Improving Research in Educational Psychology, Psychology, and the Social Sciences

Smith, K. N., Makel, M. C., & Plucker, J. A.

The past half-decade has seen the applied sciences in the throes of acute growing pains. In what has become known as the replication crisis, widespread failures to replicate prior findings have shaken several fields, including medicine, psychology, management, and economics. Investigation of these failures has alerted researchers to a host of systemic problems in current practice. In his keynote address to the Society for Research on Educational Effectiveness, Larry Hedges called this “a crisis of Kuhnian proportions” (p. 4) and underscored the need for education researchers to address these issues:

The most daunting challenge we face is making our science transparent and replicable.

The scientific replicability crisis engulfed medicine, then psychology, and it *will* threaten education research. It is not a matter of *if*, but *when* and how we will respond. This challenge is not just a potential annoyance but an existential challenge to science as we know it (Hedges, 2018, p. 4).

Indeed, something presented as scientific knowledge, particularly if intended to influence policy or practice, is assumed to stand atop more than a one-shot finding. Scientific claim to public funding and voice in policy conversations rest on the assumption that recommended “evidence-based practices” are, in fact, supported by a robust body of evidence that has meaningful implications for education contexts. A scientific literature that doesn’t replicate is little more than a hall of smoke and mirrors.

Fortunately, the systemic problems brought to light by the replication crisis have also ignited a “credibility revolution” (Vazire, 2018) among a growing mass of researchers

committed to increasing the trustworthiness of scientific findings through equally systemic reforms. The scope of these efforts and speed with which they have already transformed multiple aspects of research culture and infrastructure in some disciplines is remarkable. Paired with the additional challenges posed by evolving technologies and the rise of big data, there is both need and opportunity for the education research community to reflect on its own practices and identify areas for improvement. To that end, this entry provides a brief review of some of the core issues identified in the replication crisis, followed by a discussion of current reform efforts and their potential application in education research.

Causes of the Replication Crisis

Misaligned Incentives

The incentives problem in science has received no shortage of attention (Mahoney, 1985; Paul-Hus, Desrochers, De Rijcke, & Rushforth, 2017). Publication is the mechanism that moves science forward; it is how findings are shared and knowledge accumulated. But it is also the reputational currency needed for professional advancement. Publication counts, citation indices, and other bibliometrics drive everything from faculty hiring and promotion to funding opportunities and departmental and university rankings. Though these metrics are intended to serve as proxies of research quality, as typically happens in competitive environments, the distinction between the means and ends has blurred, leading to the current culture often described as publish or perish (Lavigne & Good, 2017). Because publication is unfortunately not synonymous with accuracy, the consequence is a tension between the goals of science and the goals of scientists (Nosek, Spies, & Motyl, 2012).

This conflict is worsened by an overwhelming preference for novelty and statistical significance in publication decisions, a preference that frequently comes at the expense of

replication and rigor. It is not enough for researchers to publish prolifically; *what* they publish must be somehow new and exciting, qualities rarely used to describe replications and null results. Fanelli (2010, 2012) found over 90% of results reported in psychology journals supported the stated hypothesis, a rate five times higher than in the hard sciences (education research was not mentioned). Martin and Clarke (2017) reviewed the aims and author guidelines of all indexed psychology journals in 2015. Only 33 (3%) of 1,151 (3 of 85 in educational psychology) across all subdisciplines mentioned accepting replications, whereas 33% openly solicited original research. Reviews of published articles in top disciplinary journals identified replication rates of 1.07% in psychology (Makel, Plucker, & Hegarty, 2012), 1.2% in marketing (Evanschitzky, Baumgarth, Hubbard, & Armstrong, 2007), and only .013% in education (Makel & Plucker, 2014).

Yet replication is the heart of the scientific method. It is what allows us to distinguish true from chance findings, extend and revise theory, and establish the boundaries of generalizability (Schmidt, 2009). The recent crisis has revealed the consequences of devaluing its role in a world where “no-one is incentivised to be right. Instead, scientists are incentivised to be productive and innovative” (Horton, 2015, p. 1380).

