Open Science and Research Ethics in I-O Psychology

Jamie Field, PhD
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Tuesday
October 26, 2021

****These PowerPoint slides and other resources can be found at:**
https://jamiefield.github.io/research/gmu2021

WestVirginiaUniversity.

John Chambers College of
Business and Economics

Agenda

- Personal introduction
- 60,000ft view of a big “The Problem” (questionable research practices)
- A (potential) solution: Open science practices (examples; limitations; etc.)
- Highways and Byways: The Open Science Infrastructure
- How to Get Involved
- Q&A session | Open discussion

Before we begin…

- Please accept my sincerest apologies for my last-minute postponement back in the spring semester!

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- Major thanks to Steven and Seth for being so understanding during a particularly stressful time.
- I am delighted that you invited me back!

Before we begin…

- I also want to recognize some of my close collaborators
  - Frank Bosco (Virginia Commonwealth U.)
  - Martin Götz (University of Zurich)
  - George Banks (U. of North Carolina at Charlotte)
  - Ernest O’Boyle (Indiana U.)
  - Frew Oswald (Rice U.)

About Me…

- Originally from Tralee, County Kerry

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About Me…

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- Came to the U.S. in 2004 on a golf scholarship

- How it started….

- How it started….

Here is 14-year-old me being presented with the "Junior Golfer of the Year" medal by Arnold Palmer

For those of you who are not familiar with golf, he's a legend!!

- How it's going…

- How it’s going…

Here’s a picture of my golf clubs (taken last night).

They hang in my garage.

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- Originally from Tralee, County Kerry
- Came to the U.S. in 2004 on a golf scholarship
- Glenville, WV → Huntington, WV, → Richmond, VA

About Me…

WestVirginiaUniversity
JOHN CHAMBERS COLLEGE OF BUSINESS AND ECONOMICS

- Originally from Tralee, County Kerry
- Came to the U.S. in 2004 on a golf scholarship
- Glenville, WV → Huntington, WV, → Richmond, VA → Morgantown, WV
- Assistant Professor at WVU since fall 2017

Research Interests

Meta-Science
(incl. Big Data)

Research Interests

Meta-Science
(incl. Big Data)

Journal of International Business Studies (2021)

www.jibs.net

More alike than different? A comparison of variance explained by cross-cultural models

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Frank A. Bosco[2],
David Kraichy[3],
Krista L. Uggerslev[4] and
Mingang K. Geiger[1]

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Abstract

Relatively little is known about the extent to which culture moderates findings in applied psychology research. To address this gap, we leverage the metaBUS database of over 1,000,000 published findings to examine the extent to which six popular cross-cultural models explain variance in findings across 136 bivariate relationships and 56 individual cultural dimensions. We compare moderating effects attributable to Hofstede's dimensions, GLOBE's practices, GLOBE's values, Schwartz's Value Survey, Ronen and Shenkar's cultural clusters, and the United Nations' M49 standard. Results from 25,296 multilevel meta-analyses indicate that, after accounting for statistical artifacts, cross-cultural models explain approximately 5–7% of the variance in findings. The variance explained did not vary substantially across models. A similar set of analyses on observed effect sizes reveal differences of $|r|$ = .05–.07 attributable to culture. Variance among the 136 bivariate relationships was explained primarily by sampling error, indicating that cross-cultural moderation assessments require atypically large sample sizes. Our results provide important information for understanding the overall level of explanatory power attributable to cross-cultural models, their relative performance, and their sensitivity to variance in the topic of study. In addition, our findings may be used to inform power analyses for future research. We discuss implications for research and practice.

Journal of International Business Studies (2021).
https://doi.org/10.1057/s41267-021-00428-z

Keywords: meta-analysis; big data; open science; cross-cultural research/measurement issues

Research Interests

Open Science

RESEARCH ARTICLE SUMMARY

PSYCHOLOGY

Estimating the reproducibility of psychological science

Open Science Collaboration*

INTRODUCTION: Reproducibility is a defining feature of science, but the extent to which it characterizes current research is unknown. Scientific claims should not gain credence because of the status or authority of their originator but by the replicability of their supporting evidence. Even research of exemplary quality may have irreproducible empirical findings because of random or systematic error.

RATIONALE: There is concern about the rate and predictors of reproducibility, but limited evidence. Potentially problematic practices include selective reporting, selective analysis, and insufficient specification of the conditions necessary or sufficient to obtain the results. Direct replication is the attempt to recreate the conditions believed sufficient for obtaining a previously observed finding and is the means of establishing reproducibility of a finding with new data. We conducted a large-scale, collaborative effort to obtain an initial estimate of the reproducibility of psychological science.

RESULTS: We conducted replications of 100 experimental and correlational studies published in three psychology journals using high-powered designs and original materials when available. There is no single standard for evaluating replication success. Here, we evaluated reproducibility using significance and *P* values, effect sizes, subjective assessments of replication teams, and meta-analysis of effect sizes. The mean effect size (r) of the replication effects (M_r = 0.197, SD = 0.257) was half the magnitude of the mean effect size of the original effects (M_r = 0.403, SD = 0.188), representing a

Research Interests

Open Science

Journal of Business and Psychology
https://doi.org/10.1007/s10869-018-9547-8

ORIGINAL PAPER

CrossMark

Answers to 18 Questions About Open Science Practices

George C. Banks [1] · James G. Field [2] · Frederick L. Oswald [3] · Ernest H. O'Boyle [4] · Ronald S. Landis [5] · Deborah E. Rupp [6] · Steven G. Rogelberg [1]

Abstract
Open science refers to an array of practices that promote openness, integrity, and reproducibility in research; the merits of which are being vigorously debated and developed across academic journals, listservs, conference sessions, and professional associations. The current paper identifies and clarifies major issues related to the use of open science practices (e.g., data sharing, study pre-registration, open access journals). We begin with a useful general description of what open science in organizational research represents and adopt a question-and-answer format. Through this format, we then focus on the application of specific open science practices and explore future directions of open science. All of this builds up to a series of specific actionable recommendations provided in conclusion, to help individual researchers, reviewers, journal editors, and other stakeholders develop a more open research environment and culture.

