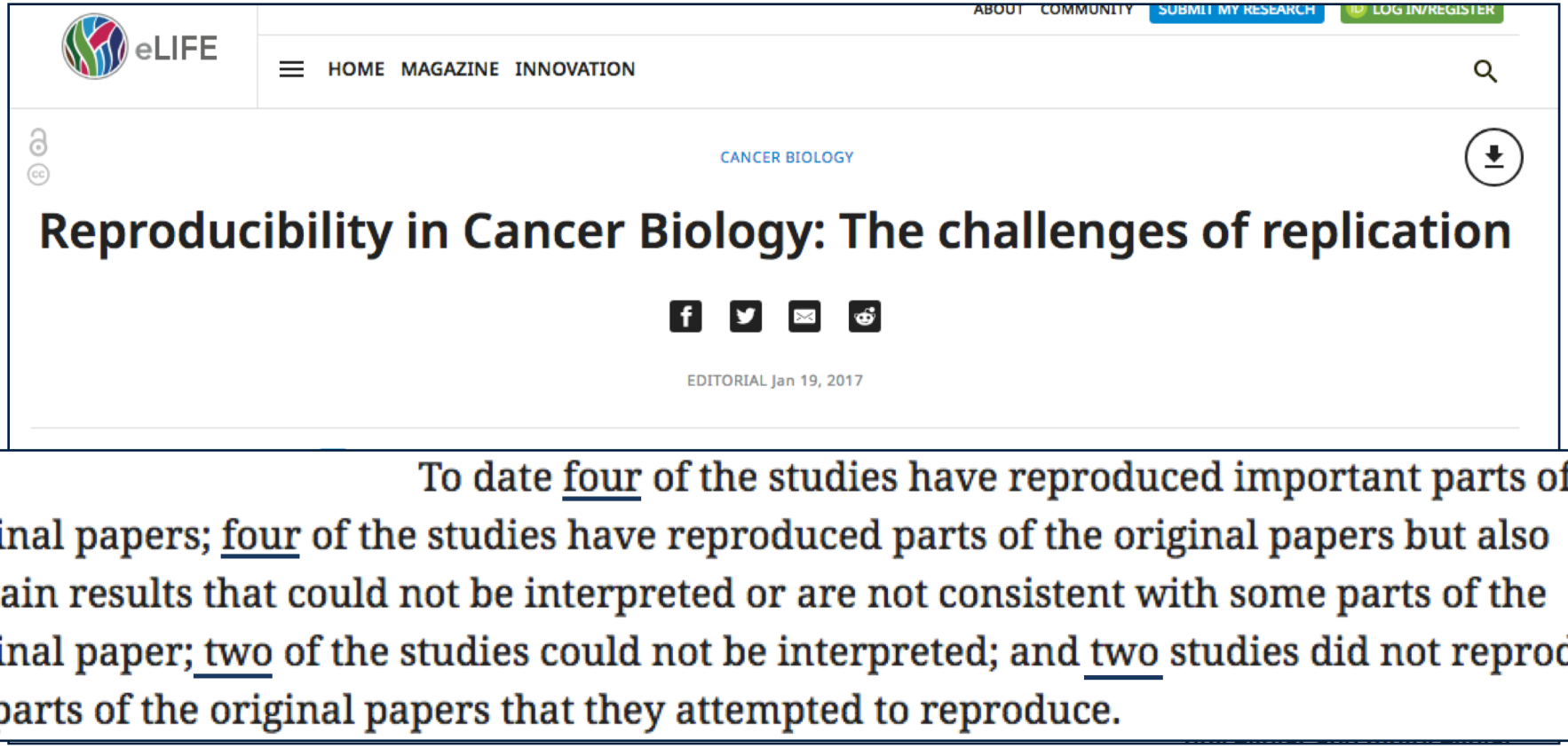
Open Science Collaboration*

- **100 studies** published in **3 psychology journals**
- Used high-powered designs and original materials
- **36%** of studies were able to be reproduced



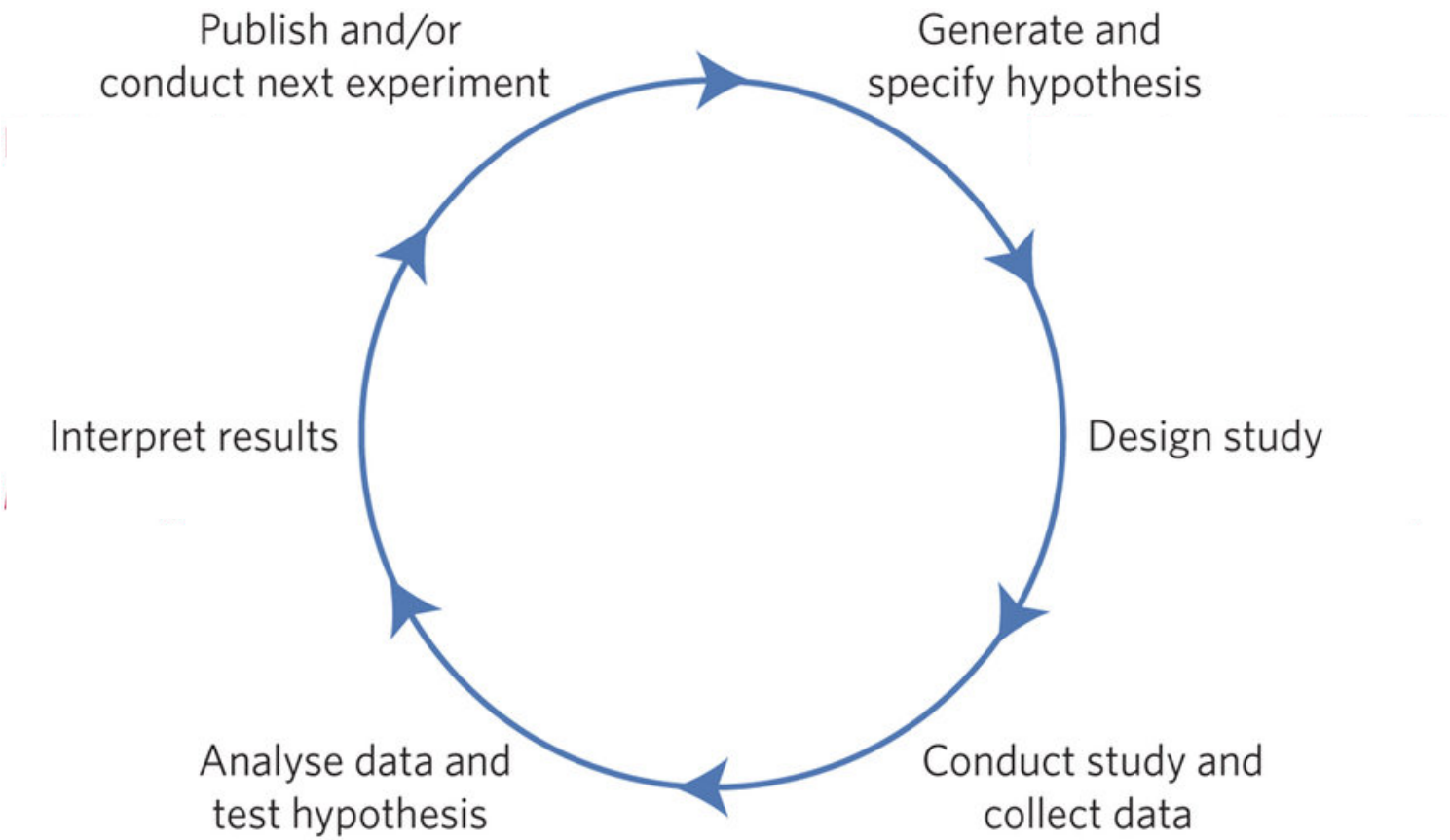
Original study effect size versus replication effect size (correlation coefficients). Diagonal line represents replication effect size equal to original effect size. Dotted line represents replication effect size of 0. Points below the dotted line were effects in the opposite direction of the original. Density plots are separated by significant (blue) and nonsignificant (red) effects.

Reproducibility is not the norm



To date four of the studies have reproduced important parts of the original papers; four of the studies have reproduced parts of the original papers but also contain results that could not be interpreted or are not consistent with some parts of the original paper; two of the studies could not be interpreted; and two studies did not reproduce the parts of the original papers that they attempted to reproduce.

Sources of the problem



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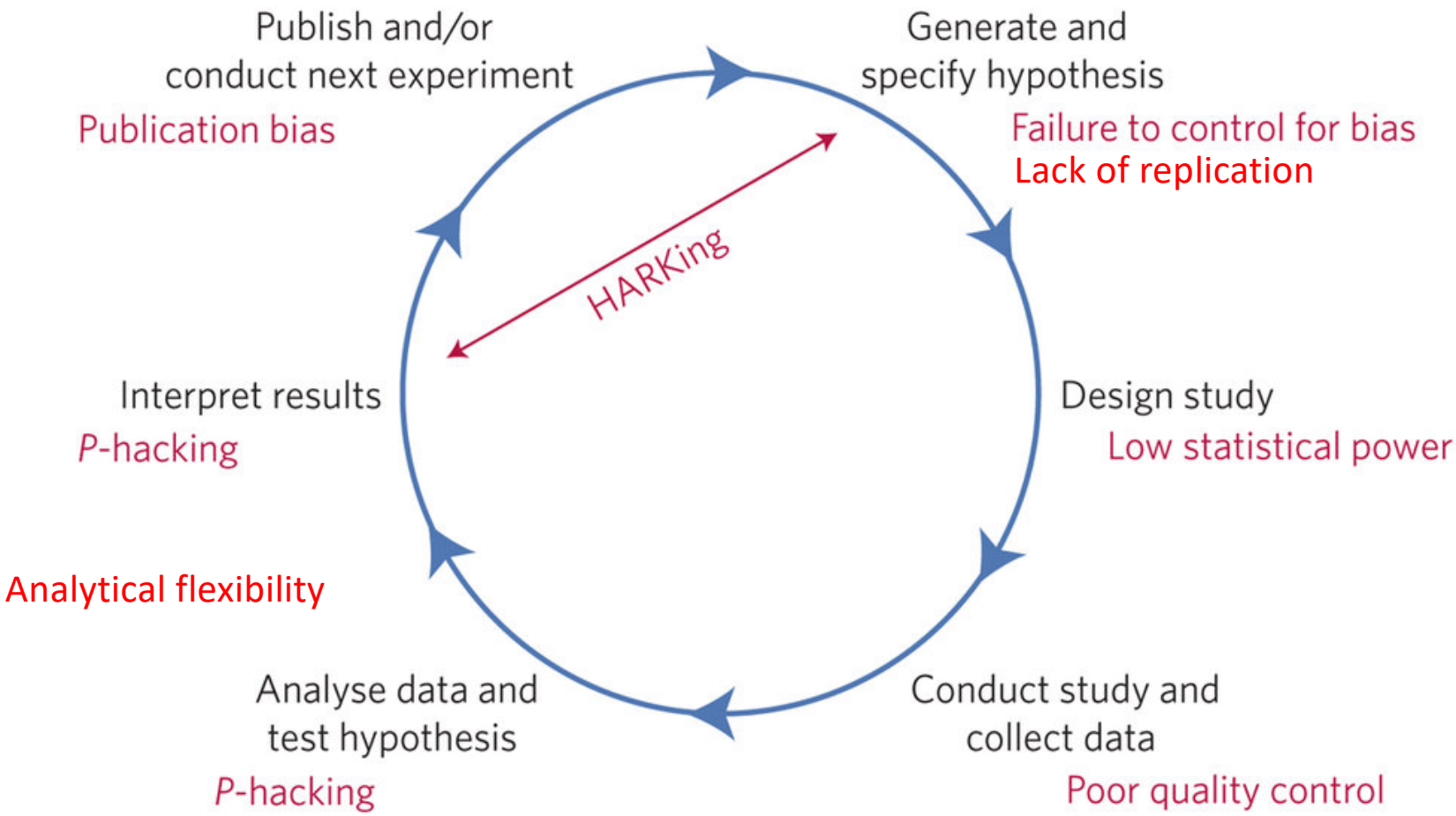
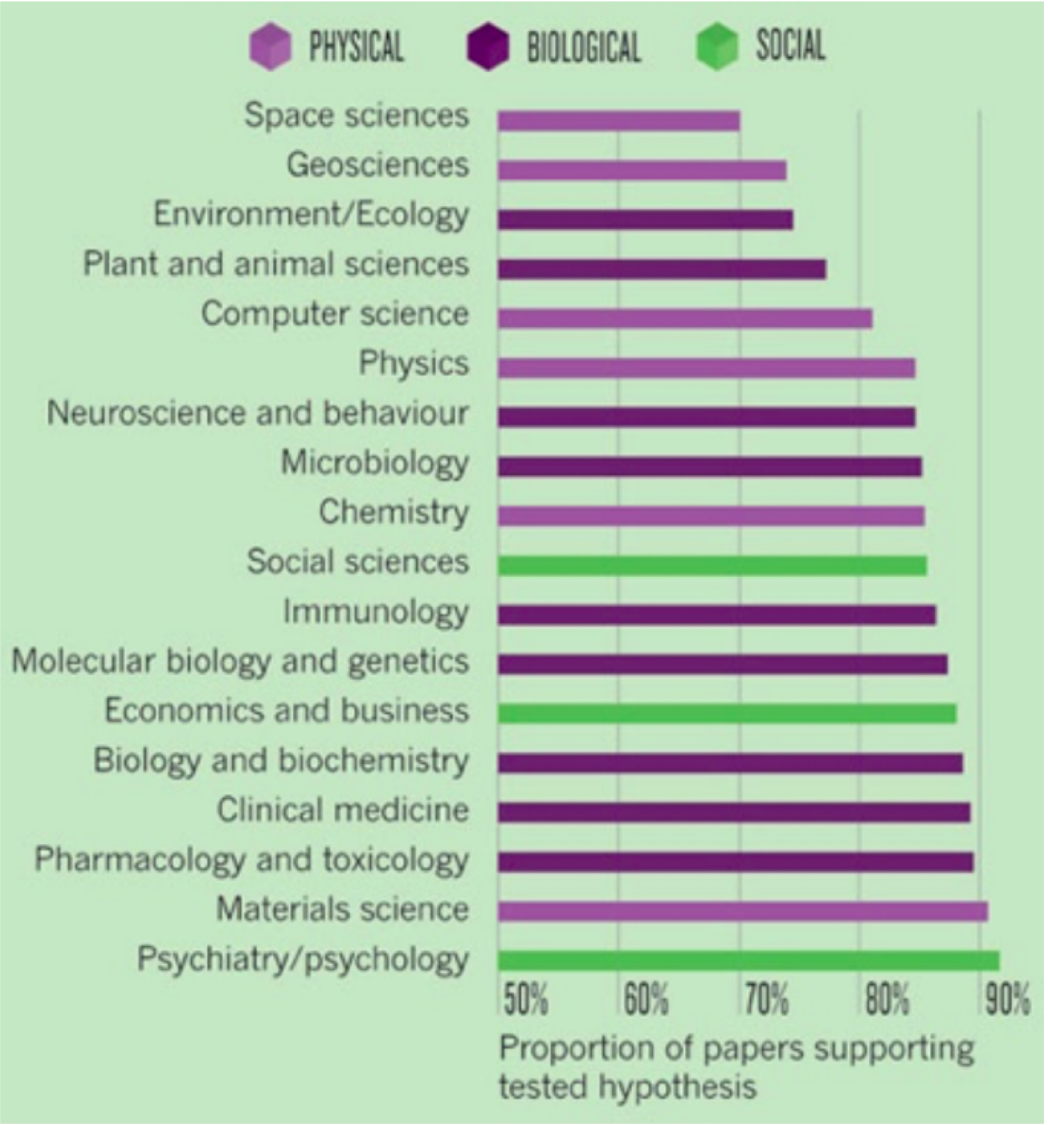