Questionable Research Practices and Analytic Flexibility

A second factor identified as contributing to the replication crisis is the prevalence of Questionable Research Practices (QRPs, John, Loewenstein, & Prelec, 2012). When the road to success is paved with a large number of novel, statistically significant results, it is not surprising that researchers find ways to satisfy those criteria. One of the most common of these is *p*-hacking, a term encompassing a variety of strategies used to produce a *p*-value below the normative default of .05, such as adding, dropping, transforming, or aggregating outcome

variables or covariates until statistical significance is achieved; collecting additional data when initial results are nonsignificant; selectively reporting outcomes and analyses; rounding p -values down; or basing data exclusion criteria on NHST results.

Another customary QRP is Hypothesizing After the Results are Known, or HARKing (Kerr, 1998). This occurs when hypotheses are created or revised based on the present data, but are nevertheless treated as confirmed predictions on the basis of NHST results from the very same data. Yet exploratory and confirmatory research serve different purposes. The data that generated a statistical model (e.g., a regression equation) cannot be used to “predict” the same data (Yarkoni & Westfall, 2016).

Alternatively, a researcher may decide not to even attempt publishing null or disconfirming results. Instead, the study is relegated to the proverbial “file drawer” (Rosenthal, 1979) and treated as a sunk cost, furthering the well-known problem of publication bias.

In a survey of more than 2,000 psychological researchers, John, Loewenstein, and Prelec (2012) found over 90% admitted to engaging in at least one of these QRPs, and 35% reported having doubts about the integrity of their own research. Simmons, Nelson, and Simonsohn (2011) demonstrated how these practices could inflate the false positive rate to upwards of 60%, allowing researchers to find “support” for virtually any assertion while actually lending credence to mere statistical artifacts. Importantly, inflated false positives exist independent of researcher fraud or self-interested motives. The problem is one of analytic flexibility broadly, what the authors called “researcher degrees of freedom” and Gelman and Loken (2013) termed “the garden of forking paths.” This refers to the myriad decisions researchers make in the course of data processing and analysis for which they could have chosen one or more equally reasonable

alternatives. Even if guided by a sincere desire for the truth, the collective influence of these choices can render p -values and other inferential statistics uninterpretable.

Statistical Misunderstandings and Reporting Errors

A third contributing factor to the replication crisis is error in statistical thinking and reporting. Methodologists have been bemoaning the erroneous application of NHST for over half a century. Studies are frequently underpowered and p -values misinterpreted as evidence supporting a particular hypothesis or as an indication of the magnitude of an effect. The replication crisis has led the field to finally begin taking these criticisms seriously.

Recent investigations have also uncovered an alarming number of inaccuracies in reported statistics. Several reviews of NHST results in psychology journals identified inconsistencies between reported p -values and associated test statistics and degrees of freedom in half of published articles, with 12-20% of these classified as gross inconsistencies that impacted the statistical conclusion (Bakker & Wicherts, 2011; Nuijten, Hartgerink, van Assen, Epskamp, & Wicherts, 2016). Additionally, errors that incorrectly reported a statistically significant result were more common than the reverse. Errors this pervasive in the peer-reviewed, scientific literature again suggest that accuracy and rigor are not sufficiently valued or incentivized by existing norms.

The Complex Reality of Psychological and Social Phenomena

A fourth contributor to replication failures is the very nature of the phenomena we study. Sometimes called “the crud factor”, this refers to the fact that in social science, “Everything is related to everything else” (Meehl, 1990, p. 8). Psychological and social phenomena are complex, multiply caused, and highly variable. Though frequently conflated, this issue is distinct from faulty statistics and various forms of bias. It speaks to the inadequacies of our theoretical

explanations themselves. Failed replication does not mean an original effect was necessarily a false positive. It might reflect a fundamental limitation of methods and measurements in their ability to account for the crud factor and identify what researchers want to know. One reason our methodological problems are so consequential is because they mask this underlying complexity. By conflating our statistical and theoretical hypotheses and giving little thought to measurement, researchers are able to get away with perpetually vague explanations that not only fail to inform, but prevent understanding. Although social scientists have long-managed to ignore this point, the replication crisis has brought it sharply into focus (De Boeck & Jeon, 2018).