Keywords Open science · Philosophy of science · Questionable research practices · Research ethics

Research Interests

Research Methods

Journal of Applied Psychology
2015, Vol. 100, No. 2, 431–449

0021-9010/15/$12.00 http://dx.doi.org/10.1037/a0038047

Correlational Effect Size Benchmarks

Frank A. Bosco
Virginia Commonwealth University

Herman Aguinis
Indiana University

Kulraj Singh
South Dakota State University

James G. Field
Virginia Commonwealth University

Charles A. Pierce
University of Memphis

Effect size information is essential for the scientific enterprise and plays an increasingly central role in the scientific process. We extracted 147,328 correlations and developed a hierarchical taxonomy of variables reported in *Journal of Applied Psychology* and *Personnel Psychology* from 1980 to 2010 to produce empirical effect size benchmarks at the omnibus level, for 20 common research domains, and for an even finer grained level of generality. Results indicate that the usual interpretation and classification of effect sizes as small, medium, and large bear almost no resemblance to findings in the field, because distributions of effect sizes exhibit tertile partitions at values approximately one-half to one-third those intuited by Cohen (1988). Our results offer information that can be used for research planning and design purposes, such as producing better informed non-nil hypotheses and estimating statistical power and planning sample size accordingly. We also offer information useful for understanding the relative importance of the effect sizes found in a particular study in relationship to others and which research domains have advanced more or less, given that larger effect sizes indicate a better understanding of a phenomenon. Also, our study offers information about research domains for which the investigation of moderating effects may be more fruitful and provide information that is likely to facilitate the implementation of Bayesian analysis. Finally, our study offers information that practitioners can use to evaluate the relative effectiveness of various types of interventions.

Keywords: effect size, statistical analysis, null hypothesis testing, big data

Research Interests

Research Methods

Journal of Business and Psychology (2021) 36:349–365
https://doi.org/10.1007/s10869-020-09687-3

ORIGINAL PAPER

Check for updates

How robust is our cumulative knowledge on turnover?

James G. Field[1] · Frank A. Bosco[2] · Sven Kepes[2]

Published online: 28 February 2020

Abstract
Although systematic reviews are considered the primary means for generating cumulative knowledge and their results are often used to inform evidence-based practice, the robustness of their meta-analytic summary estimates is rarely investigated. Consequently, the results of published systematic reviews and, by extension, our cumulative knowledge have come under scrutiny. Using a comprehensive approach to sensitivity analysis, we examined the impact of outliers and publication bias, as well as their combined effect, on meta-analytic results on employee turnover. Our analysis of 205 distributions from seven recently published meta-analyses revealed that meta-analytic results on turnover are often affected by publication bias and, less frequently, outliers. Moreover, we observed that 33% of the recommendations for practice provided in the original systematic reviews on turnover were not robust to outliers and/or publication bias, which, if implemented by practitioners, could yield unexpected consequences and, thus, widen the science-practice gap. We argue that practitioners should be skeptical about implementing practices recommended by meta-analytic studies that do not include sensitivity analyses. To improve sensitivity analysis reporting rates and, thus, the transparency of meta-analytic findings and recommendations for practice, we introduce an open-access software (metasen.shinyapps.io/gen1/) that conducts all analyses performed in the current study. We provide guidelines and recommendations for future turnover studies and sensitivity analyses in the meta-analytic context.

Keywords Turnover · Sensitivity analysis · Publication bias · Outliers

Research Interests

Research Methods

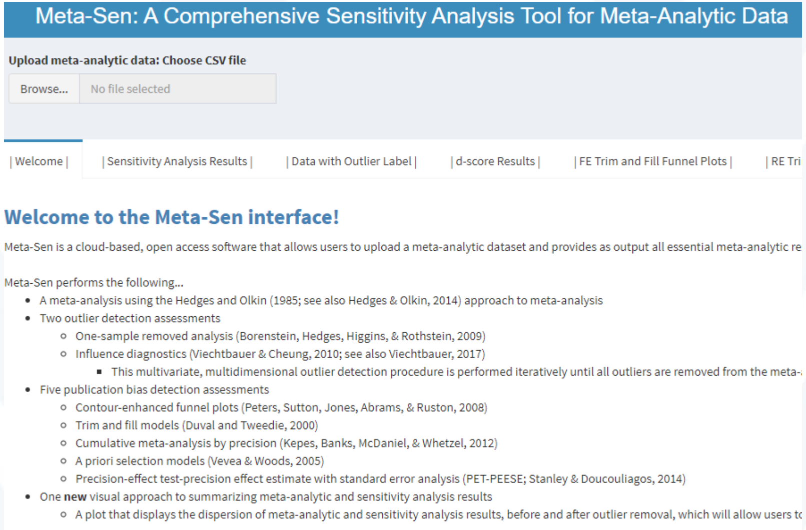
&

Software Develop.

See:

https://metasen.shinyapps.io/gen1/

https://casst.shinyapps.io/gen1/



Enough about me!