Publication bias: positive results

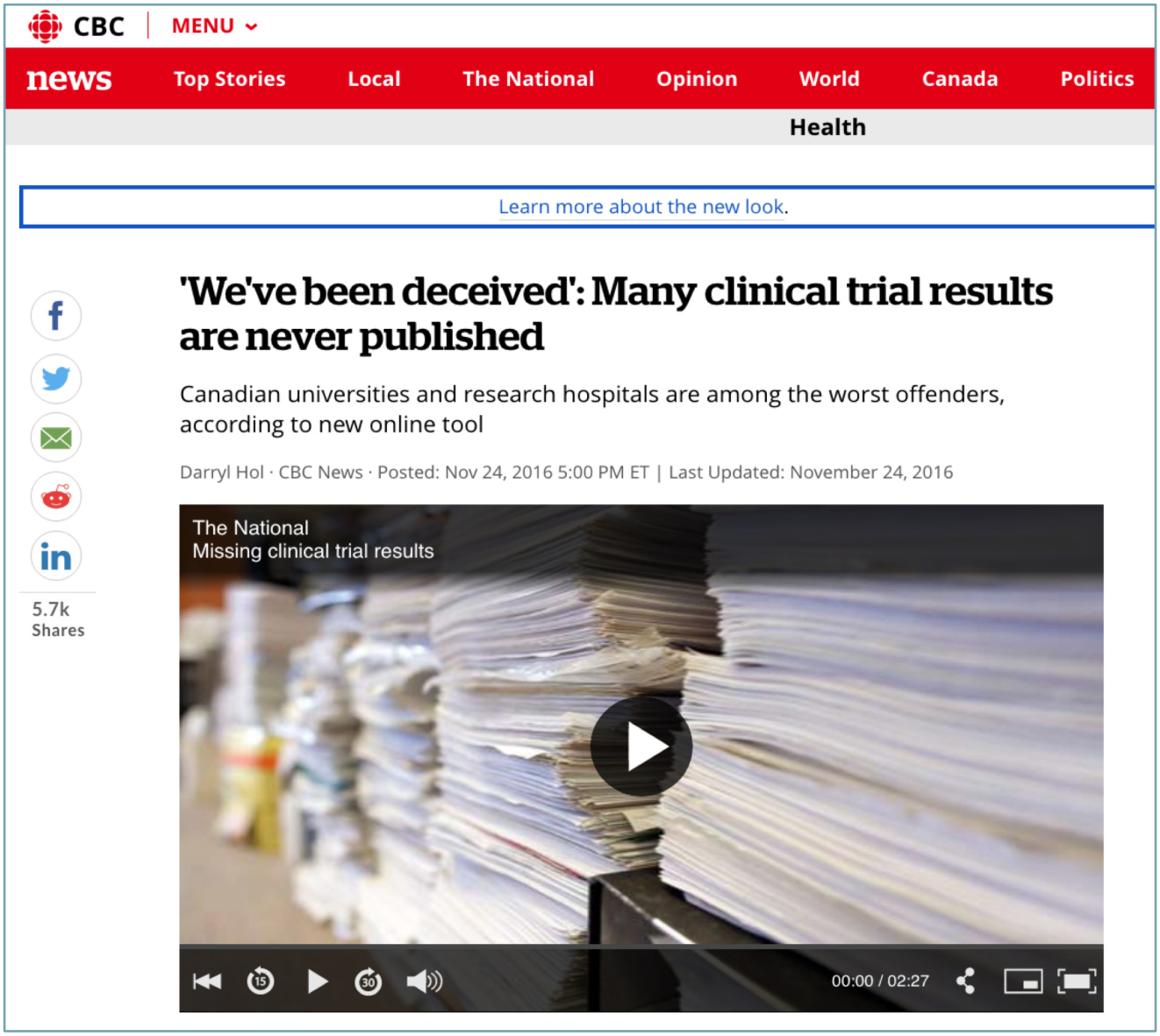
Positive Results by Discipline



Fanelli D (2010) "Positive" Results Increase Down the Hierarchy of the Sciences.
PLOS ONE 5(4): e10068. CC-BY
doi:10.1371/journal.pone.0010068

PLOS | ONE

Publication bias: file drawer



Publication bias: file drawer

University or Institution	Proportion of registered trials missing results (%)
U. Health Network	76.3
U. of Calgary	75.8
U. of British Columbia	**72.4**
Queen's University	70.2
U. of Manitoba	67.2
U. of Alberta	66.7
U. of Toronto	65.5
Ottawa Hospital Research Institute	63.8
Hospital for Sick Children	62.1
	69.9

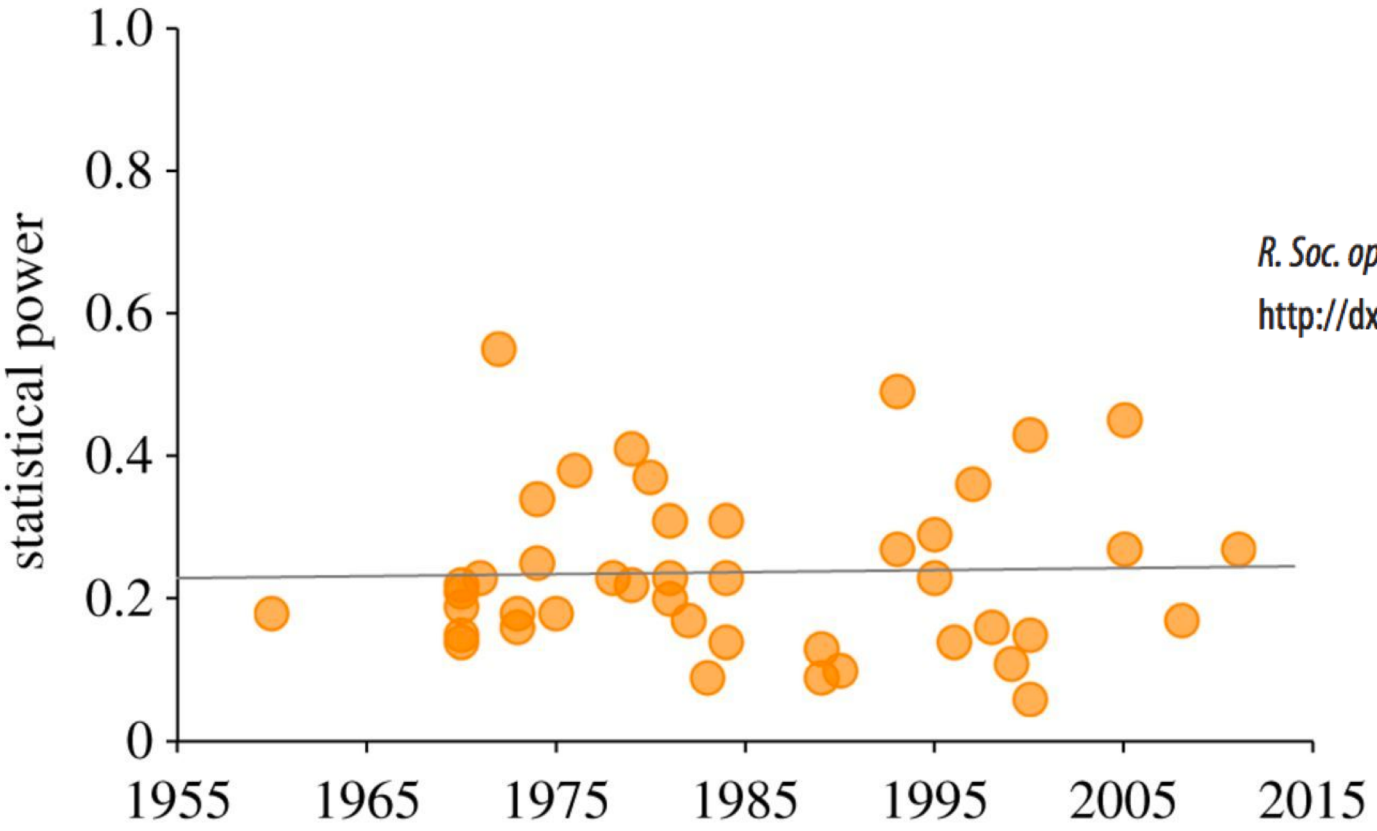
Natural selection of bad science

"The persistence of poor methods results partly from incentives that favour them, leading to the **natural selection of bad science**. This dynamic requires no conscious strategizing—no deliberate cheating nor loafing—by scientists, only that publication is a principal factor for career advancement. Some normative methods of analysis have almost certainly been selected to further publication instead of discovery. (...)

As in the real world, successful labs produce more 'progeny,' such that their methods are more often copied and their students are more likely to start labs of their own. **Selection for high output leads to poorer methods and increasingly high false discovery rates.**"

Smaldino, P. E. & McElreath, R. (2016). The natural selection of bad science. *Royal Society Open Science*, *3*, 160384.

Low power



R. Soc. open sci. **3**: 160384.
http://dx.doi.org/10.1098/rsos.160384

Average statistical power from 44 reviews of papers published in journals in the social and behavioural sciences between 1960 and 2011. Data are power to detect small effect sizes (d=0.2), assuming a false-positive rate of α=0.05, and indicate both very low power (mean=0.24) but also no increase over time (R^2=0.00097).

Low power

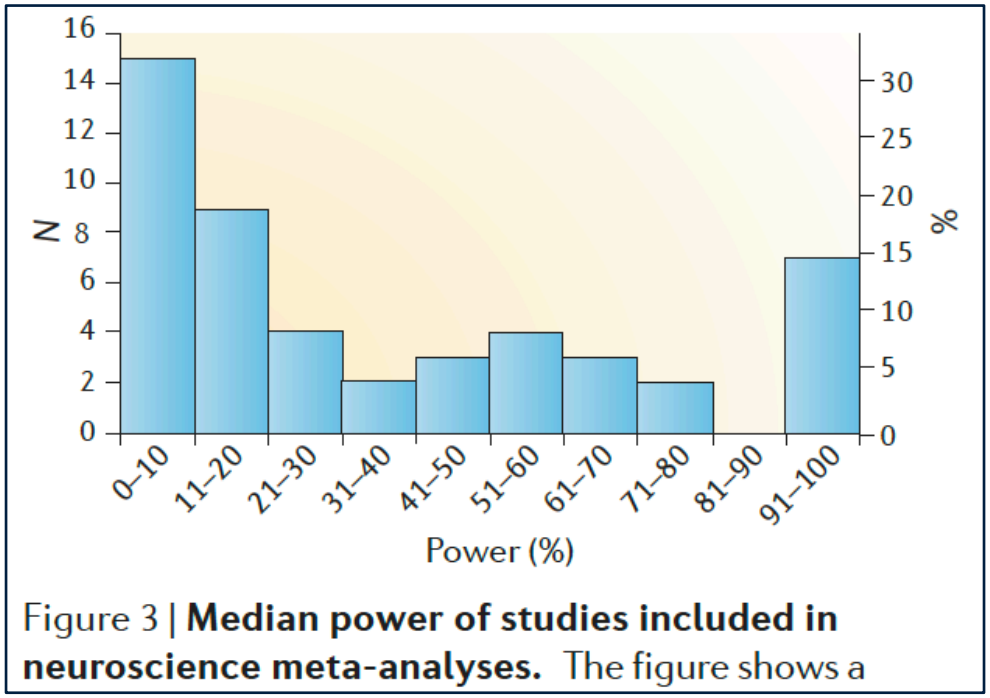


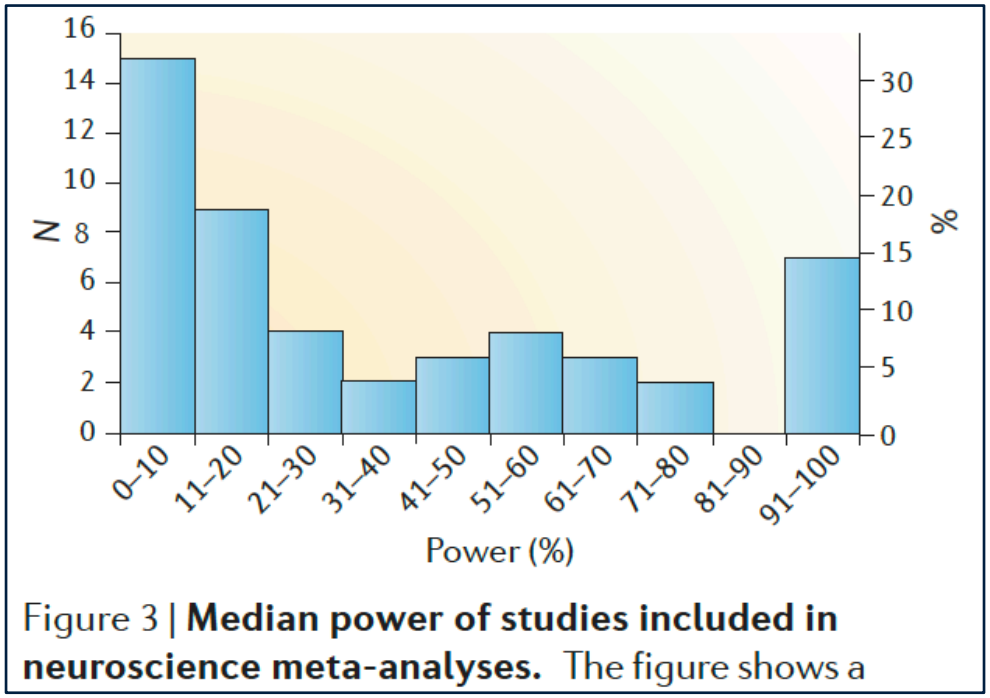
Figure 3 | **Median power of studies included in neuroscience meta-analyses.** The figure shows a

