Reproducibility, replication, etc., Part 2

APAM E4990
Modeling Social Data

Jake Hofman

Columbia University

March 1, 2019

Questions

How should one evaluate research results?

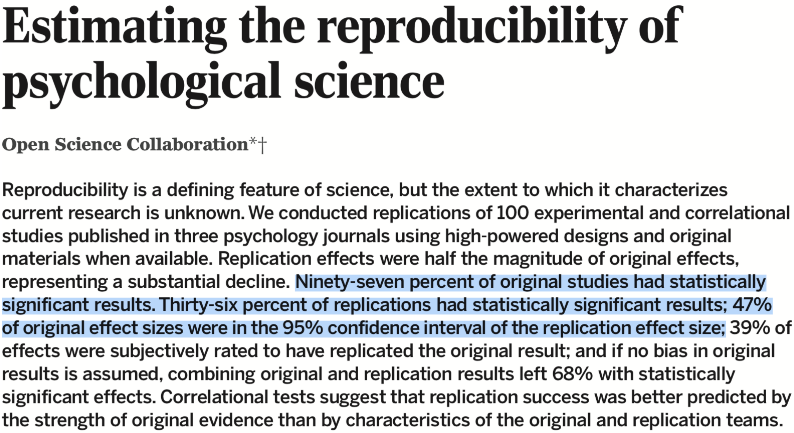
- Was the research done and reported honestly / correctly?
- Is the result "real" or an artifact of the data / analysis?
- Will it hold up over time?
- How robust is the result to small changes?
- How important / useful is the finding?

Replicability

Will the result hold up with new data but the same analysis?

- It's easy to be fooled by randomness
- Noise can dominate signal in small datasets
- Asking too many questions of the data can lead to overfitting

Crisis



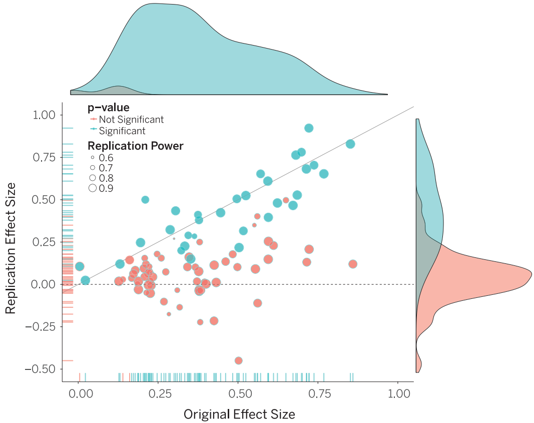
Estimating the reproducibility of psychological science

Open Science Collaboration*†

Reproducibility is a defining feature of science, but the extent to which it characterizes current research is unknown. We conducted replications of 100 experimental and correlational studies published in three psychology journals using high-powered designs and original materials when available. Replication effects were half the magnitude of original effects, representing a substantial decline. Ninety-seven percent of original studies had statistically significant results. Thirty-six percent of replications had statistically significant results; 47% of original effect sizes were in the 95% confidence interval of the replication effect size; 39% of effects were subjectively rated to have replicated the original result; and if no bias in original results is assumed, combining original and replication results left 68% with statistically significant effects. Correlational tests suggest that replication success was better predicted by the strength of original evidence than by characteristics of the original and replication teams.

Believe about half of what you read

Crisis



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.

Believe about half of what you read

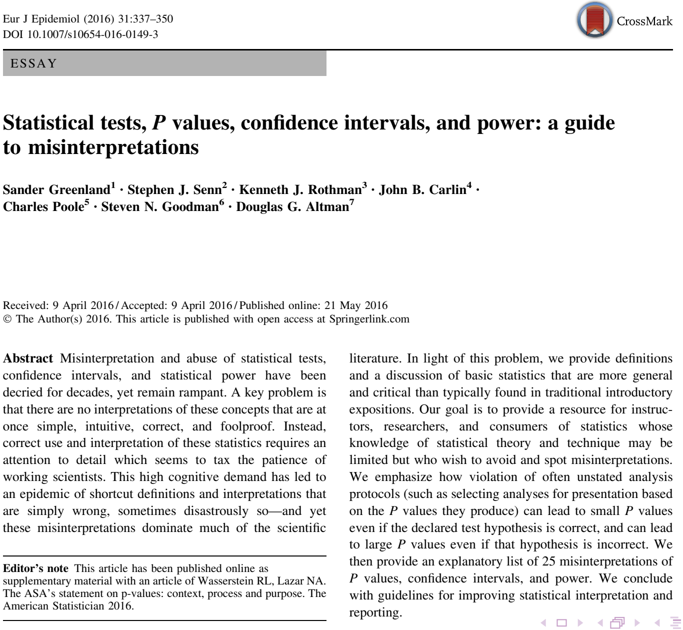
Statistics!