Let's talk about research ethics and open science practices…

Rapid Fire Motivating Question:

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What are the biggest challenges

facing our science?

Biggest Challenges Answers

- You provided lots of great answers!

Biggest Challenges Answers

- You provided lots of great answers!
- Indeed, the diversity of responses reveals how difficult it is to do what we do!

Biggest Challenges Answers

- You provided lots of great answers!
- Indeed, the diversity of responses reveals how difficult it is to do what we do!
- **Our goal should not be *perfection* (there is no such thing, IMO). Instead, our goal should be *improvement*.**

Controversial Studies

Stanford Prison Experiment

The Stanford prison experiment (SPE) was a social psychology experiment that attempted to investigate the psychological effects of perceived power, focusing on the struggle between prisoners and prison officers.

https://en.wikipedia.org/wiki/Stanford_prison_experiment

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https://en.wikipedia.org/wiki/Tuskegee_Syphilis_Study

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Project MKUltra

A program of experiments on human subjects that were designed and undertaken by the CIA were intended to identify and develop drugs and procedures to be used in interrogations in order to weaken the individual and force confessions.

https://en.wikipedia.org/wiki/Project_MKUltra

Looking ahead…

- Surely all the hard lessons are behind us… right?

Looking ahead…

- It looks like our problems may get even more complicated in the future…

Looking ahead…

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MIS Quarterly
SPECIAL ISSUE: MANAGING AI

FAILURES OF FAIRNESS IN AUTOMATION REQUIRE A DEEPER UNDERSTANDING OF HUMAN–ML AUGMENTATION[1]

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Machine learning (ML) tools reduce the costs of performing repetitive, time-consuming tasks yet run the risk of introducing systematic unfairness into organizational processes. Automated approaches to achieving fairness often fail in complex situations, leading some researchers to suggest that human augmentation of ML tools is necessary. However, our current understanding of human–ML augmentation remains limited. In this paper, we argue that the Information Systems (IS) discipline needs a more sophisticated view of and research into human–ML augmentation. We introduce a typology of augmentation for fairness consisting of four quadrants: reactive oversight, proactive oversight, informed reliance, and supervised reliance. We identify significant intersections with previous IS research and distinct managerial approaches to fairness for each quadrant. Several potential research questions emerge from fundamental differences between ML tools trained on data and traditional IS built with code. IS researchers may discover that the differences of ML tools undermine some of the fundamental assumptions upon which classic IS theories and concepts rest. ML may require massive rethinking of significant portions of the corpus of IS research in light of these differences, representing an exciting frontier for research into human–ML augmentation in the years ahead that IS researchers should embrace.

Keywords: Fairness, machine learning, augmentation, automation, artificial intelligence

Looking ahead…

- It looks like our problems may get even more complicated in the future…

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Digital Phenotyping of Big Five Personality Traits via Facebook Data Mining: A Meta-Analysis

Davide Marengo[1*] & Christian Montag[2]

[1] Department of Psychology, University of Turin, Italy

[2] Department of Molecular Psychology, Institute for Psychology and Education, Ulm University, Germany

Abstract

Background: About 2.5 billion people around the world currently have an active account on Facebook. By interacting with Facebook, users generate a vast dataset of information with potential links to psychological and behavioral characteristics. In particular, several researchers have already demonstrated that it is feasible to predict personality from activity logs, posted text, or "Like" behaviors on Facebook.

Objectives: In this study, we carried out a meta-analysis of the available literature on predicting personality from Facebook data.

Methods: Meta-analysis computations were performed using a multilevel approach.

Results: Results showed that, on average, the accuracy of prediction of user personality scores through the mining of Facebook data is moderate (r = .34). However, prediction accuracy was improved when models included demographic variables, and multiple types of digital footprints.

Discussions: Currently, generating personality predictions from Facebook data is feasible, but accuracy is at best moderate. Therefore, current predictions cannot be used for assessment purposes at the individual level, but may provide useful information when conducting group-level assessments. However, prediction accuracy is expected to improve as larger datasets and new types of data are mined for prediction purposes.

Keywords: social media, personality, Facebook, digital phenotyping, psychoinformatics

Article History
Received 29 November 2019
Revised 29 Februar 2020
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DOI 10.24989/dp.v1i1.1823

Current research environment

- The 2010s was not a good decade for science in general…

Current research environment

- The 2010s was not a good decade for science in general…
  - Statistical tests in primary studies appeared to be grossly underpowered (Götz et al., 2021; O'Boyle et al., 2019)
  - Growing empirical evidence regarding the incidence and impact of questionable research practices (Banks et al., 2016a; Banks et al., 2016b; Bosco et al., 2016)
  - Replication rates for primary studies have ranged from 39% to 77% when using a criterion of $p > .05$ (Klein et al., 2018b; Open Science Collaboration, 2015
  - Robustness of meta-analytic findings have been brought into question (Field et al., 2021; Harrison et al., 2017)

Current research environment

- Together, the accumulated evidence supported the notion that the psychological sciences are experiencing a "crisis of confidence"

(De Boeck & Jeon, 2018)

Questionable Research Practices

- The current situation is due in part to researchers engaging in questionable research practices (QRPs)

Questionable Research Practices

- QRPs operate in the ambiguous space between what one might consider best practices and academic misconduct

Questionable Research Practices

- Common examples of QRPs:

(1) Selectively report hypotheses
(see O'Boyle, Banks, & Gonzalez-Mule, 2016)

retractionwatch.com

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(2) Exclude data post hoc
(see De Vries, Anderson, & Martinson, 2006)

([illegible]) Selectively include control variables
(see Kepes & McDaniel, 2013)

([illegible]) Falsify data
(several examples from our field – see retractionwatch.com)

(6) p-hacking
(see Head et al., 2015)

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retractionwatch.com

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(6) *p*-hacking
(see Head et al., 2015; Götz et al., 2021)

Current research environment?