N = 49 studies

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

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

Low power



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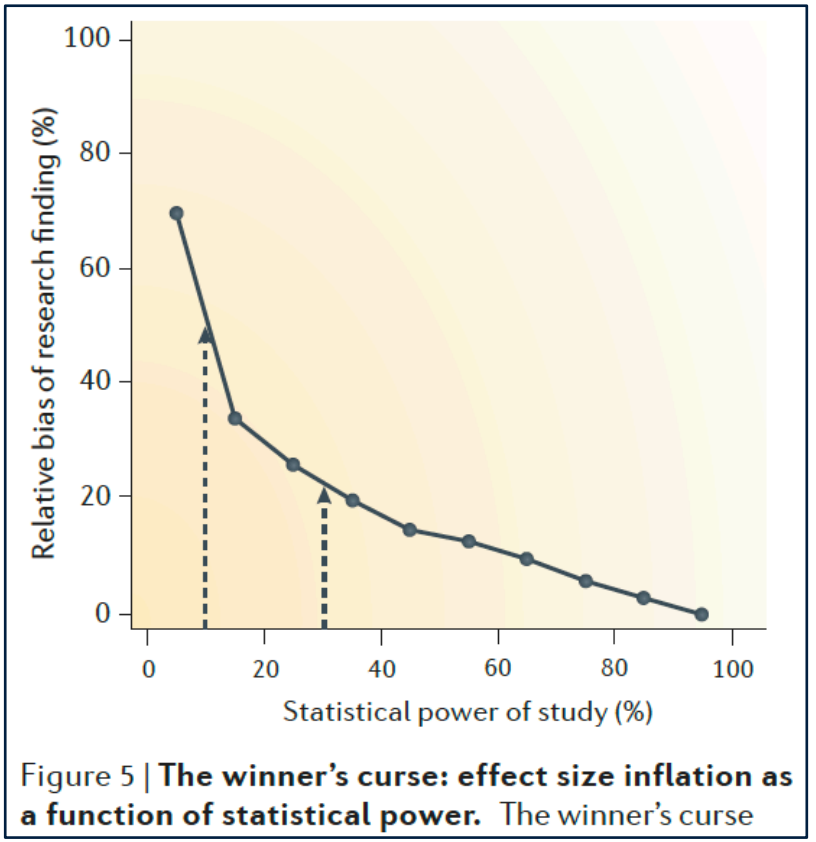

Figure 5 | **The winner's curse: effect size inflation as a function of statistical power.** The winner's curse

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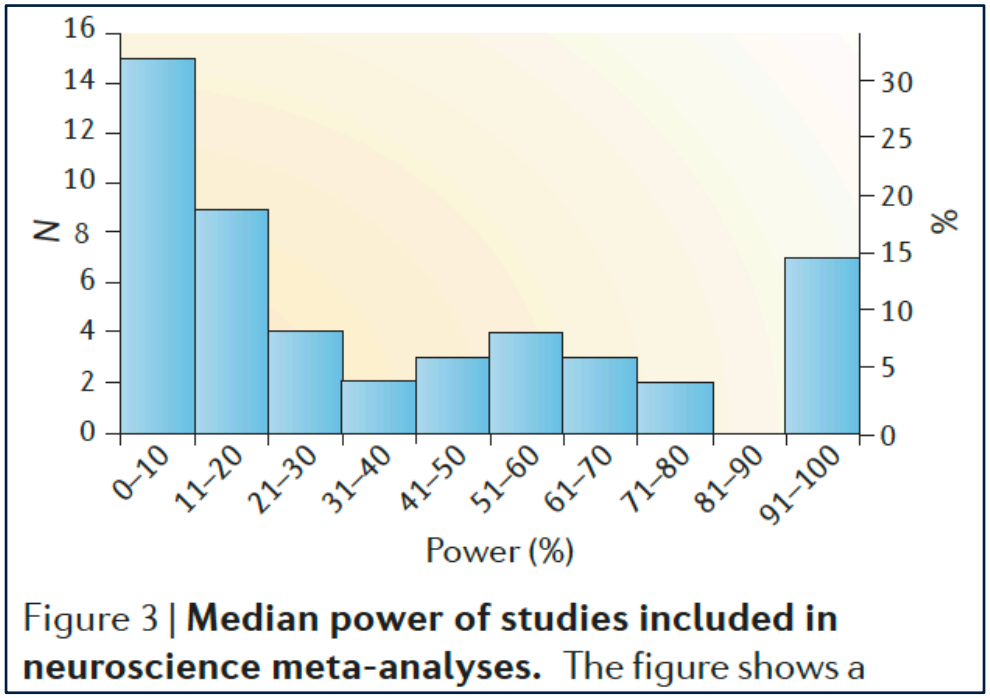

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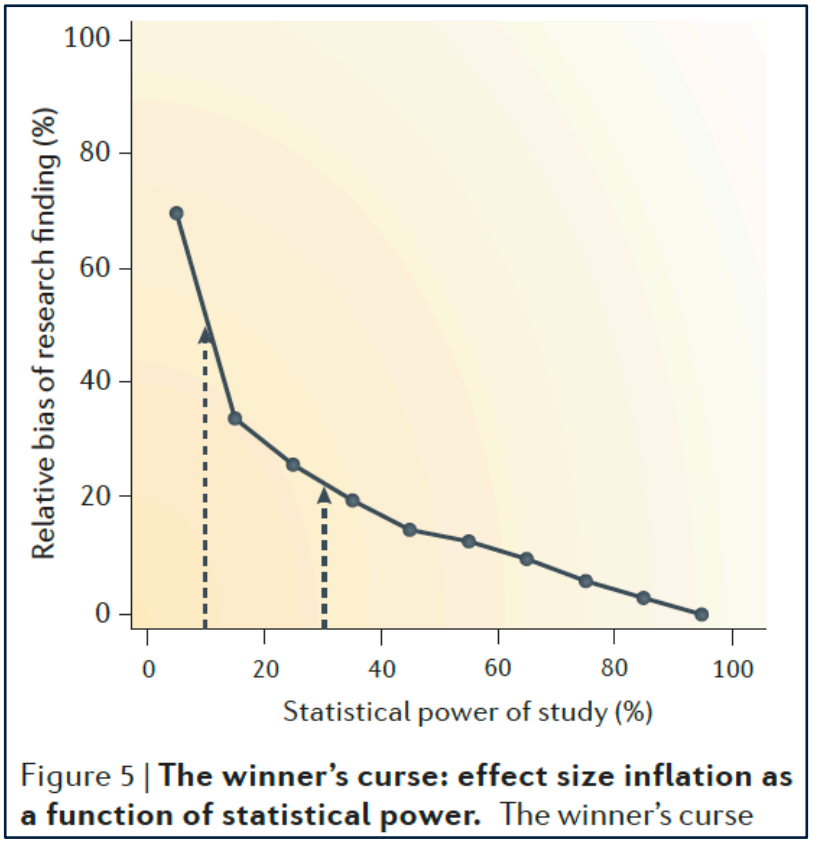

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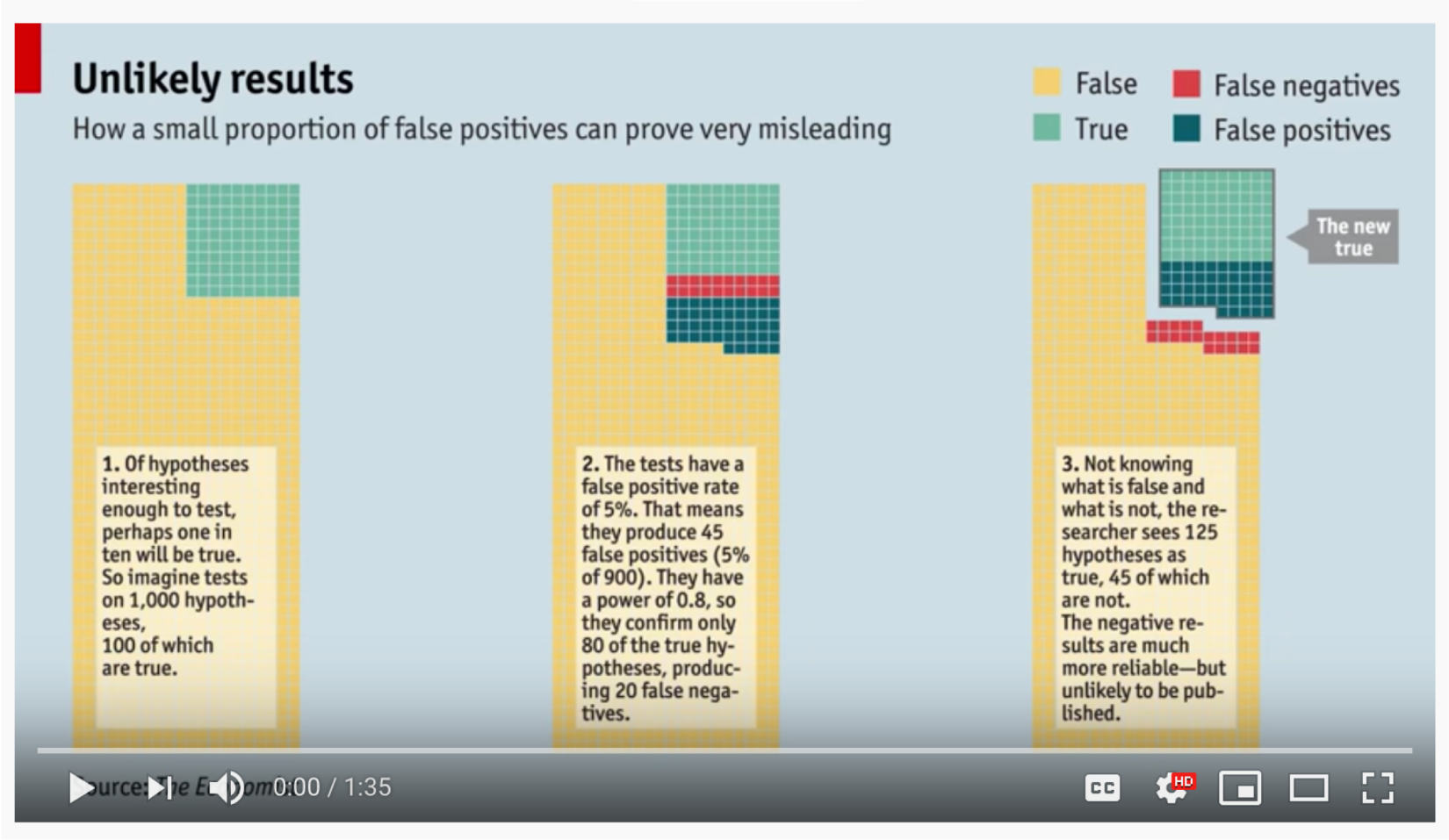
Low power studies are prone to inflated effect sizes (even if no true effect is present)!


Unlikely results
How a small proportion of false positives can prove very misleading
False
False negatives
True
False positives
The new true
1. Of hypotheses interesting enough to test, perhaps one in ten will be true. So imagine tests on 1,000 hypotheses, 100 of which are true.
2. The tests have a false positive rate of 5%. That means they produce 45 false positives (5% of 900). They have a power of 0.8, so they confirm only 80 of the true hypotheses, producing 20 false negatives.
3. Not knowing what is false and what is not, the researcher sees 125 hypotheses as true, 45 of which are not. The negative results are much more reliable—but unlikely to be published.
0:00 / 1:35

Ecology, 97(10), 2016, pp. 2554–2561

Underappreciated problems of low replication in ecological field studies

NATHAN P. LEMOINE,[1] AVA HOFFMAN, ANDREW J. FELTON, LAUREN BAUR, FRANCIS CHAVES, JESSE GRAY, QIANG YU,[2] AND MELINDA D. SMITH

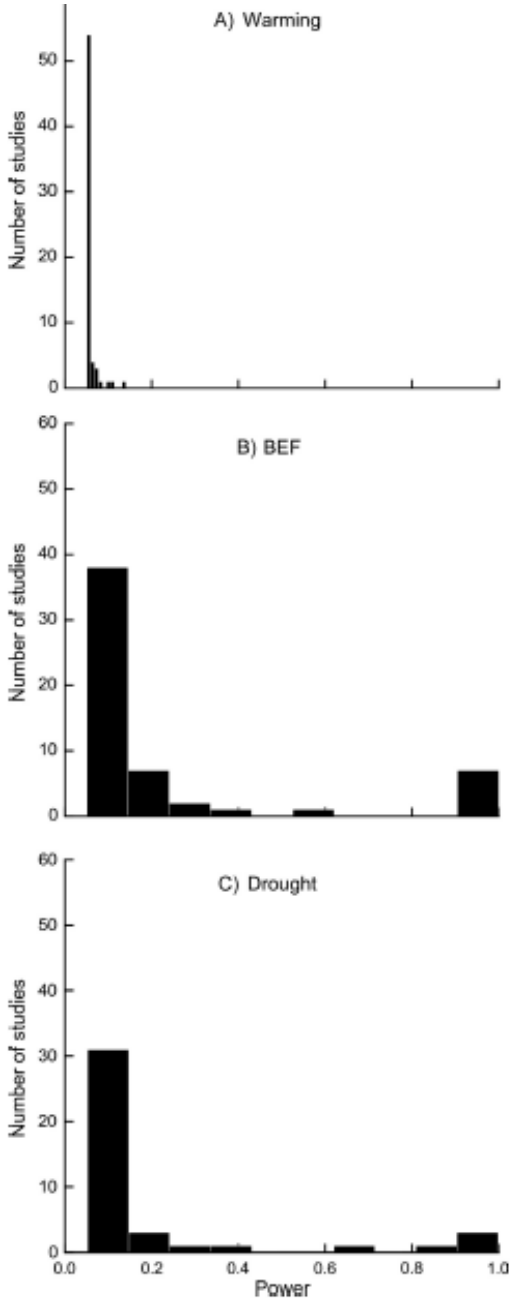
Department of Biology, Graduate Degree Program in Ecology, Colorado State University, Fort Collins, Colorado 80523 USA

Abstract. The cost and difficulty of manipulative field studies makes low statistical power a pervasive issue throughout most ecological subdisciplines. Ecologists are already aware that small sample sizes increase the probability of committing Type II errors. In this article, we address a relatively unknown problem with low power: underpowered studies must overestimate small effect sizes in order to achieve statistical significance. First, we describe how low replication coupled with weak effect sizes leads to Type M errors, or exaggerated effect sizes. We then conduct a meta-analysis to determine the average statistical power and Type M error rate for manipulative field experiments that address important questions related to global change; global warming, biodiversity loss, and drought. Finally, we provide recommendations for avoiding Type M errors and constraining estimates of effect size from underpowered studies.

Type “M” error:

Quantifies the proportion by which the critical value must exceed the effect size in order to achieve statistical significance

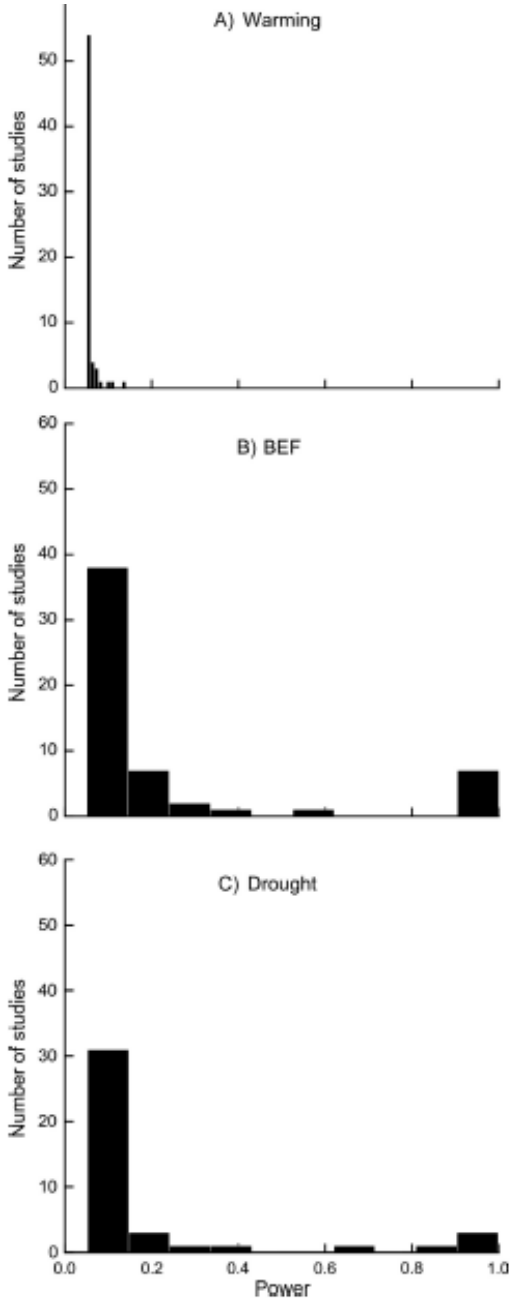
Ecological experiments on climate change typically have very low power.