Hypothesis testing?
P-values?
Statistical significance?
Confidence intervals??
Effect sizes???

I CAN'T BELIEVE SCHOOLS ARE STILL TEACHING KIDS ABOUT THE NULL HYPOTHESIS.
I REMEMBER READING A BIG STUDY THAT CONCLUSIVELY DISPROVED IT *YEARS* AGO.

xkcd.com/892

Misunderstandings



Eur J Epidemiol (2016) 31:337–350
DOI 10.1007/s10654-016-0149-3

ESSAY

Statistical tests, *P* values, confidence intervals, and power: a guide to misinterpretations

Sander Greenland[1] · Stephen J. Senn[2] · Kenneth J. Rothman[3] · John B. Carlin[4] · Charles Poole[5] · Steven N. Goodman[6] · Douglas G. Altman[7]

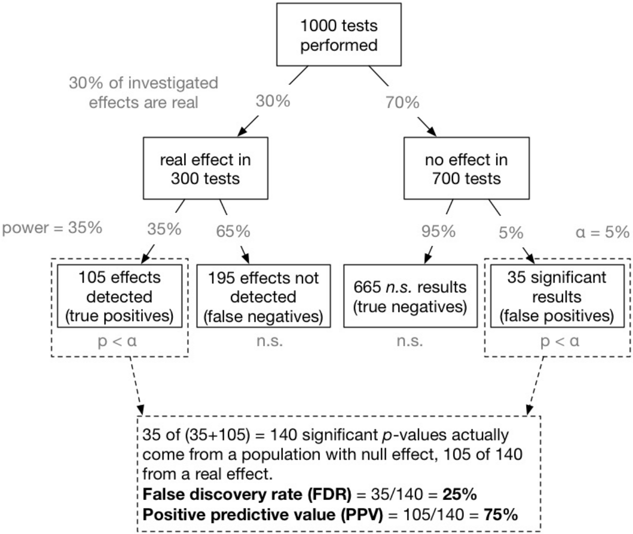
Received: 9 April 2016 / Accepted: 9 April 2016 / Published online: 21 May 2016

Abstract Misinterpretation and abuse of statistical tests, confidence intervals, and statistical power have been decried for decades, yet remain rampant. A key problem is that there are no interpretations of these concepts that are at once simple, intuitive, correct, and foolproof. Instead, correct use and interpretation of these statistics requires an attention to detail which seems to tax the patience of working scientists. This high cognitive demand has led to an epidemic of shortcut definitions and interpretations that are simply wrong, sometimes disastrously so—and yet these misinterpretations dominate much of the scientific literature. In light of this problem, we provide definitions and a discussion of basic statistics that are more general and critical than typically found in traditional introductory expositions. Our goal is to provide a resource for instructors, researchers, and consumers of statistics whose knowledge of statistical theory and technique may be limited but who wish to avoid and spot misinterpretations. We emphasize how violation of often unstated analysis protocols (such as selecting analyses for presentation based on the *P* values they produce) can lead to small *P* values even if the declared test hypothesis is correct, and can lead to large *P* values even if that hypothesis is incorrect. We then provide an explanatory list of 25 misinterpretations of *P* values, confidence intervals, and power. We conclude with guidelines for improving statistical interpretation and reporting.

Editor's note This article has been published online as supplementary material with an article of Wasserstein RL, Lazar NA. The ASA's statement on p-values: context, process and purpose. The American Statistician 2016.

Quiz

- You do 1,000 experiments for 1,000 different research questions
- Only 30% of these experiments investigate real effects
- You set your significance level α to 5%
- You use a small sample size such that your power $1-\beta$ is 35%
- Given that one of these experiments shows statistical significance, what's the probability that it's a real effect?