Open Science:

A Self-Correction Mechanism for IO Research?

- Could there be a silver lining?

Open Science:

A Self-Correction Mechanism for IO Research?

- In short order the open science movement is transforming how I-O research is done, reported, and evaluated.

What is Open Science?

- Transparent and accessible knowledge that is shared and developed through collaborative networks (Vicente-Saez & Martinez-Fuentes, 2018)

What is Open Science?

- A thriving facet of the scientific ecosystem that is nurtured by a variety of concepts, ranging from scientific philosophies and cultural norms, to specific practices that operationalize these perspectives and help scholars to enact such norms. (Banks et al., 2018; Götz & Field, in press)

Purpose of Open Science Practices

- To improve the openness, integrity, rigor, and reproducibility of research by preventing research misconduct or reducing questionable research and/or reporting practices

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- To improve the openness, integrity, rigor, and reproducibility of research by preventing research misconduct or reducing questionable research and/or reporting practices
- Can also help to…
  - Promote communication and collaboration
  - Enhance meta-analytic reviews
  - Facilitate a better understanding of the scientific process

Examples of Open Science Practices

(1) Sharing data and analytic files
(see Field et al., in press)

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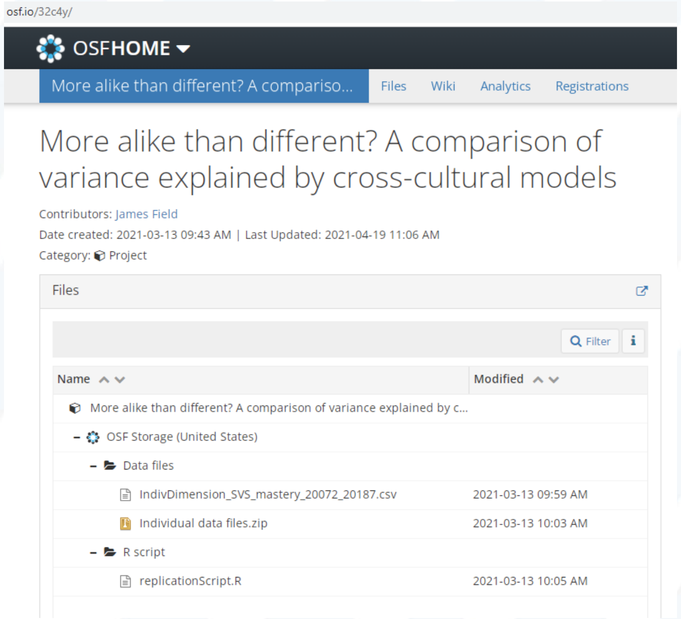

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Conclusion

Science is diverse, and it is up to scientists to justify the alpha level they decide to use. As Fisher noted[14]: "...no scientific worker has a fixed level of significance at which, from year to year, and in all circumstances, he rejects hypotheses; he rather gives his mind to each particular case in the light of his evidence and his ideas." Research should be guided by principles of *rigorous science*[15], not by heuristics and arbitrary blanket thresholds. These principles include not only sound statistical analyses, but also experimental redundancy (e.g., replication, validation, and generalisation), avoidance of logical traps, intellectual honesty, research workflow transparency, and accounting for potential sources of error. Single studies, regardless of their *p*-value, are never enough to conclude that there is strong evidence for a substantive claim. We need to train researchers to assess cumulative evidence and work towards an unbiased scientific literature. We call for a broader mandate beyond *p*-value thresholds whereby all *justifications* of key choices in research design and statistical practice are transparently evaluated, fully accessible, and pre-registered whenever feasible.

Examples of Open Science Practices

(1) Sharing data and analytic files
(see Field et al., in press)

(2) Justifying statistical significance thresholds
(see Lakens et al., 2016)

(3) A priori sample size estimation
(see Lakens, 2021;Field et al., in press)

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(see Lakens, 2021;Field et al., in press)

Table 1
Overview of possible justifications for the sample size in a study.

Type of justification	When is this justification applicable?
Measure entire population	A researcher can specify the entire population, it is finite, and it is possible to measure (almost) every entity in the population.
Resource constraints	Limited resources are the primary reason for the choice of the sample size a researcher can collect.
Accuracy	The research question focusses on the size of a parameter, and a researcher collects sufficient data to have an estimate with a desired level of accuracy.
A-priori power analysis	The research question has the aim to test whether certain effect sizes can be statistically rejected with a desired statistical power.
Heuristics	A researcher decides upon the sample size based on a heuristic, general rule or norm that is described in the literature, or communicated orally.
No justification	A researcher has no reason to choose a specific sample size, or does not have a clearly specified inferential goal and wants to communicate this honestly.