Ecological experiments on climate change typically have very low power.

Type “M” error rates:

Warming/biomass: 3.29 +/- 0.23
BEF: 1.42 +/- 0.08
Drought: 0.66 +/- 0.1



Researcher degrees of freedom

All data processing and analytical choices made after seeing and interacting with your data

Results become data dependent, and no longer adhere to the original hypothesis testing model

Researcher degrees of freedom

- Should more data be collected?
- Should I exclude this ”outlier”? Is it an ”outlier”?
- These extra variables I measured, should they be used?
- This analysis seems to behave better than the other…
- Which variable should I use as my main dependent variable?
- How should I treat this covariate?

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- How should I treat this covariate?

Often feel very reasonable and logical in the moment, but…

Inflates false-positive rates and *P*-values become uninformative

Researcher degrees of freedom

Table 1. Likelihood of Obtaining a False-Positive Result

	Significance level		
Researcher degrees of freedom	$p < .1$	$p < .05$	$p < .01$
Situation A: two dependent variables ($r = .50$)	17.8%	9.5%	2.2%
Situation B: addition of 10 more observations per cell	14.5%	7.7%	1.6%
Situation C: controlling for gender or interaction of gender with treatment	21.6%	11.7%	2.7%
Situation D: dropping (or not dropping) one of three conditions	23.2%	12.6%	2.8%
Combine Situations A and B	26.0%	14.4%	3.3%
Combine Situations A, B, and C	50.9%	30.9%	8.4%
Combine Situations A, B, C, and D	81.5%	60.7%	21.5%

Joseph P. Simmons[1], Leif D. Nelson[2], and Uri Simonsohn[1]
[1]The Wharton School, University of Pennsylvania, and [2]Haas School of Business, University of California, Berkeley

Psychological Science
22(11) 1359–1366

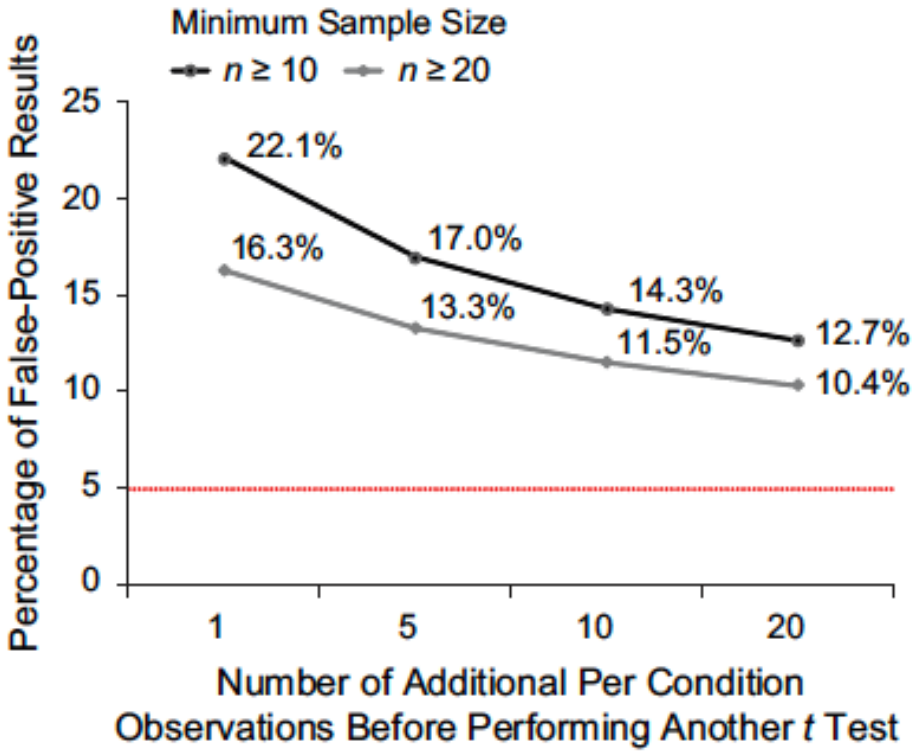

Fig. 1. Likelihood of obtaining a false-positive result when data collection ends upon obtaining significance ($p \leq .05$, highlighted by the dotted line). The figure depicts likelihoods for two minimum sample sizes, as a function of the frequency with which significance tests are performed.

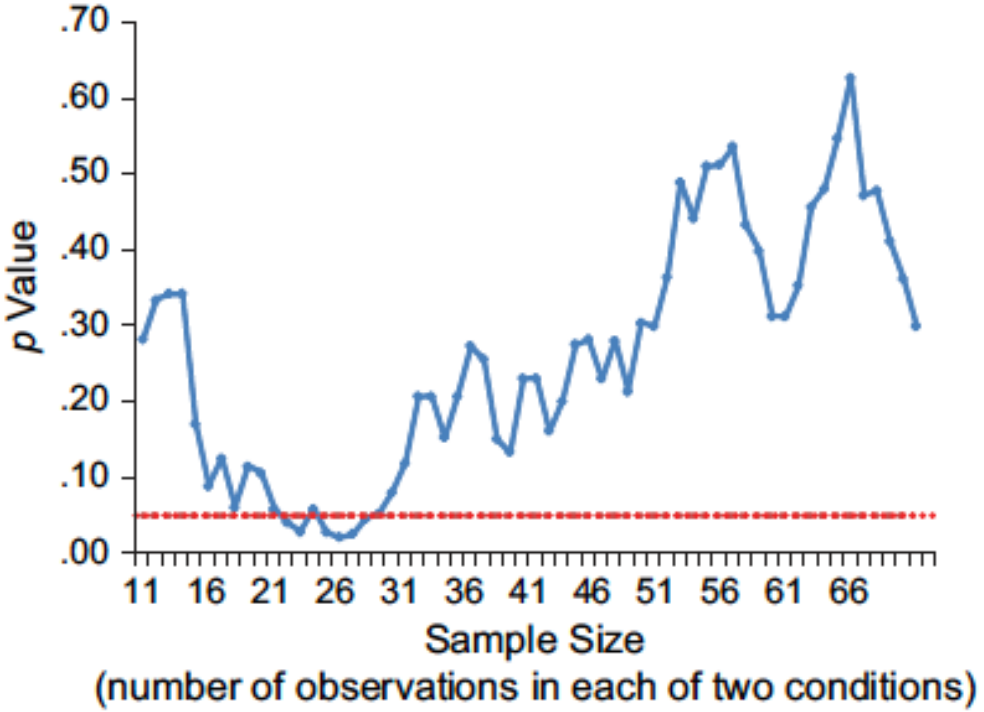

Fig. 2. Illustrative simulation of p values obtained by a researcher who continuously adds an observation to each of two conditions, conducting a t test after each addition. The dotted line highlights the conventional significance criterion of $p \leq .05$.

Joseph P. Simmons[1], Leif D. Nelson[2], and Uri Simonsohn[1]
[1]The Wharton School, University of Pennsylvania, and [2]Haas School of Business, University of California, Berkeley

Psychological Science
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Low power revisited

Degrees of Freedom in Planning, Running, Analyzing, and Reporting Psychological Studies: A Checklist to Avoid *p*-Hacking

Jelte M. Wicherts, Coosje L. S. Veldkamp, Hilde E. M. Augusteijn, Marjan Bakker, Robbie C. M. van Aert and Marcel A. L. M. van Assen*

REVIEW
published: 25 November 2016
doi: 10.3389/fpsyg.2016.01832

Sampling variability is larger with small sample sizes, and many decisions made in analyzing the data will have proportionately larger effects when sample sizes are smaller. In other words, using researcher DFs to obtain statistically significant results is typically more effective with smaller samples

Inaccessible data

META-RESEARCH ARTICLE
PLOS Biology | https://doi.org/10.1371/journal.pbio.2006930 November 20, 2018

Reproducible research practices, transparency, and open access data in the biomedical literature, 2015–2017

Joshua D. Wallach[1,2], Kevin W. Boyack[3], John P. A. Ioannidis[4,5,6,7,8]*

N = 149 randomly selected articles

Inaccessible data

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Among the 104 articles with empirical data in which protocols or data sharing would be pertinent, **19** (18.3% [11.6% to 27.3%]) discussed publicly available data; only one (1.0% [0.1% to 6.0%]) included a link to a full study protocol.

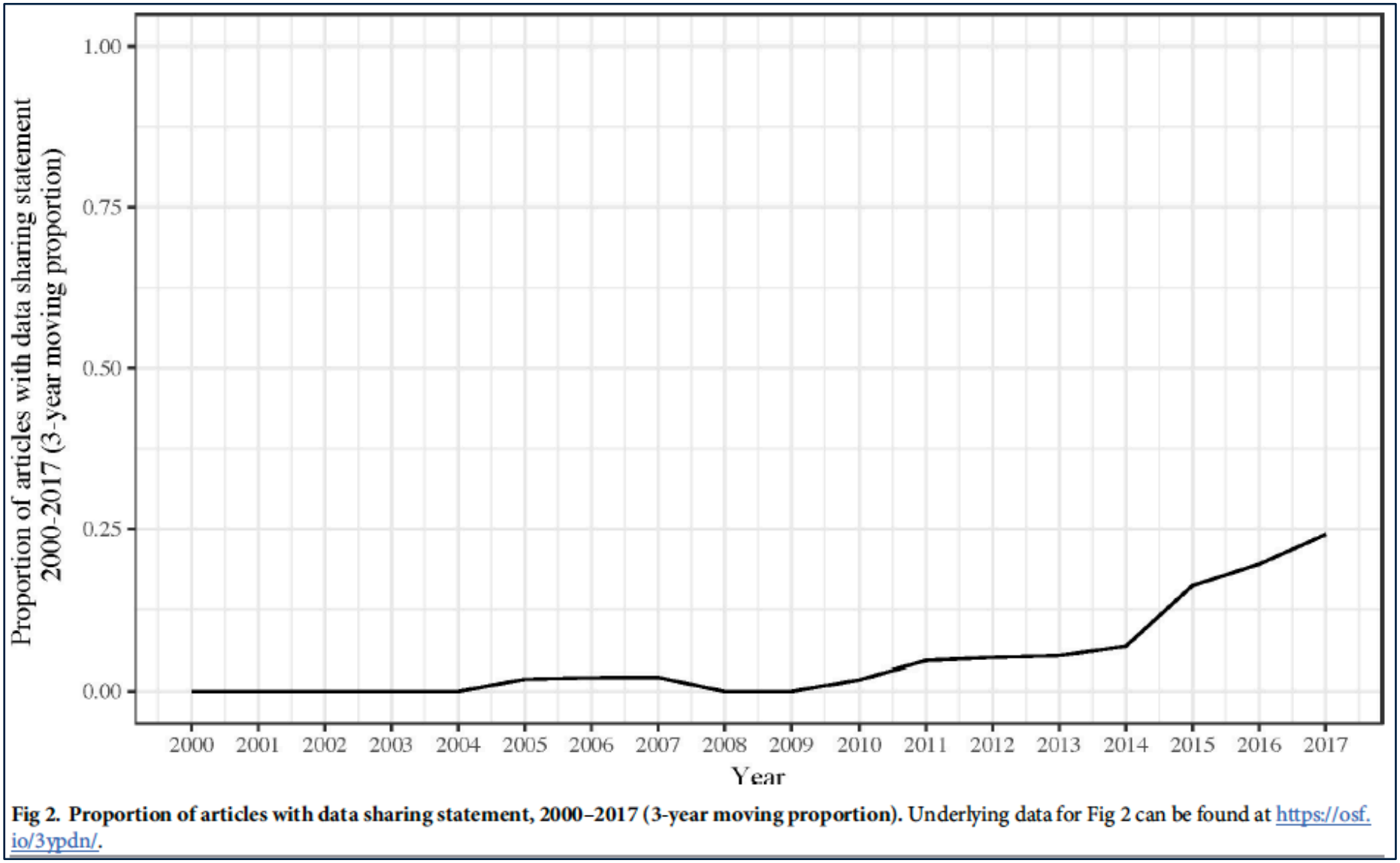
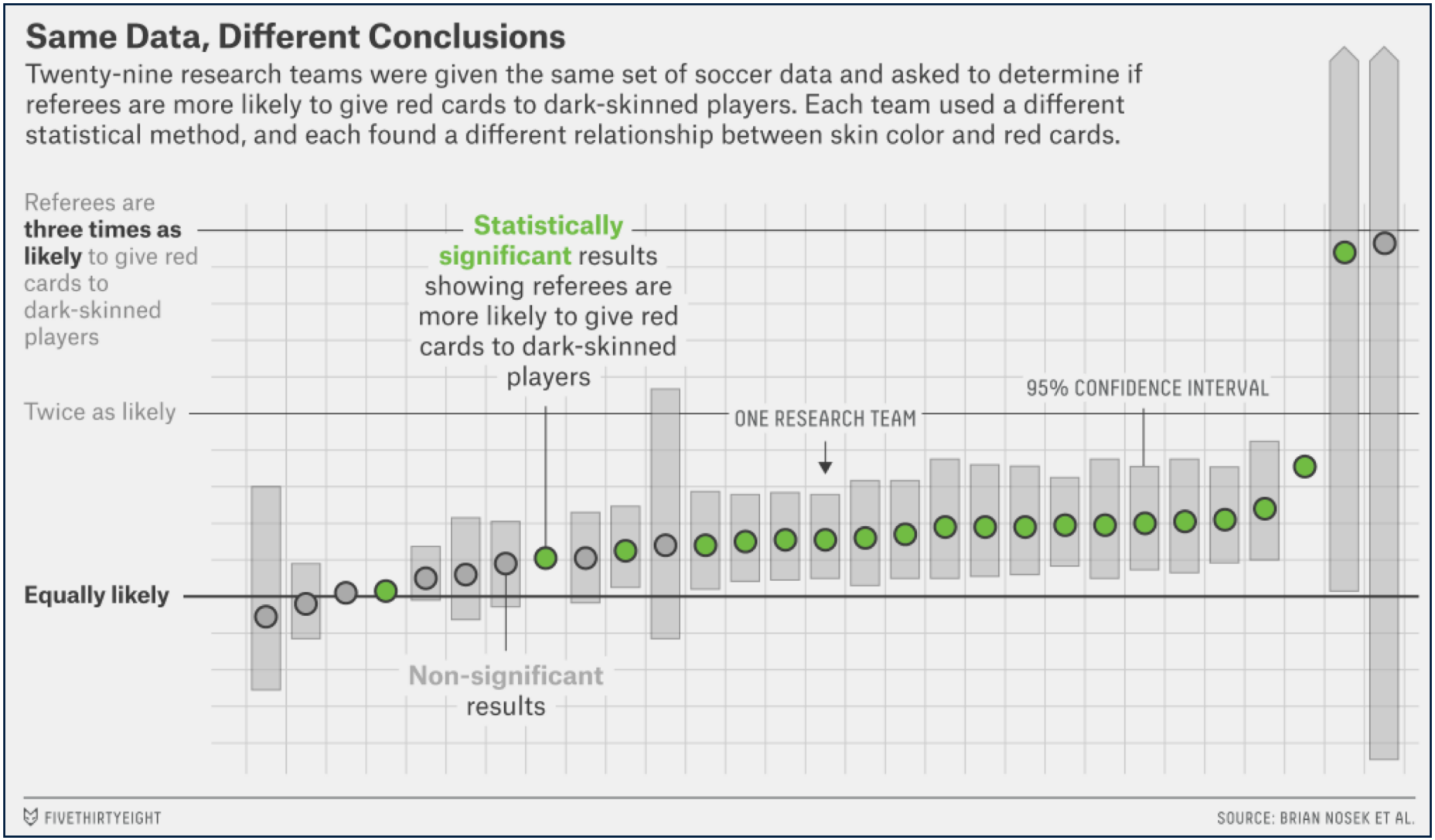


Fig 2. Proportion of articles with data sharing statement, 2000–2017 (3-year moving proportion). Underlying data for Fig 2 can be found at https://osf.io/3ypdn/.