1000 tests performed

30% of investigated effects are real

30%

70%

real effect in 300 tests

no effect in 700 tests

power = 35%

35%

65%

95%

5%

α = 5%

105 effects detected (true positives)

$p < \alpha$

195 effects not detected (false negatives)

n.s.

665 *n.s.* results (true negatives)

n.s.

35 significant results (false positives)

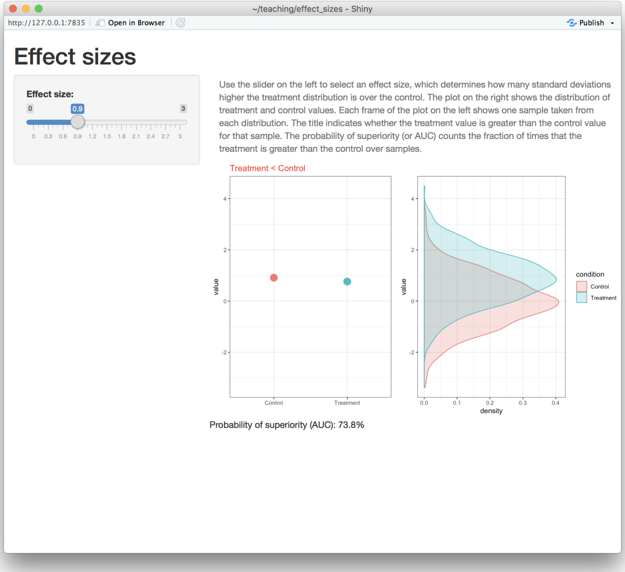
$p < \alpha$

35 of (35+105) = 140 significant *p*-values actually come from a population with null effect, 105 of 140 from a real effect.

False discovery rate (FDR) = 35/140 = **25%**

Positive predictive value (PPV) = 105/140 = **75%**

`bit.ly/fdrtree`



Effect sizes

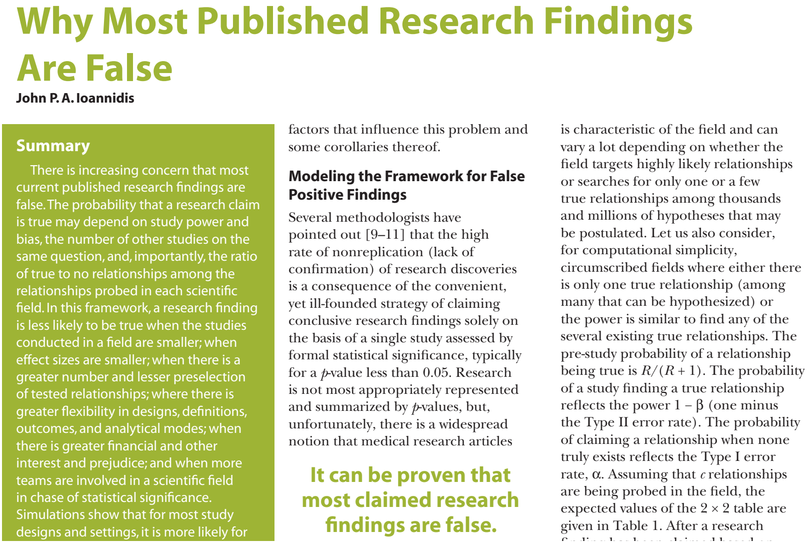
Effect size: 0.9

Use the slider on the left to select an effect size, which determines how many standard deviations higher the treatment distribution is over the control. The plot on the right shows the distribution of treatment and control values. Each frame of the plot on the left shows one sample taken from each distribution. The title indicates whether the treatment value is greater than the control value for that sample. The probability of superiority (or AUC) counts the fraction of times that the treatment is greater than the control over samples.

Treatment < Control

Probability of superiority (AUC): 73.8%

Underpowered studies



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

factors that influence this problem and some corollaries thereof.