Source: Lakens (2021)

Examples of Open Science Practices

(1) Sharing data and analytic files
(see Field et al., in press)

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(see Lakens et al., 2016)

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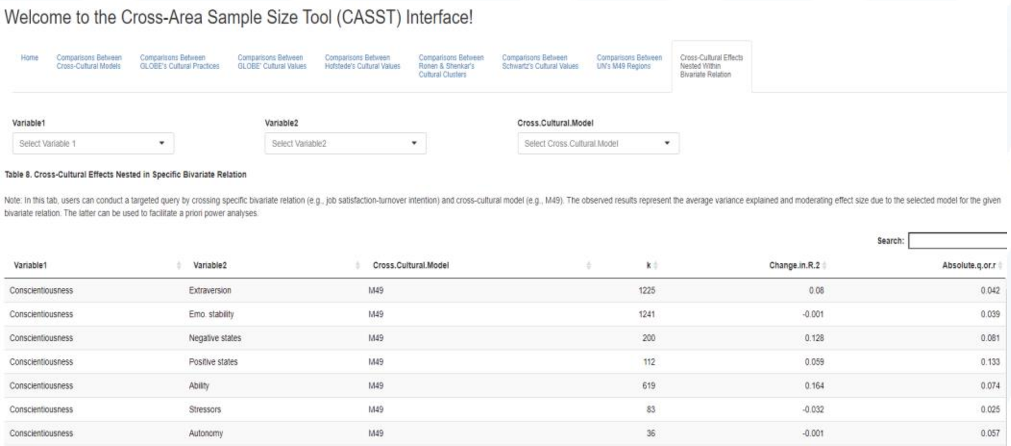
Welcome to the Cross-Area Sample Size Tool (CASST) Interface!

Home | Comparisons Between Cross-Cultural Models | Comparisons Between GLOBE's Cultural Practices | Comparisons Between GLOBE' Cultural Values | Comparisons Between Hofstede's Cultural Values | Comparisons Between Ronen & Shenkar's Cultural Clusters | Comparisons Between Schwartz's Cultural Values | Comparisons Between UN's M49 Regions | Cross-Cultural Effects Nested Within Bivariate Relation

Variable1: Select Variable 1
Variable2: Select Variable2
Cross.Cultural.Model: Select Cross.Cultural.Model

Table 8. Cross-Cultural Effects Nested in Specific Bivariate Relation

Note: In this tab, users can conduct a targeted query by crossing specific bivariate relation (e.g., job satisfaction-turnover intention) and cross-cultural model (e.g., M49). The observed results represent the average variance explained and moderating effect size due to the selected model for the given bivariate relation. The latter can be used to facilitate a priori power analyses.

Search:

Variable1	Variable2	Cross.Cultural.Model	k	Change.in.R.2	Absolute.q.or.r
Conscientiousness	Extraversion	M49	1225	0.08	0.042
Conscientiousness	Emo. stability	M49	1241	-0.001	0.039
Conscientiousness	Negative states	M49	200	0.128	0.081
Conscientiousness	Positive states	M49	112	0.059	0.133
Conscientiousness	Ability	M49	619	0.164	0.074
Conscientiousness	Stressors	M49	83	-0.032	0.025
Conscientiousness	Autonomy	M49	36	-0.001	0.057

Source: Field et al. (in press)

Examples of Open Science Practices

(1) Sharing data and analytic files
(see Field et al., in press)

(2) Justifying statistical significance thresholds
(see Lakens et al., 2016)

(3) A priori sample size estimation
(see Lakens, 2021;Field et al., in press)

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ELSEVIER

Same data, different conclusions: Radical dispersion in empirical results when independent analysts operationalize and test the same hypothesis☆

ARTICLE INFO

Keywords:
Crowdsourcing data analysis
Scientific transparency
Research reliability
Scientific robustness
Researcher degrees of freedom
Analysis-contingent results

ABSTRACT

In this crowdsourced initiative, independent analysts used the same dataset to test two hypotheses regarding the effects of scientists' gender and professional status on verbosity during group meetings. Not only the analytic approach but also the operationalizations of key variables were left unconstrained and up to individual analysts. For instance, analysts could choose to operationalize status as job title, institutional ranking, citation counts, or some combination. To maximize transparency regarding the process by which analytic choices are made, the analysts used a platform we developed called DataExplained to justify both preferred and rejected analytic paths in real time. Analyses lacking sufficient detail, reproducible code, or with statistical errors were excluded, resulting in 29 analyses in the final sample. Researchers reported radically different analyses and dispersed empirical outcomes, in a number of cases obtaining significant effects in opposite directions for the same research question. A Boba multiverse analysis demonstrates that decisions about how to operationalize variables explain variability in outcomes above and beyond statistical choices (e.g., covariates). Subjective researcher decisions play a critical role in driving the reported empirical results, underscoring the need for open data, systematic robustness checks, and transparency regarding both analytic paths taken and not taken. Implications for organizations and leaders, whose decision making relies in part on scientific findings, consulting reports, and internal analyses by data scientists, are discussed.

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nature > nature human behaviour > articles > article

Article | Published: 24 June 2021

Initial evidence of research quality of registered reports compared with the standard publishing model

Courtney K. Soderberg, Timothy M. Errington, Sarah R. Schiavone, Julia Bottesini, Felix Singleton Thorn, Simine Vazire, Kevin M. Esterling & Brian A. Nosek

Nature Human Behaviour **5**, 990–997 (2021) | Cite this article

Abstract

In registered reports (RRs), initial peer review and in-principle acceptance occur before knowing the research outcomes. This combats publication bias and distinguishes planned from unplanned research. How RRs could improve the credibility of research findings is straightforward, but there is little empirical evidence. Also, there could be unintended costs such as reducing novelty. Here, 353 researchers peer reviewed a pair of papers from 29 published RRs from psychology and neuroscience and 57 non-RR comparison papers. RRs numerically outperformed comparison papers on all 19 criteria (mean difference 0.46, scale range −4 to +4) with effects ranging from RRs being statistically indistinguishable from comparison papers in novelty (0.13, 95% credible interval [−0.24, 0.49]) and creativity (0.22, [−0.14, 0.58]) to sizeable improvements in rigour of methodology (0.99, [0.62, 1.35]) and analysis (0.97, [0.60, 1.34]) and overall paper quality (0.66, [0.30, 1.02]). RRs could improve research quality while reducing publication bias and ultimately improve the credibility of the published literature.