Analytical flexibility



A solution: practice Open Science

The workflow is key

Vast majority of the scientific workflow is obscured*

As a result:

- Hard to reproduce others' work
- Hard to reproduce our own work!
- Difficult to accumulate unpublished knowledge, or to use published results for additional analyses (e.g. meta-analyses)

* Some scientific disciplines (e.g. physics) better than others

Typical workflow

Ideal workflow

Stage 2
Peer Review

Stage 1
Pre-registration &
Peer Review
"Registered report"

Ideal workflow

Stage 2
Peer Review

Decreases researcher d.f.
Holds you accountable to yourself and others

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Stage 1
Pre-registration &
Peer Review
"Registered report"

If registration made public:
Helps replication attempts
Decreases the file drawer effect

Ideal workflow

Stage 2
Peer Review

207 journals have some form of RR adoption!

Decreases researcher d.f.
Holds you accountable to yourself and others

Stage 1
Pre-registration &
Peer Review
"Registered report"

If registration made public:
Helps replication attempts
Decreases the file drawer effect

Ideal workflow

See here for list of current journals offering some form of registered report

Example registered reports

ROYAL SOCIETY OPEN SCIENCE

royalsocietypublishing.org/journal/rsos

Registered report

Check for updates

Cite this article: Przybylski AK, Weinstein N. 2019 Violent video game engagement is not associated with adolescents' aggressive behaviour: evidence from a registered report. *R. Soc. open sci.* **6**: 171474.
http://dx.doi.org/10.1098/rsos.171474

Violent video game engagement is not associated with adolescents' aggressive behaviour: evidence from a registered report

Andrew K. Przybylski[1,2] and Netta Weinstein[3]

[1]Oxford Internet Institute, University of Oxford, Oxford OX1 3JS, UK
[2]Department of Experimental Psychology, University of Oxford, Oxford, UK
[3]School of Psychology, Cardiff University, Cardiff, UK

AKP, 0000-0001-5547-2185

Example registered reports

Reproducibility project: Cancer Biology

Estimating the reproducibility of psychological science

All contributing studies include registered reports.

Reality check

Ideal workflow

Open science lite

Open science lite

Central to most definitions of open science:

- Research workflow is transparent, open, and thoroughly documented from the start
- Annotated scripts are shared
- The data themselves are open*

* This is not strictly necessary to ensure reproducibility

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On their own, these features go a long way towards ensuring reproducibility of research.

Open science lite

Central to most definitions of open science:

- Research workflow is transparent, open, and thoroughly documented from the start
- Annotated scripts are shared
- The data themselves are shared or at least accessible

On their own, these features go a long way towards ensuring reproducibility of research.

Even better:

- Pre-register study (different from full registered report)

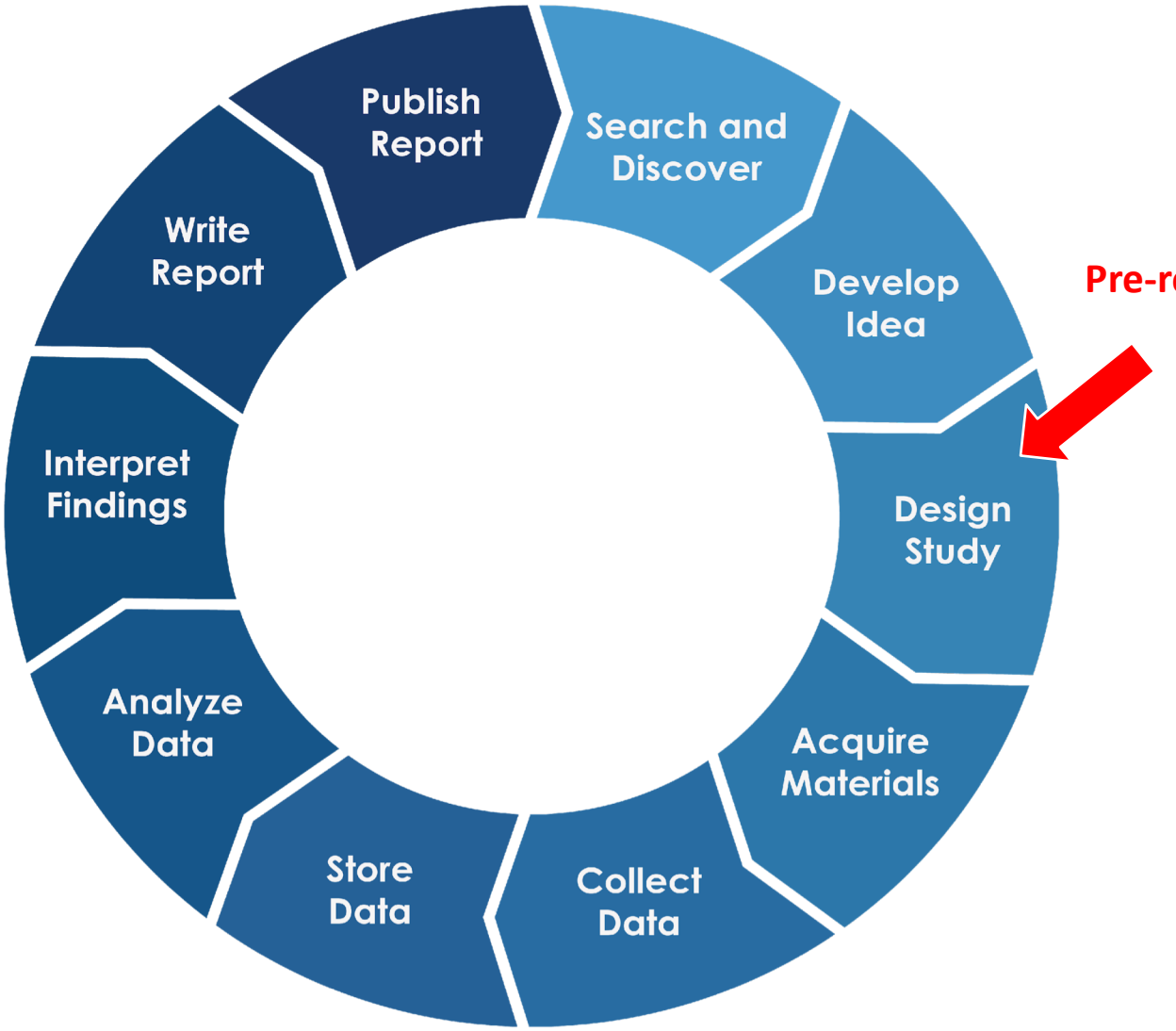
Pre-registration

Documenting your research plan in a read-only public repository before you conduct the study

At a minimum, a pre-registration should include the "what" of a study:

- Research question
- **Target population and sample size based on power analyses or, better, estimates of Type M error**
- General design
- Variables to be measured / dataset you'll be using

Workflow for the masses



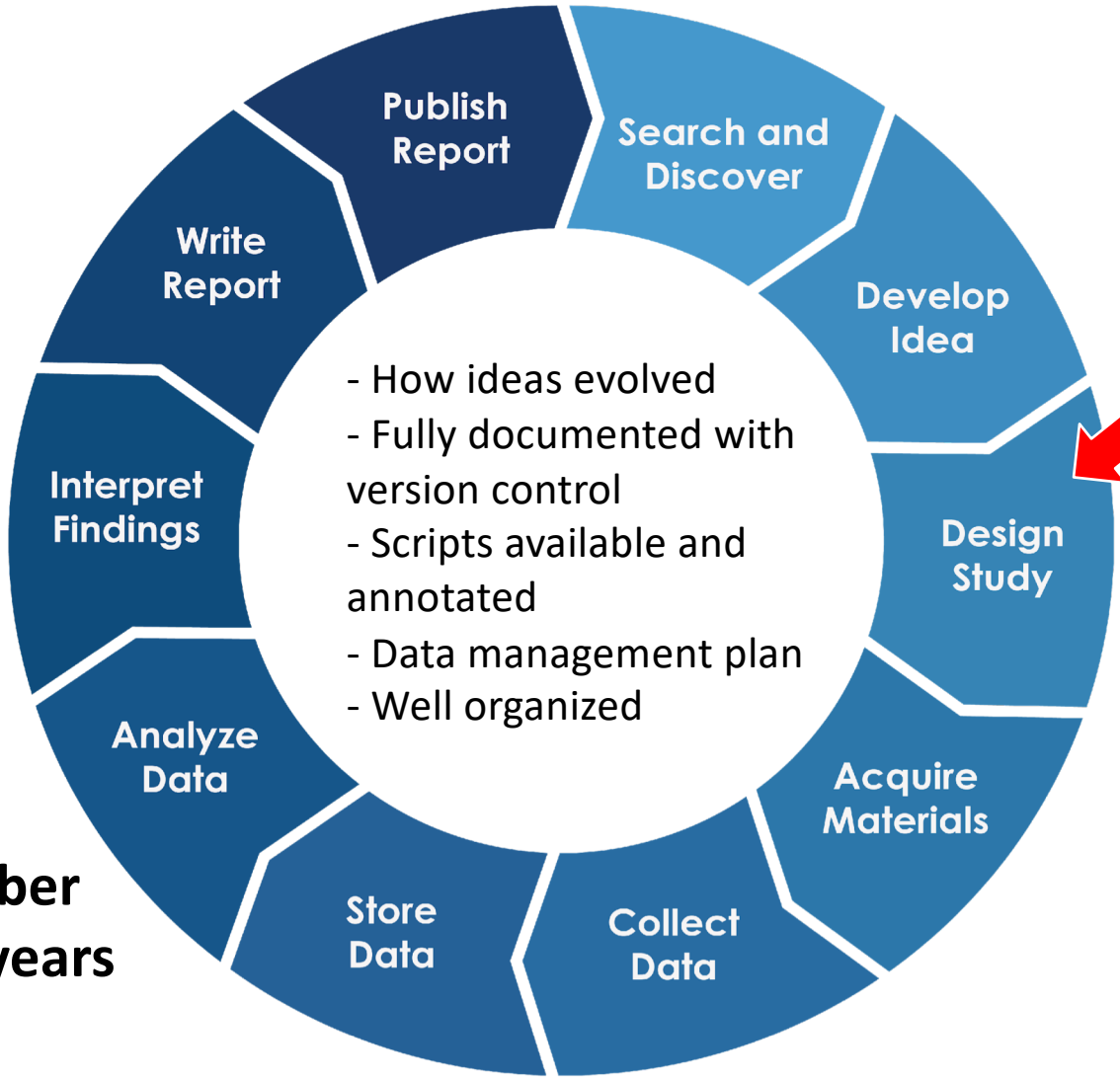
Pre-registration

Helps reduce publication bias, specifically the “file drawer effect”, by increasing discoverability of unpublished studies.

Helps you as a researcher plan ahead more carefully, and fosters greater awareness of pitfalls associated with researcher degrees of freedom.

Focuses attention on effect sizes and reducing type M errors

Workflow for the masses



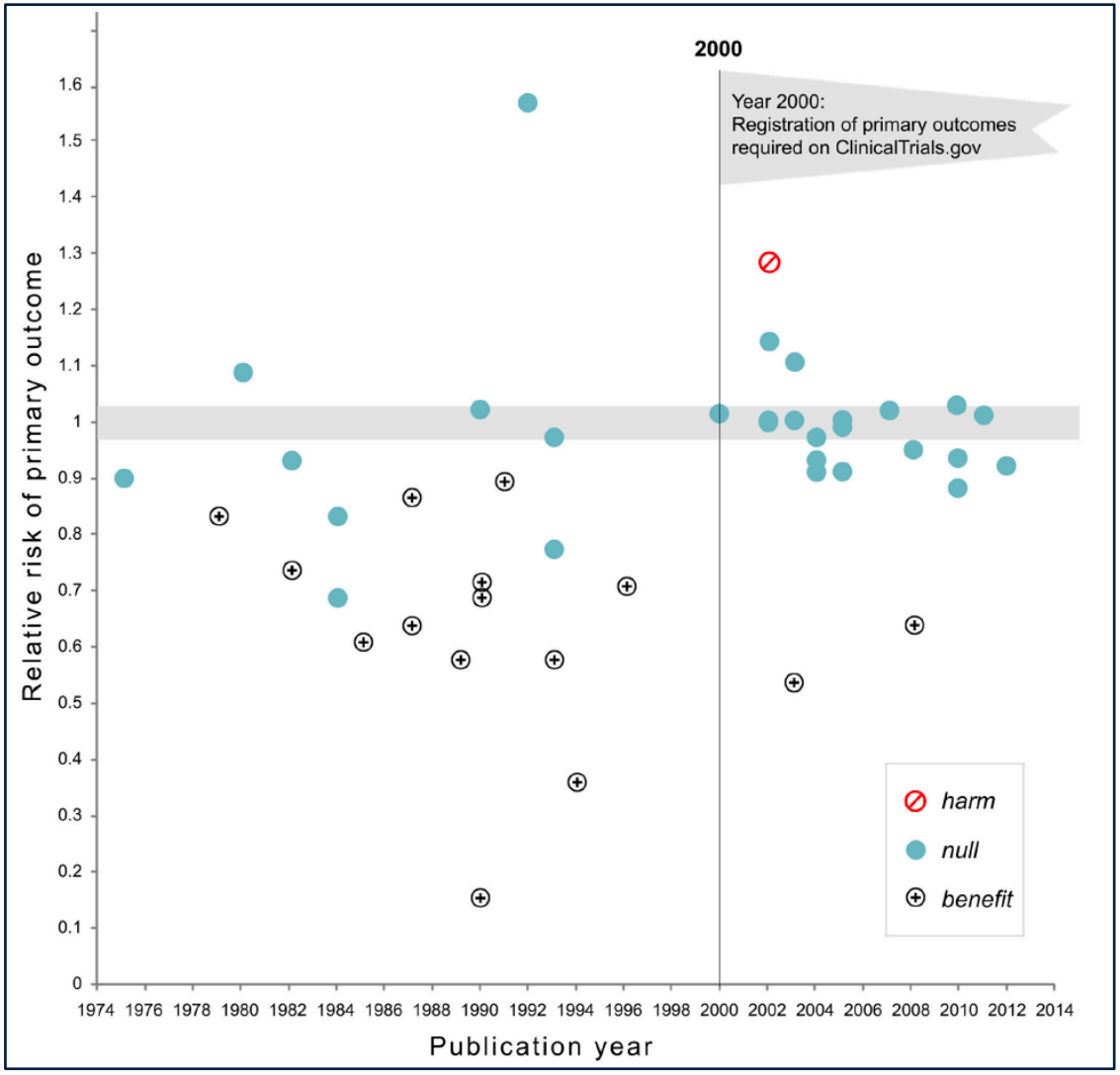
Pre-registration

Will you remember what you did 2 years later, and why?