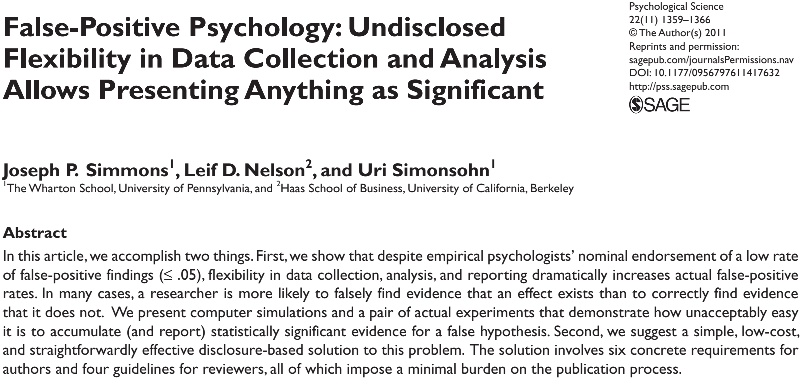
Modeling the Framework for False Positive Findings

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.

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

P-hacking



Psychological Science
22(11) 1359–1366
© The Author(s) 2011
Reprints and permission:
sagepub.com/journalsPermissions.nav
DOI: 10.1177/0956797611417632
http://pss.sagepub.com
SAGE

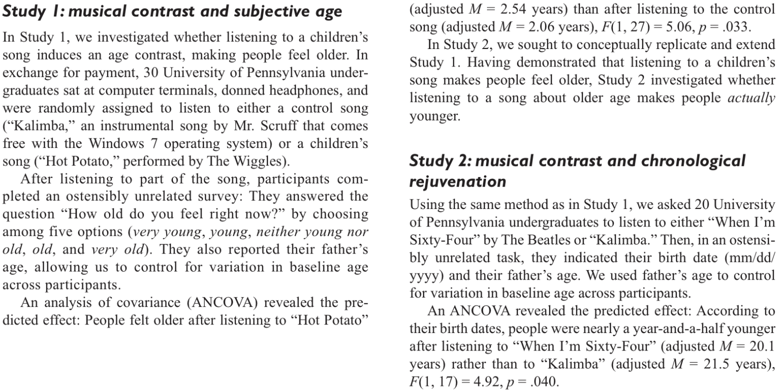
False-Positive Psychology: Undisclosed Flexibility in Data Collection and Analysis Allows Presenting Anything as Significant

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

Abstract

In this article, we accomplish two things. First, we show that despite empirical psychologists' nominal endorsement of a low rate of false-positive findings ($\leq .05$), flexibility in data collection, analysis, and reporting dramatically increases actual false-positive rates. In many cases, a researcher is more likely to falsely find evidence that an effect exists than to correctly find evidence that it does not. We present computer simulations and a pair of actual experiments that demonstrate how unacceptably easy it is to accumulate (and report) statistically significant evidence for a false hypothesis. Second, we suggest a simple, low-cost, and straightforwardly effective disclosure-based solution to this problem. The solution involves six concrete requirements for authors and four guidelines for reviewers, all of which impose a minimal burden on the publication process.

P-hacking



Study 1: musical contrast and subjective age

In Study 1, we investigated whether listening to a children's song induces an age contrast, making people feel older. In exchange for payment, 30 University of Pennsylvania undergraduates sat at computer terminals, donned headphones, and were randomly assigned to listen to either a control song ("Kalimba," an instrumental song by Mr. Scruff that comes free with the Windows 7 operating system) or a children's song ("Hot Potato," performed by The Wiggles).

After listening to part of the song, participants completed an ostensibly unrelated survey: They answered the question "How old do you feel right now?" by choosing among five options (*very young*, *young*, *neither young nor old*, *old*, and *very old*). They also reported their father's age, allowing us to control for variation in baseline age across participants.

An analysis of covariance (ANCOVA) revealed the predicted effect: People felt older after listening to "Hot Potato" (adjusted M = 2.54 years) than after listening to the control song (adjusted M = 2.06 years), $F(1, 27) = 5.06$, $p = .033$.