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Table 1
Recommendations for narrowing the science-practice gap in open science: Updating the knowledge-production process.

Recommendation	Benefits	Primary decision-makers involved in implementing the recommendations	Resources needed to implement and enforce the recommendations
1. Require preregistration of quantitative and qualitative primary studies	**Definition of the research problem** • Improved explanation of theoretical and practical problems **Study design** • Improved planning of study design **Data analyses** • Improved planning of analyses **Reporting and publishing** • Improved transparency (e.g., improved differentiation between confirmatory and exploratory analyses)	Editors, funding agencies, and authors	• **Financial resources**: None • **Time**: 30–60 min of authors' time to preregister using the Open Science Framework and creating an anonymous link for peer-review • **Additional resources**: None • **Enforcement**: Editors can desk-reject noncompliant submissions and funding agencies can make funding contingent upon commitment to preregistration
2. Introduce a review track using a registered-report format	**Reporting and publishing** • Improved credibility of findings and reputations of journals and authors • Improved evaluation of contributions and methodological rigor	Editors	• **Financial resources**: Standard production costs • **Time**: 12 months' time of action editor and reviewer • **Additional resources**: none • **Enforcement**: None
3. Introduce a second submission track for results-blind reviews	**Reporting and publishing** • Improved reviewer evaluations that minimize reviewer biases • Improved transparency	Editors and publishers	• **Financial resources**: Compensation for web developer • **Time**: 2 months' time of a web developer • **Additional resources**: Training materials for action editors and reviewers, author guidelines • **Enforcement**: None
4. Motivate authors to discuss validity threats honestly and precisely to re-invigorate the Discussion sections of papers	**Reporting and publishing** • Improved credibility and practical usefulness of scientific findings	Editors and authors	• **Financial resources**: None • **Time**: Possible involvement of specialized reviewers • **Additional resources**: Training materials for action editors and reviewers; author guidelines • **Enforcement**: Requirement for publication

Source: Aguinis et al. (2020)

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Table 2. Descriptive statistics from the quantitative data.

Item	Mean Rating	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree	% Favourable
1. The organizational sciences would benefit from the results-blind initiative	3.86	3.00%	7.40%	15.80%	48.80%	25.10%	73.90%
2. The results-blind review initiative would be possible to implement in organizational science journals.	3.33	5.90%	23.60%	18.70%	35.00%	16.70%	51.70%
3. The results-blind review initiative would help combat questionable research practices (e.g., selective reporting of hypotheses, hypothesizing after results are known [HARKing], selective use of control variables).	3.64	5.40%	13.30%	16.70%	40.90%	23.60%	64.50%
4. The results-blind review initiative would help advance the cumulative knowledge in our science.	3.83	3.00%	6.90%	17.70%	48.80%	23.60%	72.40%
5. The potential benefits of implementing the results-blind review initiative outweigh the costs.	3.51	3.00%	10.80%	32.50%	39.90%	13.80%	53.70%
6. Journals should offer the results-blind review as a path to submission, in addition to the traditional path	3.76	5.00%	6.00%	16.90%	52.20%	19.90%	72.10%
7. As an *author*, I would want to pursue a results-blind review path to publication as opposed to the traditional path.	3.25	7.50%	13.90%	33.80%	35.30%	9.50%	44.80%

The response scale for each item was 1–5. "% Favourable" refers to the percentage of respondents who "Agree" and "Strongly Agree." Participants were randomly assigned to one of two versions (positively worded and negatively worded) of item numbers 1–5. There was an additional item asking whether participants would want to review a results-blind submission, but we dropped it due to a lack of a control item assessing participants' desire to review in general.

Source: Woznyj et al. (2018)

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(Köhler et al. 2020; Zhang et al., 2020)

Examples of Open Science Practices

Industrial and Organizational Psychology (2020), **13**, 1–27
doi:10.1017/iop.2019.121

CAMBRIDGE
UNIVERSITY PRESS

FOCAL ARTICLE

Supporting robust, rigorous, and reliable reviewing as the cornerstone of our profession: Introducing a competency framework for peer review

Tine Köhler[1,*], M. Gloria González-Morales[2], George C. Banks[3], Ernest H. O'Boyle[4], Joseph A. Allen[5], Ruchi Sinha[6], Sang Eun Woo[7], and Lisa M. V. Gulick[8]

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(Received 15 December 2018; revised 16 September 2019; accepted 21 September 2019)

Abstract
Peer review is a critical component toward facilitating a robust science in industrial and organizational (I-O) psychology. Peer review exists beyond academic publishing in organizations, university departments, grant agencies, classrooms, and many more work contexts. Reviewers are responsible for judging the quality of research conducted and submitted for evaluation. Furthermore, they are responsible for treating authors and their work with respect, in a supportive and developmental manner. Given its central role in our profession, it is curious that we do not have formalized review guidelines or standards and that most of us never receive formal training in peer reviewing. To support this endeavor, we are proposing a competency framework for peer review. The purpose of the competency framework is to provide a definition of excellent peer reviewing and guidelines to reviewers for which types of behaviors will lead to good peer reviews. By defining these competencies, we create clarity around expectations for peer review, standards for good peer reviews, and opportunities for training the behaviors required to deliver good peer reviews. We further discuss how the competency framework can be used to improve peer reviewing and suggest additional steps forward that involve suggestions for how stakeholders can get involved in fostering high-quality peer reviewing.