Likelihood of Null Effects of Large NHLBI Clinical Trials Has Increased over Time

Robert M. Kaplan[1]*, Veronica L. Irvin[2]

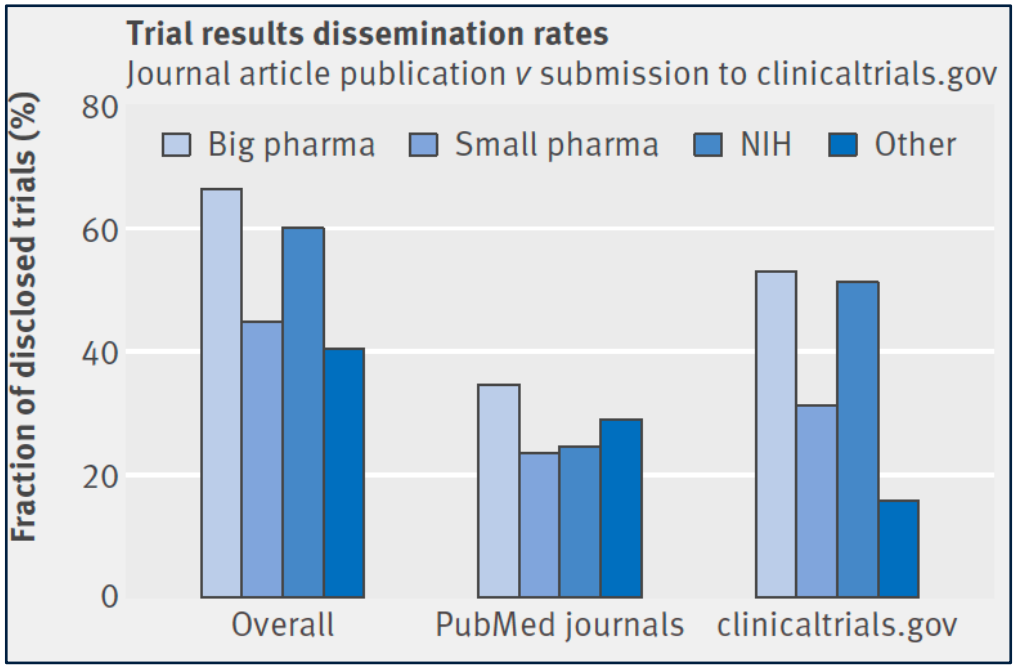
Science is improving

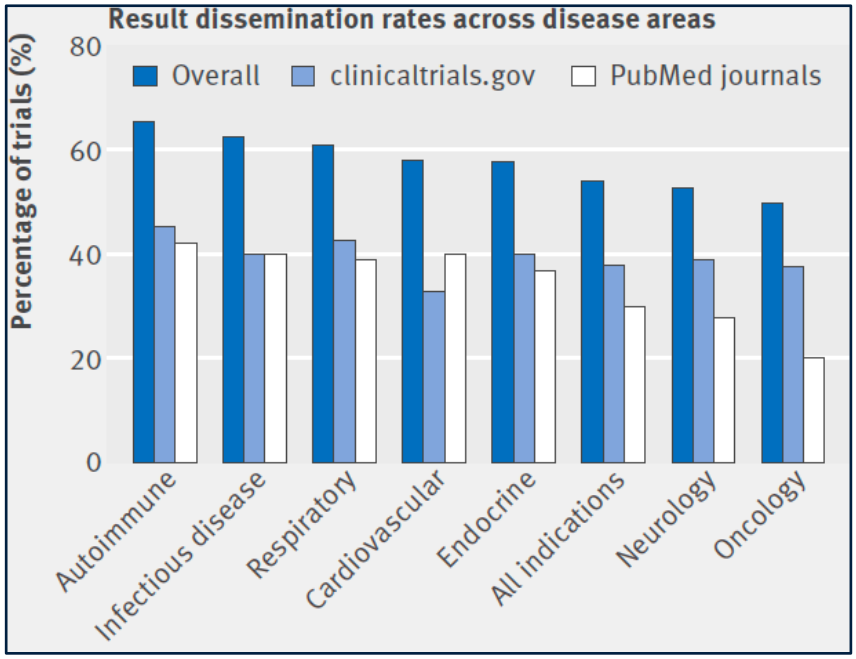


Citation: Kaplan RM, Irvin VL (2015) Likelihood of Null Effects of Large NHLBI Clinical Trials Has Increased over Time. PLoS ONE 10(8): e0132382. doi:10.1371/journal.pone.0132382

Clinical trial design and dissemination: comprehensive analysis of clinicaltrials.gov and PubMed data since 2005

Magdalena Zwierzyna,[1,2] Mark Davies,[1] Aroon D Hingorani,[2,3] Jackie Hunter[1,4]





But still lots of work to do…

Cite this as: *BMJ* 2018;361:k2130
http://dx.doi.org/10.1136/bmj.k2130

Why embrace Open Science?

POINT OF VIEW

McKiernan *et al.* eLife 2016;5:e16800. DOI: 10.7554/eLife.16800

How open science helps researchers succeed

Abstract Open access, open data, open source and other open scholarship practices are growing in popularity and necessity. However, widespread adoption of these practices has not yet been achieved. One reason is that researchers are uncertain about how sharing their work will affect their careers. We review literature demonstrating that open research is associated with increases in citations, media attention, potential collaborators, job opportunities and funding opportunities. These findings are evidence that open research practices bring significant benefits to researchers relative to more traditional closed practices.

DOI: 10.7554/eLife.16800.001

ERIN C MCKIERNAN*, PHILIP E BOURNE, C TITUS BROWN, STUART BUCK, AMYE KENALL, JENNIFER LIN, DAMON MCDOUGALL, BRIAN A NOSEK, KARTHIK RAM, COURTNEY K SODERBERG, JEFFREY R SPIES, KAITLIN THANEY, ANDREW UPDEGROVE, KARA H WOO AND TAL YARKONI

Benefits of adopting Open Science

Improves Efficiency

- Saves time and $$
- Re-use methods / code
- Avoids duplication while enabling replication
- Facilitates meta-analyses
- Promotes accurate discovery

Benefits of adopting Open Science

- Funding agencies (e.g. Tri-Council) are increasingly demanding aspects of OS (e.g. open data, open access)
- OS practices are increasingly being favoured at academic institutions
- Many aspects of OS will eventually be required

Annex 4

G7 EXPERT GROUP ON OPEN SCIENCE

28th September 2017

Focus: Incentives and the researcher ecosystem

Ambition: Foster a research environment in which career advancement takes into account Open Science activities, through incentives and rewards for researchers, and valuing the skills and capabilities in the Open Science workforce.

Recommendations:

At national levels: G7 nations should each engage with research stakeholders to identify and implement enhancements to research evaluation and reward systems that take into consideration the Open Science activities carried out by researchers and research institutions. Topics that could be discussed include:

- Recognizing Open Science practices during evaluation of research funding proposals, and research outcomes;
- Recognizing and rewarding research productivity and impact that reflect open science activities by researchers during career advancement reviews;
- Including credit for service activities such as reviewing, evaluating, and curation and management of research data; and,
- Developing metrics of Open Science practices.

Government of Canada / Gouvernement du Canada

Mona Nemer, Chief Science Advisor

"Canada needs a roadmap for open science, with a plan that moves beyond an incremental approach drawing on existing resources. In the coming year, my office will be working with senior leadership from federal science-based departments and agencies, in coordination with the federal granting agencies, to create a roadmap by July 2019. The aim is to make the results of federally funded research open and to help Canadian researchers keep pace with the global open science movement." – March 2019

Annual report

Tools that can help

- Open Science Framework (https://osf.io)
- Scripting (e.g. using R instead of Excel! R Markdown)
- Git / Github (see lesson here)
- Data management plan tools e.g. here

R / R Markdown
Open Science Framework

BIOL202: Introduction to Biostatistics

This page was last updated on September 17, 2019.

It is continually being updated, so be sure to refresh the page in your browser each time you visit!

You should download copies of these helpful **cheatsheets** and have them on hand:

- RStudio cheatsheet
- R Markdown cheatsheet

These cheat sheets deal with packages that will increasingly be used in the tutorials:

- ggplot2 cheatsheet
- dplyr cheatsheet

Starter Tutorials

These tutorials teach you the fundamentals of R and R Markdown, and should be completed prior to attempting any subsequent tutorials.

Introduction to R & RStudio

- What is R and RStudio?
- Installing R and RStudio
- How do I code in R?
- What are "packages"?
- Additional resources for learning R and RStudio

Reproducible R with R Markdown **Updated**: Friday Sept 7, 3pm: I clarified instructions on creating new projects in RStudio

- Creating a reproducible lab report
- What is R Markdown?
- Workflow: create a project and R Markdown document
- More R Markdown information

Importing data into R **Work in progress**

Tutorial 00: Preparing and formatting assignments for submission

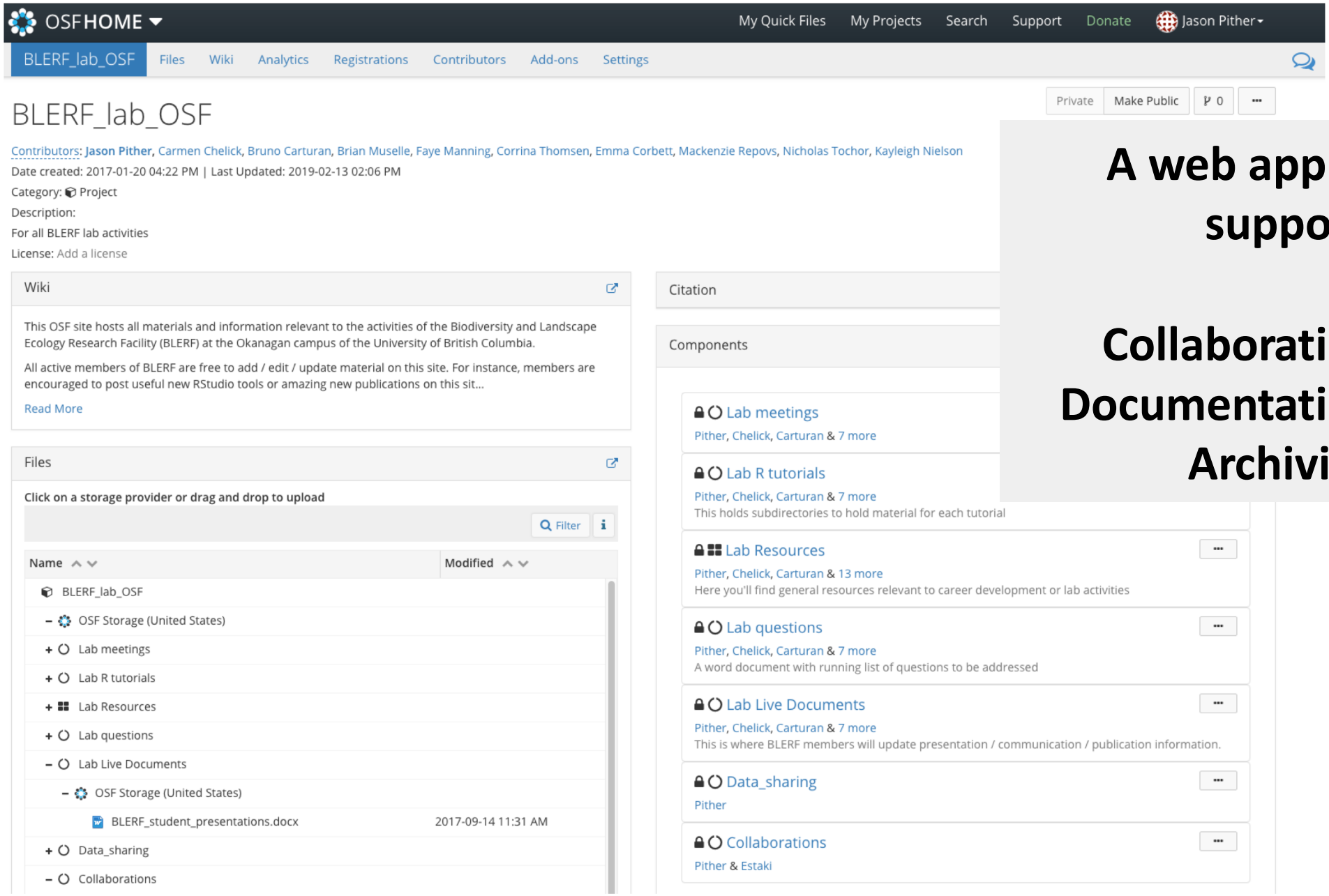
This tutorial provides instructions on how to prepare your assignments for submission.