The Credibility Revolution

Although none of the problems identified in the replication crisis are new, the collective recognition and response from the scientific community has been unprecedented. Broadly captured under the umbrella heading of “open science,” this response includes a range of practices, standards, infrastructure, and tools aimed at cultivating new norms and increasing the validity of research findings (van der Zee & Reich, 2018). Brief introductions to several of these developments are provided below, along with references to more in-depth treatments.

Preregistration

One of the simplest but potentially most impactful reforms is the use of preregistration (Gehlbach & Robinson, 2018). In the traditional research model, scientists design a study, collect and analyze the data, write up the results, and then submit the completed manuscript for peer review and hopefully publication. As denoted above, this approach fails to distinguish between exploratory and confirmatory research programs, as the same data is often inappropriately used to create and test hypotheses while also allowing for Hypothesizing After the Results are Known (Kerr, 1998). One way to preserve these distinctions is for researchers to preregister their

confirmatory study designs prior to data collection. For example, the Open Science Framework (OSF) allows researchers to preregister a study in a way that produces a certified time stamp and record of subsequent changes. The researcher can choose if and when to make the preregistration public. The contents of the preregistration can range from a simple specification of the hypotheses of interest to a detailed account of the intended research design, measures, sample, data collection procedures, and analytic plan. By establishing precedence of prediction, preregistration serves as an added layer of transparency and independent credibility to research results.

Registered Reports

A registered report is a specific type of preregistration that undergoes peer review prior to data collection (Chambers, Dienes, McIntosh, Rotshtein, & Willmes, 2015). Researchers submit the entirety of a manuscript to a journal, except the results and discussion sections. Reviewers evaluate the registered report and recommend revisions or acceptance solely on the basis of the hypotheses and proposed methods. An approved registered report is granted in-principle acceptance by the journal, essentially a promise to publish the completed study contingent only on faithful implementation of the stated design and analysis plan, but regardless of the outcome.

The registered report format offers several benefits to individual researchers, but also aligns with the goals of science itself (Nosek & Lakens, 2014). Most importantly, registered reports formalize the difference between hypothesis building and hypothesis testing within the publication process. They also minimize the problem of researcher (and reviewer!) degrees of freedom by specifying data processing and analytic decisions beforehand, thereby reducing the data-dependence of any applied statistical models. Researchers remain free to conduct exploratory analyses, but they are reported separately and clearly designated as such.

Open Data and Materials

Reforms also target ways to enable and incentivize researchers to share their study materials, including data files, procedures, measures and manipulations, codebooks, and analysis scripts/syntax (Nosek et al., 2015). This level of openness facilitates future replications and incentivizes vigilance among individual researchers. Ideally, a reader should be able to independently reproduce all results reported in an article. This not only memorializes the path that generated the reported findings, but permits robustness checks by illuminating the rest of the garden of forking paths (Gelman & Loken, 2013). Openness also maximizes resource efficiency by allowing others to conduct secondary analyses and address additional research questions.

Several digital innovations expand upon the principles of openness to facilitate research collaborations. For example, StudySwap (<https://osf.io/view/studyswap/>) is an online platform where researchers can post their resource “NEEDs” and “HAVEs”, to either request or offer support (e.g., collecting data from additional participants). Similarly, the Psychological Science Accelerator (Moshontz et al., 2018) extends this concept to full studies, helping forge large scale collaborations with labs from across the globe. This can be especially advantageous for those who study hard-to-recruit populations, rely on costly methods, or are interested in assessing whether cultural differences exist.

Open Access Publishing

Open access refers to scholarly outputs that are freely available online without a paywall. Support for open access extends beyond empirical disciplines and reflects a basic belief that knowledge generated by academic institutions should generally be accessible by the public. Two innovations of particular relevance for education researchers are open access journals and

preprint repositories (van der Zee & Reich, 2018). Open access journals are similar to any other academic journal, except that readers do not require special access or payment.