Keywords: peer review; competency framework; developmental feedback; reliable reviewing

(6) Transparent review process
(Köhler et al. 2020; Zhang et al., 2020)

Examples of Open Science Practices

(1) Sharing data and analytic files
(see Field et al., in press)

(2) Justifying statistical significance thresholds

Conclusion

In conclusion, we believe the benefits of open peer review outweigh its limitations. As a field, we ought not to let the fear of incivility obstruct the betterment of our science. Despite its limitations, open peer review is a viable solution toward improving the overall quality of peer reviews. For open review to thrive, however, we believe other changes in reviewer expectations, civility norms, and editorial policy are needed.

Source: Zhang et al. (2020)

(5) Promoting alternate submission options
(see Aguinis et al., 2020; Woznyj et al., 2018)

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(7) Utilizing open access interfaces (e.g., metaBUS)
(see Bosco et al., 2020)

Examples of Open Science Practices

We then searched the metaBUS database (Bosco, Aguinis, Singh, Field, & Pierce, 2015) for existing relationships between variables not identified by Web of Science and gathered three additional estimates. We contacted

Source: Chamberlin et al. (2017)

3.3. Variability in effect size among various subpopulations

Using the Yu et al. (2016) technique, we can discern relationships in the JD-R model which have high levels of variability in effect size in the population. High variability (i.e., 80% CV_{β} widths ≥ 0.55; Bosco et al., 2015; Yu et al., 2016)—particularly if the 80% CV_{β} includes estimates where the sign (+/−) of the path estimate switches—indicates the presence of significant boundary conditions within the population. The implication, as discussed below, is that there are certain subpopulations (e.g., samples within certain industries, cultures, or various individual differences) which moderate such relationships within the JD-R model. We identify relationships based on suggested benchmarks set forth by Bosco et al. (2015) as an update to Cohen's (1992) conventional benchmarks, and calculated for use in interpreting MASEM effect size distributions by Yu et al. (2016) per the following: small heterogeneity (i.e., the relationship is consistent across the entire population; 80% CV_{β} width of less than 0.18), moderate heterogeneity (i.e., 80% CV_{β} width between 0.18 and 0.54), and large heterogeneity (80% CV_{β} width greater than 0.54).

Source: Goering et al. (2017)

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(see Bosco et al., 2020)

(8) Removing paywalls to increase access
(see Nosek et al., 2012)

(9) Implementing new reward systems
(see N[illegible] et al., 2012)

(10) Encouraging replications
(see Ebersole et al., 2020; Open Science Framework, 2015)

Examples of Open Science Practices

Psychological Inquiry, 23: 217–243, 2012

ISSN: 1047-840X print / 1532-7965 online
DOI: 10.1080/1047840X.2012.692215

Psychology Press
Taylor & Francis Group

TARGET ARTICLE

Scientific Utopia: I. Opening Scientific Communication

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Department of Psychology, University of Virginia, Charlottesville, Virginia

Yoav Bar-Anan
Department of Psychology, Ben-Gurion University, Beer Sheva, Israel

Existing norms for scientific communication are rooted in anachronistic practices of bygone eras making them needlessly inefficient. We outline a path that moves away from the existing model of scientific communication to improve the efficiency in meeting the purpose of public science—knowledge accumulation. We call for six changes: (a) full embrace of digital communication; (b) open access to all published research; (c) disentangling publication from evaluation; (d) breaking the "one article, one journal" model with a grading system for evaluation and diversified dissemination outlets; (e) publishing peer review; and (f) allowing open, continuous peer review. We address conceptual and practical barriers to change and provide examples showing how the suggested practices are being used already. The critical barriers to change are not technical or financial; they are social. Although scientists guard the status quo, they also have the power to change it.

(6) Transparent review process
(Köhler et al. 2020; Zhang et al., 2020)

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Examples of Open Science Practices

PLOS | BIOLOGY

META-RESEARCH ARTICLE

Badges to Acknowledge Open Practices: A Simple, Low-Cost, Effective Method for Increasing Transparency

Mallory C. Kidwell[1]*, Ljiljana B. Lazarević[2], Erica Baranski[3], Tom E. Hardwicke[4], Sarah Piechowski[5], Lina-Sophia Falkenberg[5], Curtis Kennett[6], Agnieszka Slowik[7], Carina Sonnleitner[7], Chelsey Hess-Holden[6], Timothy M. Errington[1], Susann Fiedler[5], Brian A. Nosek[1,8]

OPEN ACCESS

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Academic Editor: Malcolm R Macleod, University of Edinburgh, UNITED KINGDOM

Received: January 20, 2016

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Published: May 12, 2016

Abstract

Beginning January 2014, *Psychological Science* gave authors the opportunity to signal open data and materials if they qualified for badges that accompanied published articles. Before badges, less than 3% of *Psychological Science* articles reported open data. After badges, 23% reported open data, with an accelerating trend; 39% reported open data in the first half of 2015, an increase of more than an order of magnitude from baseline. There was no change over time in the low rates of data sharing among comparison journals. Moreover, reporting openness does not guarantee openness. When badges were earned, reportedly available data were more likely to be actually available, correct, usable, and complete than when badges were not earned. Open materials also increased to a weaker degree, and there was more variability among comparison journals. Badges are simple, effective signals to promote open practices and improve preservation of data and materials by using independent repositories.