Tutorial 01: Visualizing and describing a single variable

Before conducting any analyses, it is crucial to visualize your data with effective graphs. This can help identify potential problems with

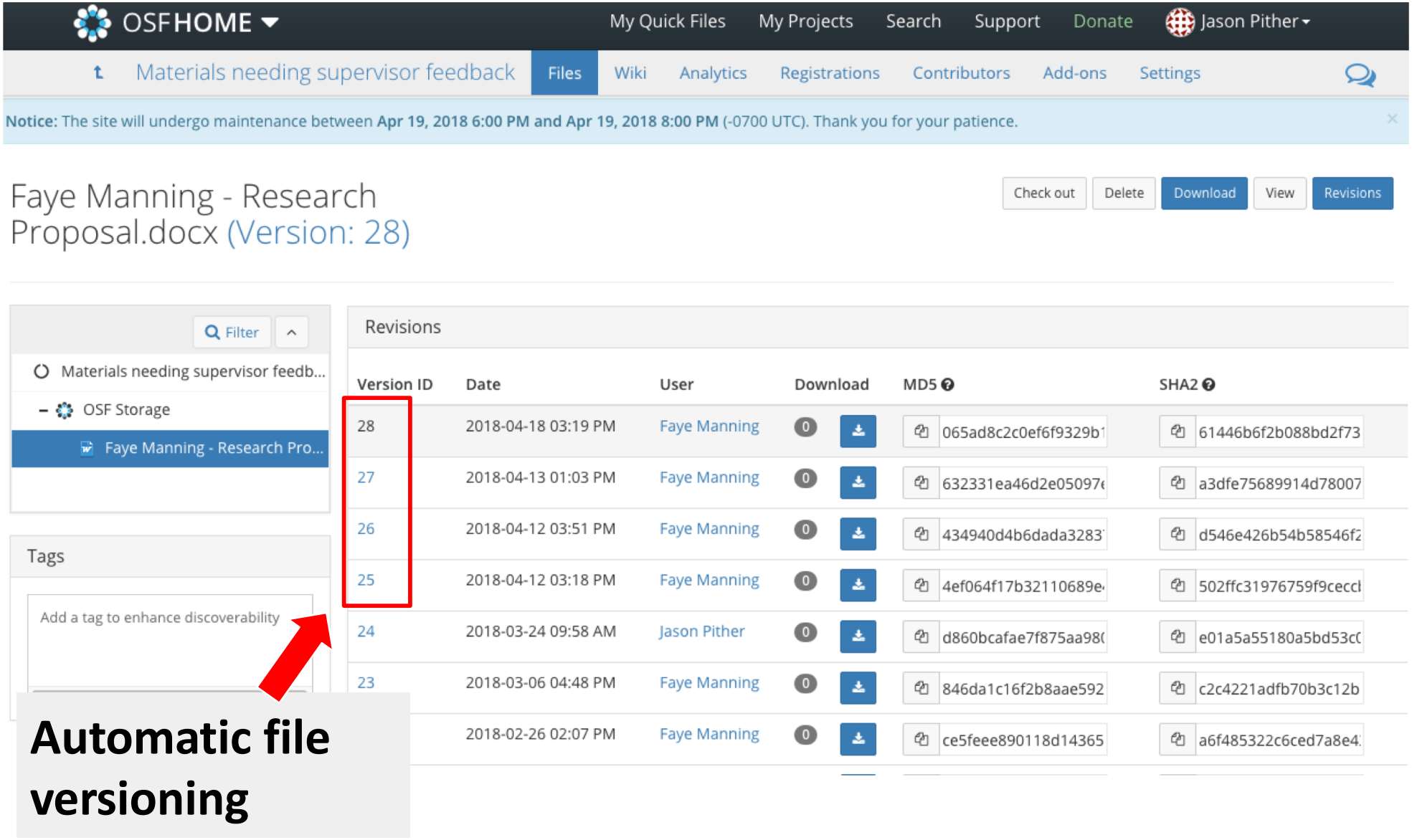
https://people.ok.ubc.ca/jpither/modules/biol202_home.html

Learn with simulated data!



A web app to support:

Collaboration
Documentation
Archiving


OSFHOME
My Quick Files
My Projects
Search
Support
Donate
Jason Pither
Materials needing supervisor feedback
Files
Wiki
Analytics
Registrations
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Add-ons
Settings
Notice: The site will undergo maintenance between Apr 19, 2018 6:00 PM and Apr 19, 2018 8:00 PM (-0700 UTC). Thank you for your patience.
Faye Manning - Research Proposal.docx (Version: 28)
Check out
Delete
Download
View
Revisions
Filter
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Faye Manning - Research Pro...
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Add a tag to enhance discoverability
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27 2018-04-13 01:03 PM Faye Manning 0 632331ea46d2e05097(a3dfe75689914d78007
26 2018-04-12 03:51 PM Faye Manning 0 434940d4b6dada3283 d546e426b54b58546f2
25 2018-04-12 03:18 PM Faye Manning 0 4ef064f17b32110689e(502ffc31976759f9cecc
24 2018-03-24 09:58 AM Jason Pither 0 d860bcafae7f875aa98(e01a5a55180a5bd53c(
23 2018-03-06 04:48 PM Faye Manning 0 846da1c16f2b8aae592 c2c4221adfb70b3c12b
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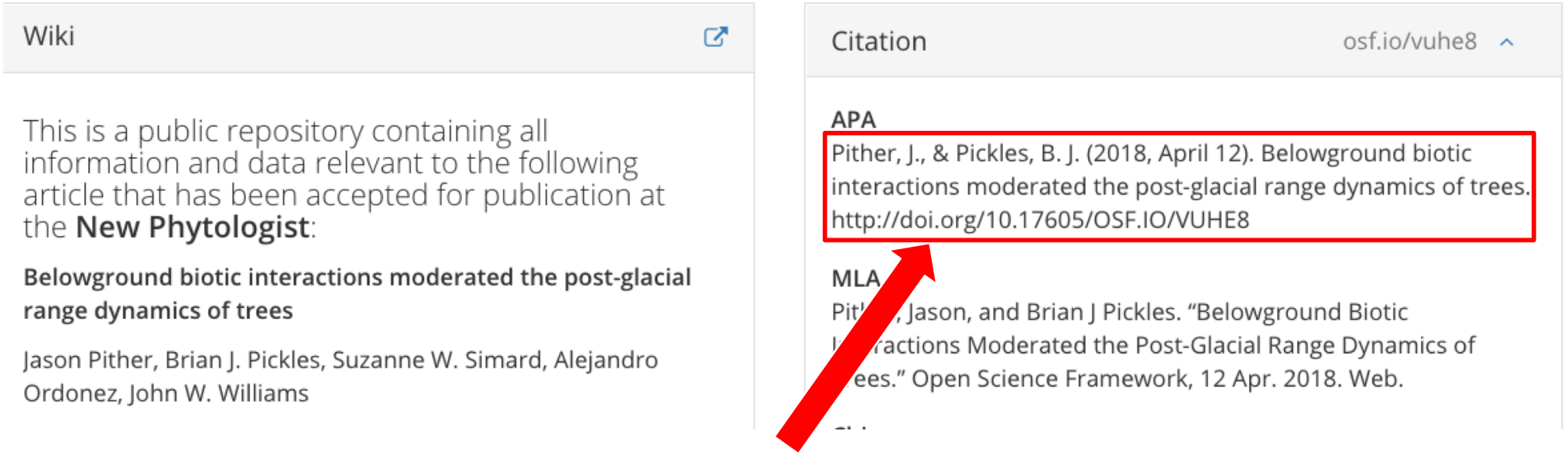
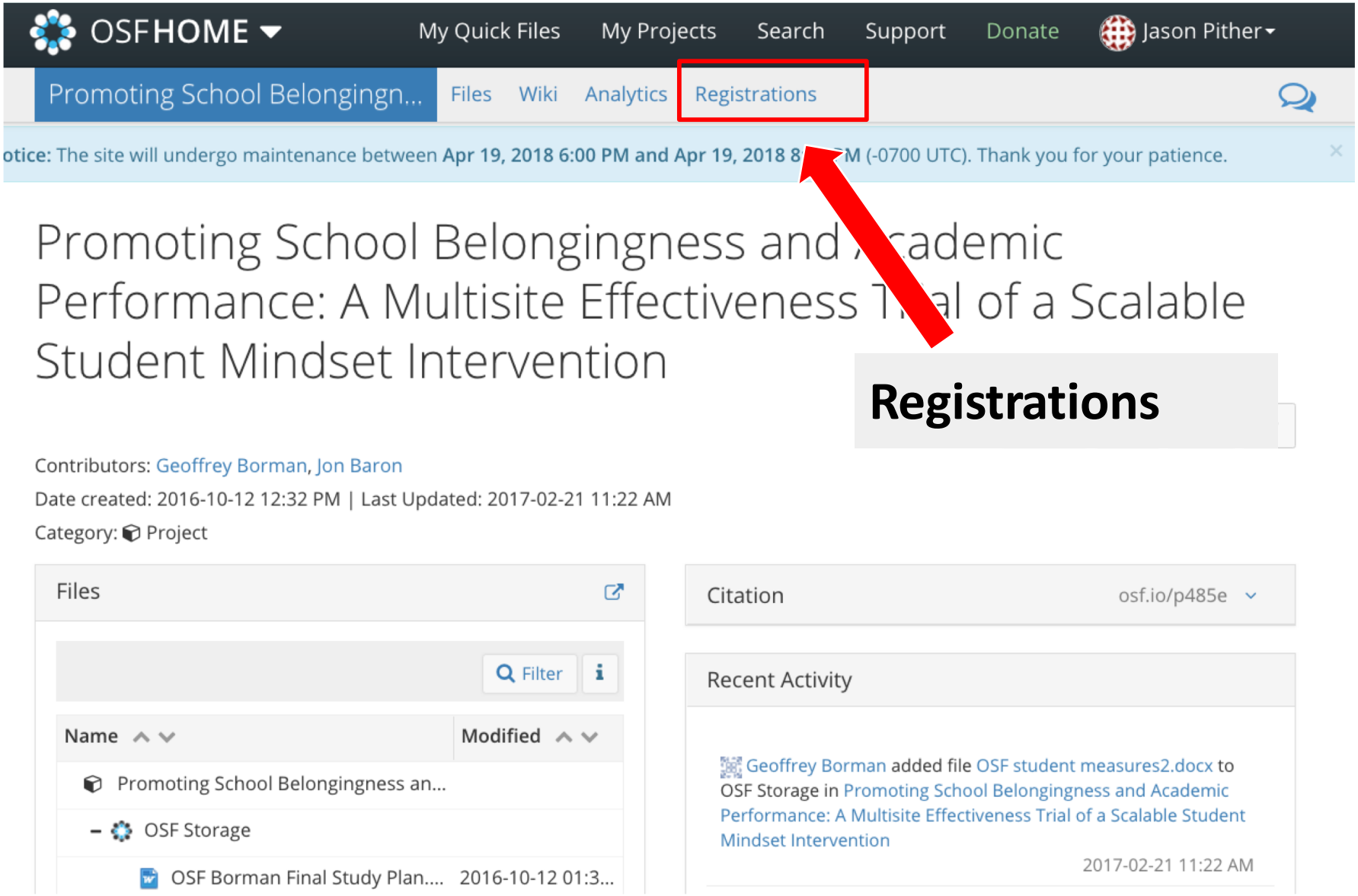
Automatic file versioning



Persistent citable identifiers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Jason Pither
Promoting School Belongingn...
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otice: The site will undergo maintenance between Apr 19, 2018 6:00 PM and Apr 19, 2018 8
M (-0700 UTC). Thank you for your patience.
Promoting School Belongingness and Academic Performance: A Multisite Effectiveness Trial of a Scalable Student Mindset Intervention
Registrations
Contributors: Geoffrey Borman, Jon Baron
Date created: 2016-10-12 12:32 PM | Last Updated: 2017-02-21 11:22 AM
Category: Project
Files
Filter
Name
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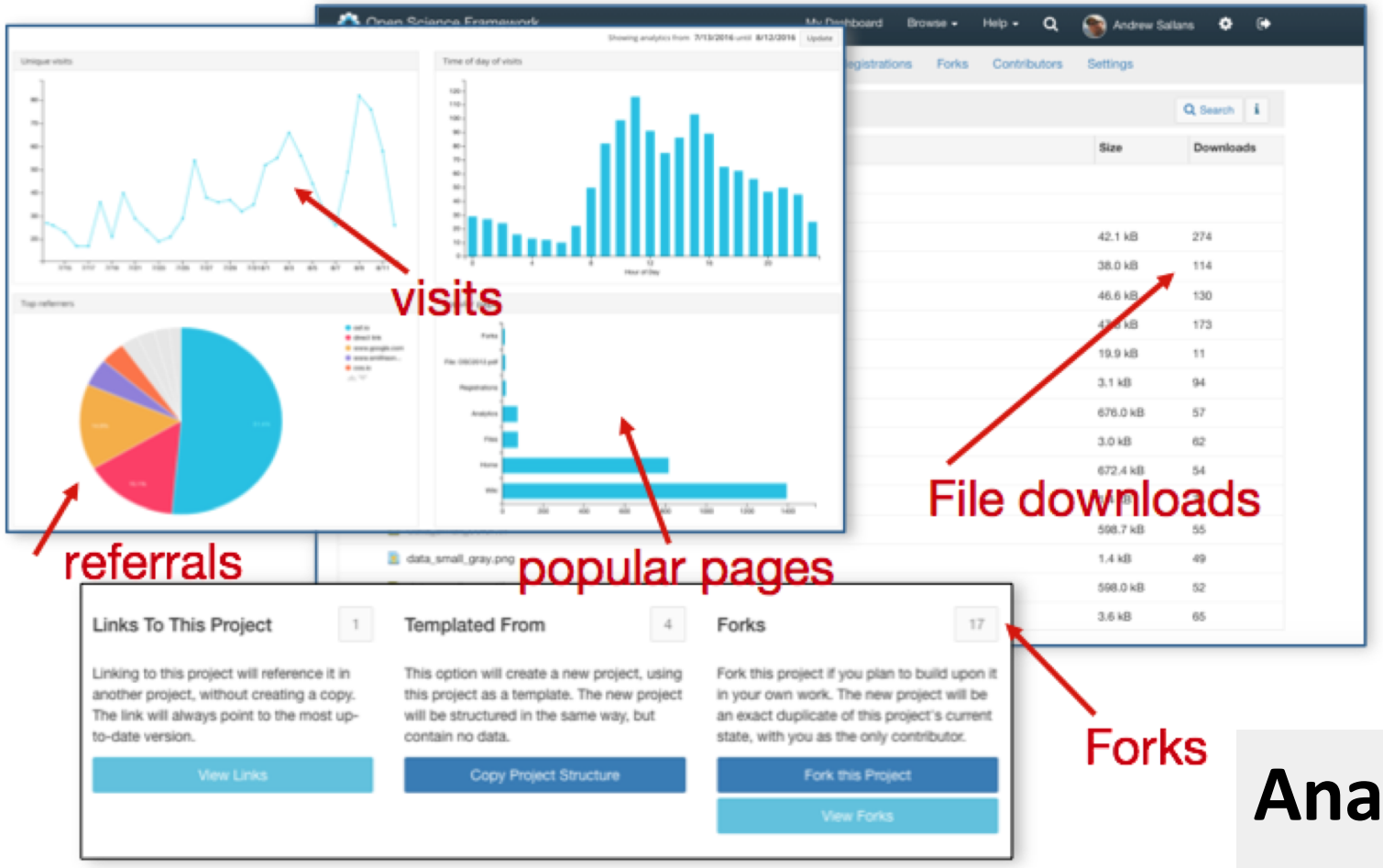
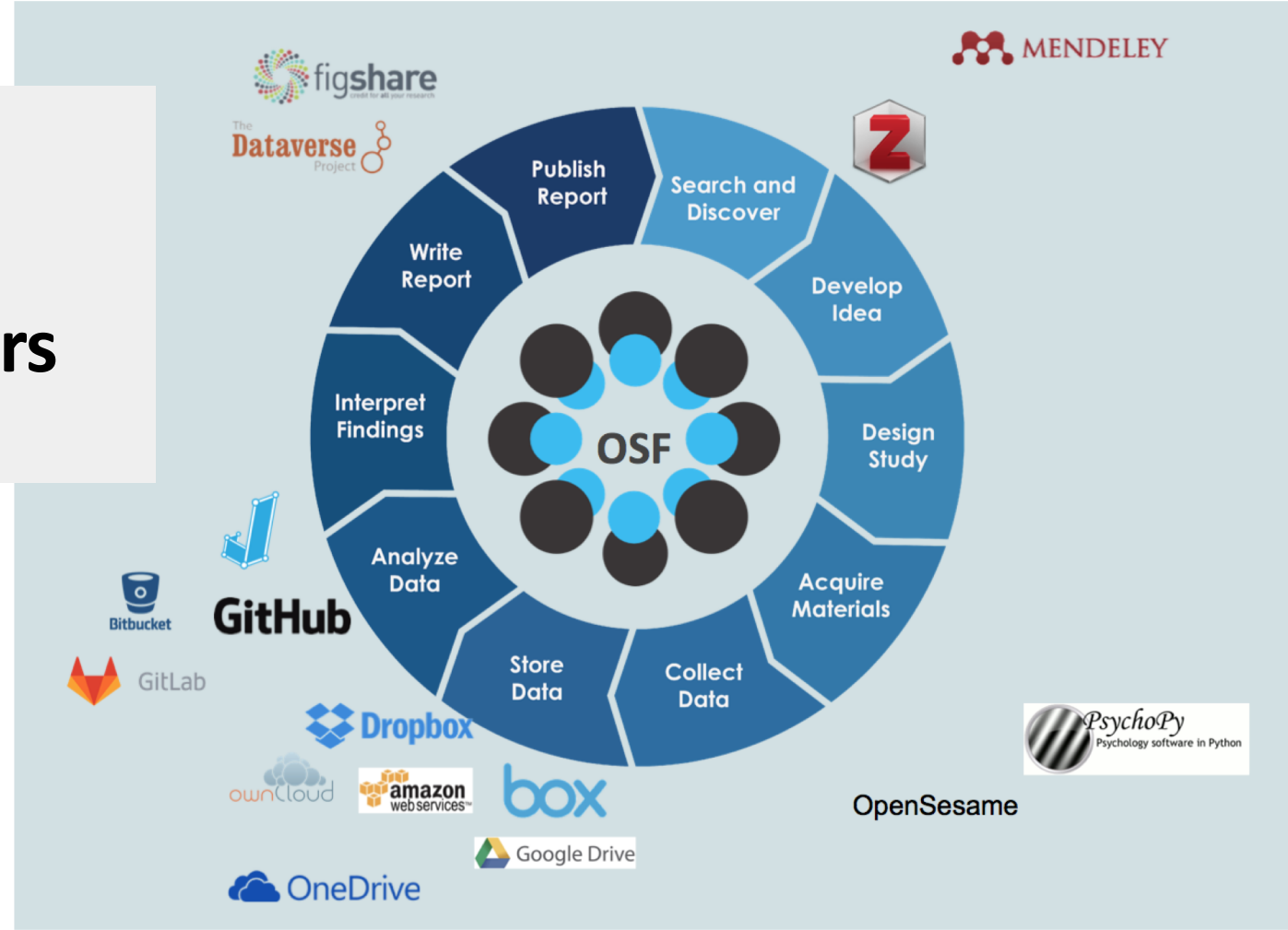
OSF Storage
OSF Borman Final Study Plan.... 2016-10-12 01:3...
Citation
osf.io/p485e
Recent Activity
Geoffrey Borman added file OSF student measures2.docx to OSF Storage in Promoting School Belongingness and Academic Performance: A Multisite Effectiveness Trial of a Scalable Student Mindset Intervention
2017-02-21 11:22 AM