A preprint is a manuscript not yet published in a journal. This could be an initial draft that has not undergone peer review or the version of a manuscript accepted for publication but lacking the journal's formatting (sometimes called a postprint). Preprint servers now exist in dozens of fields and are indexed by academic search tools. Like most open science initiatives, they offer advantages to both scientists and science, such as separating publication from peer review, limiting publication bias, and reducing QRPs by offering an outlet for research regardless of results. They also provide a way to broaden the distribution of research findings, giving researchers greater autonomy in how and when their research is disseminated (McBee, Makel, Peters, & Matthews, 2018).

Computational Innovations to Foster Statistical Accuracy and Robustness

The past few years have also seen an increasing number of computational tools designed to catch errors in reported statistics. For instance, *statcheck* (Nuijten et al., 2016) recalculates p values from extracted NHST results and flags inconsistencies; *GRIM* (Brown & Heathers, 2015) identifies errors in mean and standard deviation pairs as a function of sample size; and *SPRITE* (Heathers, Anaya, van der Zee, & Brown, 2017) and *CORVIDS* (Wilner, Wood, & Simons, 2018) enable reconstruction of possible data distributions based on reported descriptive statistics. These tools are available as open source software packages and many as simple web applications that require nothing more than a few keystrokes or a pdf upload. Originally developed to inform meta-research, or research on research, their accessibility also offers easy returns at early stages of the research process, as journals can use them to screen submissions and authors to double-check their own manuscripts or those they are reviewing.

Future Directions of Education Research: Progress, Challenges, and Opportunities

Although awareness of the replication crisis and ensuing credibility reforms are just becoming salient to many education researchers, the field has seen a number of positive developments. Most notably, the Institute of Education Sciences (IES) and National Science Foundation (2018) released the *Companion Guidelines on Replication and Reproducibility in Education Research*, a supplement to the 2013 *Common Guidelines*. The report affirms the value of replication studies as “essential to building a strong, scientific evidence base” (p. 1) and provides 14 recommendations for conceptualizing replications and designing and reporting research with reproducibility and replication in mind. Giving teeth to its policy declaration, IES also funded development of the Registry of Efficacy and Effectiveness Studies in Education (Anderson, Spybrook, & Maynard, 2018), a public and searchable repository of causal studies in education research. The site specifies requirements for registering randomized controlled trials, quasi-experimental designs with a comparison group, regression discontinuity designs, and single case designs.

On the publication side, 2019 saw the launch of EdArXiv, a preprint service hosted on the OSF specifically for education research. Several education journals joined the growing ranks of those accepting registered report submissions, two others released calls for special issues comprised entirely of registered reports, and articles extolling the benefits of open science reforms appeared in a number of education research publications (Cook, Lloyd, Mellor, Nosek, & Therrien, 2018; Gehlbach & Robinson, 2018; McBee et al., 2018; van der Zee & Reich, 2018).

These advances and others like them have laid the initial groundwork for vital education research reform. If education is to continue to build on and expand these efforts, the field must address any unique challenges. Not every reform developed in social psychology or other

disciplines will translate directly to education (e.g., data collection procedures for working with schools or special populations can differ substantially). There remains a need for communal dialogue to determine standards and best practices for what open, rigorous, and robust research looks like specifically in the education research context.

Big Data, Data Sharing, & the Education Policy Context

Big data refers to the unprecedented amount and kinds of information continuously being generated and made available for collection and analysis (Franke et al., 2016). Big data brings a host of opportunities for education research, but several hurdles must be overcome to realize its promise. Even as scholars begin to share their own research materials, gaining access to existing and future data that is neither generated nor stored by researchers, but nonetheless relevant for understanding and enhancing learning, remains a much greater challenge. This not only includes traditional types of assessment data housed within the administrative offices of schools, districts, states, universities, and countries, but the exponentially larger amount held by the private sector. Addressing issues of access, interoperability, and privacy is critical (Cope & Kalantzis, 2016).