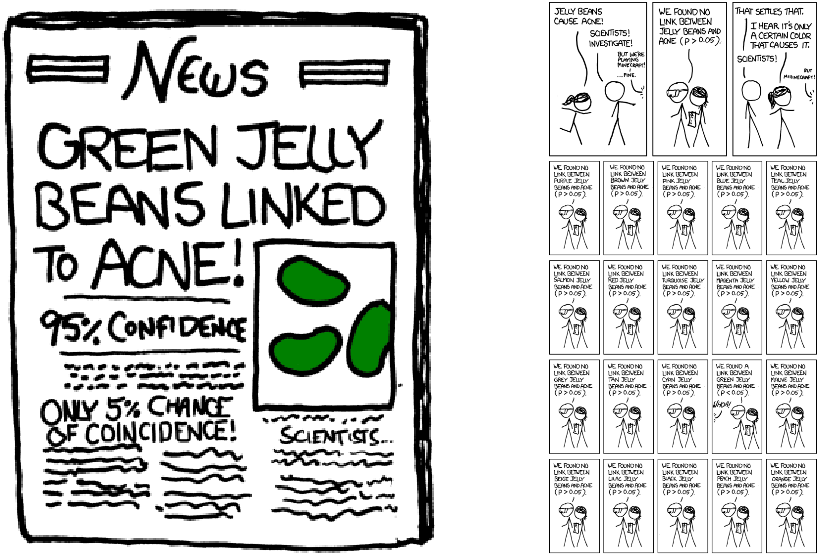
In Study 2, we sought to conceptually replicate and extend Study 1. Having demonstrated that listening to a children's song makes people feel older, Study 2 investigated whether listening to a song about older age makes people *actually* younger.

Study 2: musical contrast and chronological rejuvenation

Using the same method as in Study 1, we asked 20 University of Pennsylvania undergraduates to listen to either "When I'm Sixty-Four" by The Beatles or "Kalimba." Then, in an ostensibly unrelated task, they indicated their birth date (mm/dd/yyyy) and their father's age. We used father's age to control for variation in baseline age across participants.

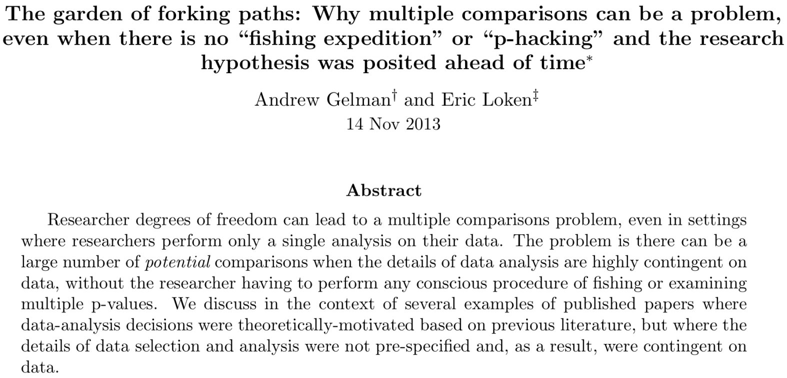
An ANCOVA revealed the predicted effect: According to their birth dates, people were nearly a year-and-a-half younger after listening to "When I'm Sixty-Four" (adjusted M = 20.1 years) rather than to "Kalimba" (adjusted M = 21.5 years), $F(1, 17) = 4.92$, $p = .040$.

P-hacking


JELLY BEANS CAUSE ACNE!
SCIENTISTS! INVESTIGATE!
BUT WE'RE PLAYING MINECRAFT!
...FINE.
WE FOUND NO LINK BETWEEN JELLY BEANS AND ACNE (P > 0.05).
THAT SETTLES THAT.
I HEAR IT'S ONLY A CERTAIN COLOR THAT CAUSES IT.
SCIENTISTS!
BUT MIIINECRAFT!
WE FOUND NO LINK BETWEEN PURPLE JELLY BEANS AND ACNE (P > 0.05).
WE FOUND NO LINK BETWEEN BROWN JELLY BEANS AND ACNE (P > 0.05).
WE FOUND NO LINK BETWEEN PINK JELLY BEANS AND ACNE (P > 0.05).
WE FOUND NO LINK BETWEEN BLUE JELLY BEANS AND ACNE (P > 0.05).
WE FOUND NO LINK BETWEEN TEAL JELLY BEANS AND ACNE (P > 0.05).
WE FOUND NO LINK BETWEEN SALMON JELLY BEANS AND ACNE (P > 0.05).
WE FOUND NO LINK BETWEEN RED JELLY BEANS AND ACNE (P > 0.05).
WE FOUND NO LINK BETWEEN TURQUOISE JELLY BEANS AND ACNE (P > 0.05).
WE FOUND NO LINK BETWEEN MAGENTA JELLY BEANS AND ACNE (P > 0.05).
WE FOUND NO LINK BETWEEN YELLOW JELLY BEANS AND ACNE (P > 0.05).
WE FOUND NO LINK BETWEEN GREY JELLY BEANS AND ACNE (P > 0.05).
WE FOUND NO LINK BETWEEN TAN JELLY BEANS AND ACNE (P > 0.05).
WE FOUND NO LINK BETWEEN CYAN JELLY BEANS AND ACNE (P > 0.05).
WE FOUND A LINK BETWEEN GREEN JELLY BEANS AND ACNE (P < 0.05).
WHOA!
WE FOUND NO LINK BETWEEN MAUVE JELLY BEANS AND ACNE (P > 0.05).
WE FOUND NO LINK BETWEEN BEIGE JELLY BEANS AND ACNE (P > 0.05).
WE FOUND NO LINK BETWEEN LILAC JELLY BEANS AND ACNE (P > 0.05).
WE FOUND NO LINK BETWEEN BLACK JELLY BEANS AND ACNE (P > 0.05).
WE FOUND NO LINK BETWEEN PEACH JELLY BEANS AND ACNE (P > 0.05).
WE FOUND NO LINK BETWEEN ORANGE JELLY BEANS AND ACNE (P > 0.05).
NEWS
GREEN JELLY BEANS LINKED TO ACNE!
95% CONFIDENCE
ONLY 5% CHANCE OF COINCIDENCE!
SCIENTISTS...