visits
referrals
popular pages
File downloads
Forks
Links To This Project
Templated From
Forks
Linking to this project will reference it in another project, without creating a copy. The link will always point to the most up-to-date version.
This option will create a new project, using this project as a template. The new project will be structured in the same way, but contain no data.
Fork this project if you plan to build upon it in your own work. The new project will be an exact duplicate of this project's current state, with you as the only contributor.
View Links
Copy Project Structure
Fork this Project
View Forks

Analytics

Connects services researchers use



Preprint services enhance research visibility

Open Science @

Excellence fund strategic initiative:

FOSTERING OPEN SCIENCE AT UBC

This project targets research support and educational initiatives at the undergraduate and graduate levels in order to integrate Open Science practices. Open Science represents an approach to research that emphasizes reproducibility, transparency and accessibility. This project has two strategic goals: first, to establish the expertise and infrastructure required to foster the practice of Open Science among willing members of the entire UBC research community at both campuses. Secondly, to ensure that the core tenets of Open Science are of second nature to graduates of UBC's undergraduate and graduate programs.

Related strategy(ies): Strategy 8: Student Research, Strategy 9: Knowledge Exchange, Strategy 10: Research Culture, Strategy 12: Program Redesign and Strategy 14: Practical Learning
Project sponsor: Provost and Vice-President Academic UBCV; Provost and Vice-Principal Academic UBCO; Associate Vice-President Research & Vice-Principal Research
Target end date: Winter 2020
Progress: On track

UBC-wide initiatives

- Funded by UBC Excellence Fund: strategic initiative
- Promoting best practices in OS throughout UBC community
- Library and Advanced Research Computing developing sustainable infrastructure and expertise to support Open Science and **OSF**
- Establishment of OSF Institutions for UBC (coming soon!)
- Providing regular workshops, seminars, outreach at both campuses
- Developing instructional material for credit - BIOLOGY
- Engaging with Faculty Association and administration to encourage collaborative policy development
- openscience.ubc.ca

Organize and increase visibility of your institutional research.

OSF Institutions is a scholarly web tool that enhances transparency, fosters collaboration, and increases the visibility of research outputs at leading research institutions. The Center for Open Science partners with these institutions to create central hubs for research projects on a branded, dedicated OSF page.

OSF INSTITUTIONS

Single sign-on authentication creates a seamless and integrated framework that accommodates custom research workflows and streamlines institutional data management. You can focus your efforts on generating and sharing research, not on building and maintaining research infrastructure.

Key Benefits for Your Institution

- Collaborate at all levels of a project within the institution as well as outside collaborators
- Conveniently share and make whole projects or just parts of them public, and retain security and privacy for project elements that are not shareable because of ethical or proprietary considerations
- Archive and cite projects easily
- Connect 3rd party tools and services & eliminate silos or redundancy
- Provide visibility for ongoing and unpublished research across the entire institution
- Gain insight and data on research collaboration throughout your organization
- Evaluate impact of research investment beyond citations

Get Started Now

At UBC's Okanagan campus

Pilot project underway

Integrating best practices in Open Science into the Biology undergraduate program. Starting with small steps...

- Developing and deploying introductory instructional material regarding OS (currently in 1st year BIOL)
- Uploading / archiving digital photos of lab book notes to Canvas
- Teaching R Markdown in 2nd year core Biostats course (BIOL202)
- Encouraging use of Markdown for upper-year lab assignments
- Encouraging instructors to reward transparency and honesty

Longer-term goal

- Accreditation for undergrads and grads

Acknowledgments

- Dr. Eric Eich (Vice-Provost and AVP Academic Affairs)
- Heather Berringer (Chief Librarian, Okanagan campus)
- Sharon Hanna (UBCO librarian helping with OS initiatives)
- Centre for Open Science (https://osf.io)
- Wade Klaver (UBC ARC)
- Carmen Chelick and Brian Muselle (MSc Biology students)
- Department of Biology (Okanagan campus)
- Steve Cundy and UBC's Advanced Research Computing team
- UBC Excellence Fund

Discussion points:

- Early career researchers
- Promotion & Tenure
- How to effect change
- Lab practices
- Exploratory vs confirmatory data analysis
- Open Access publications
- eLife interactive articles

Table 1: A manifesto for reproducible science.

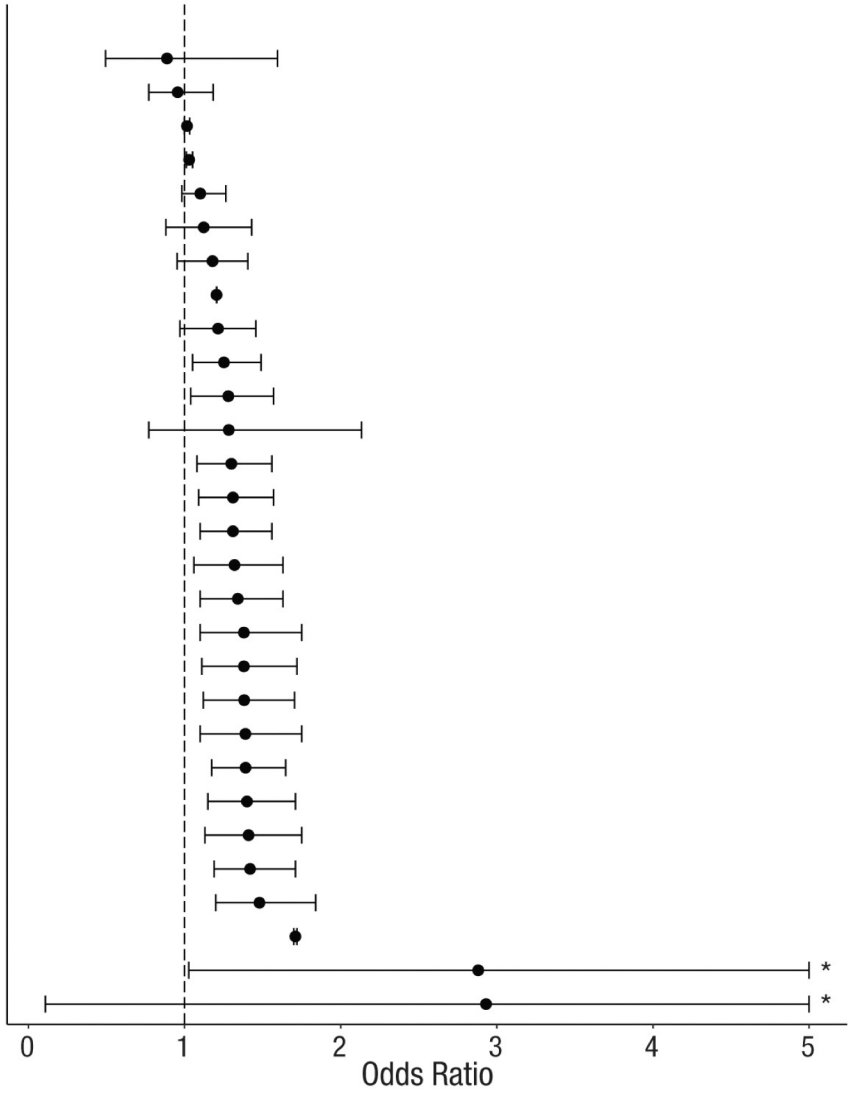
From: A manifesto for reproducible science

Theme	Proposal	Examples of initiatives/potential solutions (extent of current adoption)	Stakeholder(s)
Methods	Protecting against cognitive biases	All of the initiatives listed below (* to ****) Blinding (**)	J, F
	Improving methodological training	Rigorous training in statistics and research methods for future researchers (*) Rigorous continuing education in statistics and methods for researchers (*)	I, F
	Independent methodological support	Involvement of methodologists in research (**) Independent oversight (*)	F
	Collaboration and team science	Multi-site studies/distributed data collection (*) Team-science consortia (*)	I, F
Reporting and dissemination	Promoting study pre-registration	Registered Reports (*) Open Science Framework (*)	J, F
	Improving the quality of reporting	Use of reporting checklists (**) Protocol checklists (*)	J
	Protecting against conflicts of interest	Disclosure of conflicts of interest (***) Exclusion/containment of financial and non-financial conflicts of interest (*)	J
Reproducibility	Encouraging transparency and open science	Open data, materials, software and so on (* to **) Pre-registration (**** for clinical trials, * for other studies)	J, F, R
Evaluation	Diversifying peer review	Preprints (* in biomedical/behavioural sciences, **** in physical sciences) Pre- and post-publication peer review, for example, Publons, PubMed Commons (*)	J
Incentives	Rewarding open and reproducible practices	Badges (*) Registered Reports (*) Transparency and Openness Promotion guidelines (*) Funding replication studies (*) Open science practices in hiring and promotion (*)	J, I, F

Estimated extent of current adoption: *, <5%; **, 5-30%; ***, 30-60%; ****, >60%. Abbreviations for key stakeholders: J, journals/publishers; F, funders; I, institutions; R, regulators.

Munafò et al. 2017. Mhttp://dx.doi.org/10.1038/s41562-016-0021

Team	Analytic Approach	Odds Ratio
12	Zero-Inflated Poisson Regression	0.89
17	Bayesian Logistic Regression	0.96
15	Hierarchical Log-Linear Modeling	1.02
10	Multilevel Regression and Logistic Regression	1.03
18	Hierarchical Bayes Model	1.10
31	Logistic Regression	1.12
1	OLS Regression With Robust Standard Errors, Logistic Regression	1.18
4	Spearman Correlation	1.21
14	WLS Regression With Clustered Standard Errors	1.21
11	Multiple Linear Regression	1.25
30	Clustered Robust Binomial Logistic Regression	1.28
6	Linear Probability Model	1.28
26	Hierarchical Generalized Linear Modeling With Poisson Sampling	1.30
3	Multilevel Logistic Regression Using Bayesian Inference	1.31
23	Mixed-Model Logistic Regression	1.31
16	Hierarchical Poisson Regression	1.32
2	Linear Probability Model, Logistic Regression	1.34
5	Generalized Linear Mixed Models	1.38
24	Multilevel Logistic Regression	1.38
28	Mixed-Effects Logistic Regression	1.38
32	Generalized Linear Models for Binary Data	1.39
8	Negative Binomial Regression With a Log Link	1.39
20	Cross-Classified Multilevel Negative Binomial Model	1.40
13	Poisson Multilevel Modeling	1.41
25	Multilevel Logistic Binomial Regression	1.42
9	Generalized Linear Mixed-Effects Models With a Logit Link	1.48
7	Dirichlet-Process Bayesian Clustering	1.71
21	Tobit Regression	2.88
27	Poisson Regression	2.93



Soccer study

Publication bias: file drawer

Original Paper

Nonpublication Rates and Characteristics of Registered Randomized Clinical Trials in Digital Health: Cross-Sectional Analysis

Mustafa Al-Durra[1,2], BSc, MSc ; Robert P Nolan[3,4], PhD, CPsych ; Emily Seto[1,2], PEng, PhD ;
Joseph A Cafazzo[1,2,5], PEng, PhD ; Gunther Eysenbach[1,2], MD, MPH, FACMI

Results: In total, 6717 articles matched the *a priori* search terms, of which 803 trials matched our latest completion date criteria. After screening, 556 trials were included in this study. We found that 150 (27%) of all included trials remained unpublished 5 years after their completion date. In bivariate analyses, we observed statistically significant differences in trial characteristics between published and unpublished trials in terms of the intervention target condition, country, trial size, trial phases, recruitment, and prospective trial registration. In multivariate analyses, differences in trial characteristics between published and unpublished trials remained statistically significant for the intervention target condition, country, trial size, trial phases, and recruitment; the odds of publication for non-US–based trials were significant, and these trials were 3.3 (95% CI 1.845-5.964) times more likely to be published than US–based trials. We observed a trend of 1.5 times higher nonpublication rates for industry-funded trials. However, the trend was not statistically significant.

Conclusions: In the domain of digital health, 27% of registered clinical trials results are unpublished, which is lower than nonpublication rates in other fields. There are substantial differences in nonpublication rates between trials funded by industry and nonindustry sponsors. Further research is required to define the determinants and reasons for nonpublication and, more importantly, to articulate the impact and risk of publication bias in the field of digital health trials.

Accessibility

Open Access: publications in peer-reviewed journals are freely accessible to the general public

Open Data: data and codes of scholarly publications freely accessible

Open Materials: having the methodologies of scholarly publications freely accessible

Open Source (software): program's source code is freely available to the public