Research to Practice and Constraints on Generality

Education researchers must do a much better job of making sure the uncertainty in their results is mirrored in their abstracts, discussion sections, and press releases. It is all too common for authors to pay lip service to these qualifications in a limitation section while seemingly doing everything possible in the rest of the paper to make sure they are ignored. Recommendations for policy or practice should not be made in the absence of robust, replicable effects. In light of the lack of truly confirmatory research described above, our literature should reveal very few policy or practice recommendations. Instead, it is rare not to see such recommendations, and some journals even require them. This is a dangerous tendency, especially given how porous the

information landscape has become and the difficulty of retracting or correcting misinformation. Robinson, Levin, Schraw, Patall, and Hunt (2013) urged education journal editors to adopt policies expressly prohibiting these kinds of speculations in published articles, and Simons, Shoda, and Lindsay (2017) recommended all articles include “Constraints on Generality” statements to specify the limits of generalizability.

Conclusion

Science does not progress by avoiding mistakes, but by its ability to identify and correct them. The replication crisis has exposed substantial flaws in traditional self-corrective mechanisms. Education research has taken the first steps toward recognizing and addressing these issues. To fully benefit from the reforms being developed in the credibility revolution, education researchers must adopt and adapt practices in its pursuits.

References

- Anderson, D., Spybrook, J., & Maynard, R. (2018). REES: A registry of efficacy and effectiveness studies in education. *Educational Researcher*, 0013189X18810513. <https://doi.org/10.3102/0013189X18810513>
- Bakker, M., & Wicherts, J. M. (2011). The (mis) reporting of statistical results in psychology journals. *Behavior Research Methods*, 43, 666-678. <http://doi/10.3758/s13428-011-0089-5>
- Brown, N. J. and Heathers, J. A. (2017). The grim test: A simple technique detects numerous anomalies in the reporting of results in psychology. *Social Psychological and Personality Science*, 8, 363-369. <https://doi.org/10.1177/1948550616673876>
- Chambers, C. D., Dienes, Z., McIntosh, R. D., Rotshtein, P., & Willmes, K. (2015). Registered reports: Realigning incentives in scientific publishing. *Cortex*, 66, A1-A2. <http://dx.doi.org/10.1016/j.cortex.2015.03.022>
- Cook, B. G., Lloyd, J. W., Mellor, D., Nosek, B. A., & Therrien, W. J. (2018). Promoting open science to increase the trustworthiness of evidence in special education. *Exceptional Children*, 85, 104-118. <https://doi.org/10.1177/0014402918793138>
- Cope, B., & Kalantzis, M. (2016). Big data comes to school: Implications for learning, assessment, and research. *AERA Open*, 2(2), 2332858416641907. <https://doi.org/10.1177%2F2332858416641907>
- De Boeck, P., & Jeon, M. (2018). Perceived crisis and reforms: Issues, explanations, and remedies. *Psychological Bulletin*, 144, 757-777. <http://dx.doi.org/10.1037/bul0000154>

- Evanschitzky, H., Baumgarth, C., Hubbard, R., & Armstrong, J. S. (2007). Replication research's disturbing trend. *Journal of Business Research*, 60, 411-415.
<https://doi.org/10.1016/j.jbusres.2006.12.003>
- Fanelli, D. (2010). Do pressures to publish increase scientists' bias? An empirical support from US states data. *PLoS ONE*, 5(4), e10271. <https://doi.org/10.1371/journal.pone.0010271>
- Fanelli, D. (2012). Negative results are disappearing from most disciplines and countries. *Scientometrics*, 90, 891–904. <https://doi.org/10.1007/s11192-011-0494-7>
- Franke, B., Plante, J. F., Roscher, R., Lee, E. S. A., Smyth, C., Hatefi, A., ... & Hoffman, M. M. (2016). Statistical inference, learning and models in big data. *International Statistical Review*, 84(3), 371-389. <https://doi.org/10.1111/insr.12176>
- Gelman, A., & Loken, E. (2013). 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. Unpublished manuscript.
- Gehlbach, H., & Robinson, C. D. (2018). Mitigating illusory results through preregistration in education. *Journal of Research on Educational Effectiveness*, 11, 296-315. <https://doi.org/10.1080/19345747.2017.1387950>
- Heathers, J. A., Anaya, J., van der Zee, T., & Brown, N. J. (2018). Recovering data from summary statistics: Sample Parameter Reconstruction via Iterative TEchniques (SPRITE). *PeerJ Preprints*, e26968v1. <https://doi.org/10.7287/peerj.preprints.26968v1>
- Hedges, L. V. (2018). Challenges in building usable knowledge in education. *Journal of Research on Educational Effectiveness*, 11, 1-21.
<https://doi.org/10.1080/19345747.2017.1375583>

Horton, R. (2015). Offline: What is medicine's 5 sigma?. *Lancet*, 385(9976), 1380.