(6) Transparent review process
(Köhler et al. 2020; Zhang et al., 2020)

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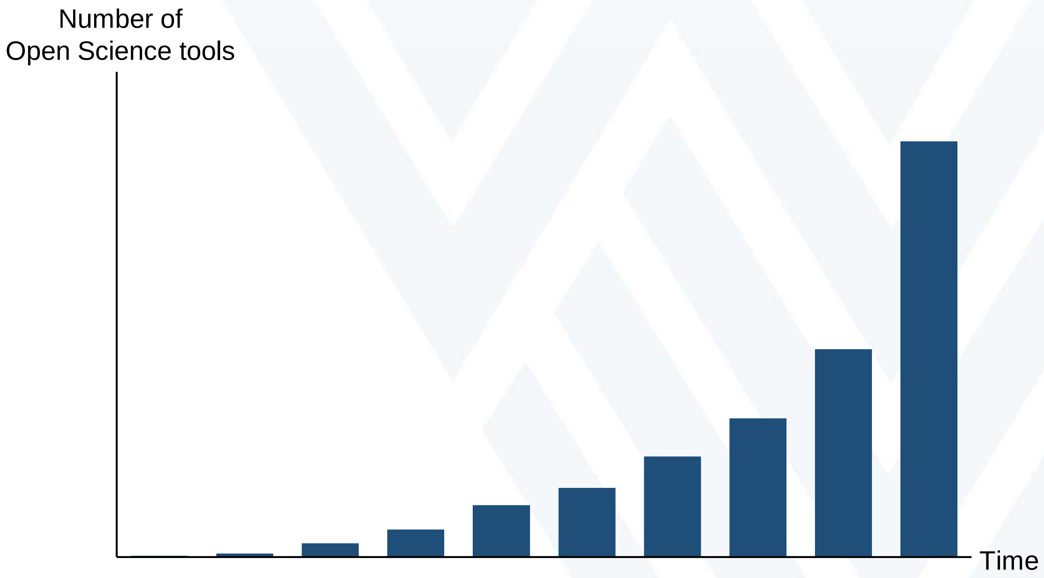
Highways and Byways: The Open Science Infrastructure



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- Open Science Guidelines
  - Transparency and Openness Promotion (TOP) guidelines (see Nosek et al., 2015)

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Highways and Byways: The Open Science Infrastructure

- Open Science Guidelines
  - Transparency and Openness Promotion (TOP) guidelines (see Nosek et al., 2015)
  - Revised reporting standards (Appelbaum et al., 2018)
  - SIOP's Committee for the Advancement of Professional Ethics (CAPE; see https://www.siop.org/Career-Center/Professional-Ethics)
  - Flagship journals are now encouraging (and in some cases are requiring) researchers to engage in certain open science practices

Highways and Byways: The Open Science Infrastructure

- Open Access Platforms
  - Open Science Framework (https://osf.io/)

Highways and Byways: The Open Science Infrastructure

- Open Access Platforms
  - Open Science Framework (https://osf.io/)
  - Hypergraph (http://www.hypergraph.xyz)
  - Statcheck (http://statcheck.io/)
  - GRIM: Granularity Related Inconsistent Means (https://osf.io/3fcbr/)
  - metaBUS (https://www.metabus.org)
  - Meta-Sen (https://metasen.shinyapps.io/gen1/)

Potential Folly of Open Science

- Increased transparency and rigor may come at the expense of serendipitous discovery (see Leavitt, 2013)
- Requiring data sharing may deter members of sensitive populations (e.g., marginalized employees in the workplace) from participating in studies (Gabriel & Wessel, 2013)
- Studies that adhere to certain open science practices may be perceived as being “messier” than traditional studies

Potential Folly of Open Science

- Feasibility concerns (see Banks et al., 2018)
  - Science-publishing industry generates ~$13 billion annually (see Healy, 2015)
  - Publication sales earns the APA and the *Academy of Management* roughly $13 million and $3 million each year, respectively (per IRS records)

Limitations of Open Science

Limitations of Open Science

- Open science is not a panacea and cannot address all of the problems inherent to contemporary research

Limitations of Open Science

- Open science alone does not fully address rigor or relevance issues.
- Open science efforts do not directly speak to *what* we study

Limitations of Open Science

- Open science alone does not directly address or improve statistical power.

Limitations of Open Science

- Law of unintended consequences

Conclusion

- The 2010s revealed a painful truth

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- The 2010s revealed a painful truth
  - The “crisis” experienced across the psychological sciences could be traced back to decades of loyalism to indoctrinated systems (see Chambers, 2017; Giner-Sorolla, 2012)
  - Broadly speaking, psychological scientists got lost in the excitement of novel discovery and, in the process, ran the risk of losing their legitimacy (Bedeian et al., 2010; Tihanyi, 2020).

Conclusion

- Simply put, in the last 10 years, we have come to learn that many of the challenges facing psychological scientists are systemic and cultural, which means that they can likely be addressed through prudent intervention (Munafò et al., 2017; Washburn et al., 2018)

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- Simply put, in the last 10 years, we have come to learn that many of the challenges facing psychological scientists are systemic and cultural, which means that they can likely be addressed through prudent intervention (Munafò et al., 2017; Washburn et al., 2018)
- Open science is one possible treatment for these problems, but its effectiveness is not guaranteed.

Conclusion

- We can all play a part in the movement

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- We can all play a part in the movement
- “It is time for that to change” (Thau & Moore, 2020)

Conclusion

- We can all play a part in the movement
- “It is time for that to change” (Thau & Moore, 2020)
- Future research will determine if open science is a worthwhile endeavor

Thank you for attending today!

Remember…

You can find this presentation and some other potentially helpful resources at:

jamiefield.github.io/research/gmu2021

Questions?
Comments?
Complaints?

Feel free to follow up with me…

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