xkcd.com/882

Researcher degrees of freedom



The garden of forking paths: Why multiple comparisons can be a problem, even when there is no “fishing expedition” or “p-hacking” and the research hypothesis was posited ahead of time[*]

Andrew Gelman[†] and Eric Loken[‡]

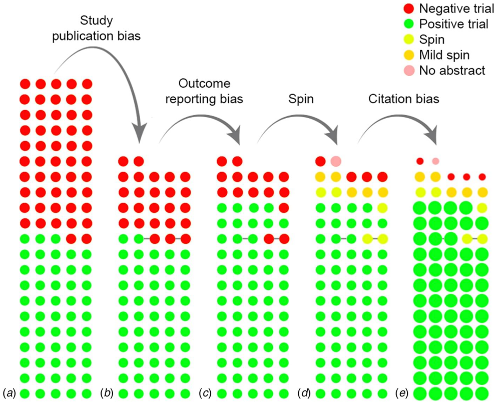
14 Nov 2013

Abstract

Researcher degrees of freedom can lead to a multiple comparisons problem, even in settings where researchers perform only a single analysis on their data. The problem is there can be a large number of *potential* comparisons when the details of data analysis are highly contingent on data, without the researcher having to perform any conscious procedure of fishing or examining multiple p-values. We discuss in the context of several examples of published papers where data-analysis decisions were theoretically-motivated based on previous literature, but where the details of data selection and analysis were not pre-specified and, as a result, were contingent on data.

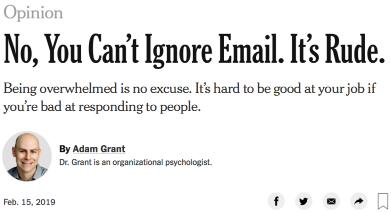
Publication / citation bias

While only 50% of FDA-registered studies on antidepressants find positive results, but 95% of publications report positive findings.



bit.ly/depressionspin

Robustness



Opinion

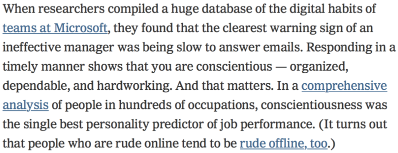
No, You Can't Ignore Email. It's Rude.

Being overwhelmed is no excuse. It's hard to be good at your job if you're bad at responding to people.

By Adam Grant

Dr. Grant is an organizational psychologist.

Feb. 15, 2019



When researchers compiled a huge database of the digital habits of teams at Microsoft, they found that the clearest warning sign of an ineffective manager was being slow to answer emails. Responding in a timely manner shows that you are conscientious — organized, dependable, and hardworking. And that matters. In a comprehensive analysis of people in hundreds of occupations, conscientiousness was the single best personality predictor of job performance. (It turns out that people who are rude online tend to be rude offline, too.)

So, what should you do?

- Read the literature
- Formulate your study
- Run a simple pilot
- Analyze the results
- Revise your study (null != nil)
- Do a power calculation
- Pre-register your plans
- Run your study
- Create a reproducible report
- Think critically about results
- Disclose everything you did