[doi:10.1016/S0140-6736\(15\)60696-1](https://doi.org/10.1016/S0140-6736(15)60696-1)

Institute of Education Sciences & National Science Foundation (2018). *Companion guidelines on replication & reproducibility in education research*. Retrieved from

<https://ies.ed.gov/pdf/CompanionGuidelinesReplicationReproducibility.pdf>

John, L. K., Loewenstein, G., & Prelec, D. (2012). Measuring the prevalence of questionable research practices with incentives for truth telling. *Psychological Science*, 23, 524-532.

<https://doi.org/10.1177/0956797611430953>

Kerr, N. L. (1998). HARKing: Hypothesizing after the results are known. *Personality and Social Psychology Review*, 2, 196-217. https://doi.org/10.1207/s15327957pspr0203_4

Lavigne, A. L., & Good, T. L. (2017). Citing, being cited, not citing, and not being cited:

Citations as intellectual footprints. In J. A. Plucker & M. C. Makel (Eds.), *Toward a more perfect psychology: Improving trust, accuracy, and transparency in research* (pp. 97–116). Washington, DC: American Psychological Association.

Mahoney, M. J. (1985). Open exchange and epistemic progress. *American Psychologist*, 40, 29-39. <http://dx.doi.org/10.1037/0003-066X.40.1.29>

Makel, M. C., & Plucker, J. A. (2017) (Eds.). *Toward a more perfect psychology: Improving trust, accuracy, and transparency in research*. Washington, DC: American Psychological Association. <http://dx.doi.org/10.1037/0000033-000>

Makel, M. C., Plucker, J. A. (2014). Facts are more important than novelty: Replication in the education sciences. *Educational Researcher*, 43, 304–316.

<https://doi.org/10.3102/0013189X14545513>

- Makel, M. C., Plucker, J. A., & Hegarty, B. (2012). Replications in psychology research: How often do they really occur?. *Perspectives on Psychological Science*, 7, 537-542.
<https://doi.org/10.1177/1745691612460688>
- Martin, G. N., & Clarke, R. M. (2017). Are psychology journals anti-replication? A snapshot of editorial practices. *Frontiers in Psychology*, 8(523). Retrieved from
<http://journal.frontiersin.org/article/10.3389/fpsyg.2017.00523/full>
- McBee, M. T., Makel, M. C., Peters, S. J., & Matthews, M. S. (2018). A call for open science in giftedness research. *Gifted Child Quarterly*, 62, 374-388.
<https://doi.org/10.1177/0016986218784178>
- Meehl, P. E. (1990). Appraising and amending theories: The strategy of Lakatosian defense and two principles that warrant it. *Psychological Inquiry*, 1, 108-141.
https://doi.org/10.1207/s15327965pli0102_1
- Moshontz, H., Campbell, L., Ebersole, C. R., IJzerman, H., Urry, H. L., Forscher, P. S., ... & Castille, C. M. (2018). The Psychological Science Accelerator: Advancing psychology through a distributed collaborative network. *Advances in Methods and Practices in Psychological Science*, 2515245918797607.
<https://doi.org/10.1177%2F2515245918797607>
- Nosek, B. A., Alter, G., Banks, G. C., Borsboom, D., Bowman, S. D., Breckler, S. J., . . . Contestabile, M. (2015). Promoting an open research culture. *Science*, 348(6242), 1422–1425. <http://doi/10.1126/science.aab2374>
- Nosek, B. A., Lakens, D. (2014). Registered reports: A method to increase the credibility of published results. *Social Psychology*, 45, 137–141. <https://doi.org/10.1027/1864-9335/a000192>

- Nosek, B. A., Spies, J. R., & Motyl, M. (2012). Scientific utopia: II. Restructuring incentives and practices to promote truth over publishability. *Perspectives on Psychological Science*, 7, 615-31. <http://dx.doi.org/10.1177/1745691612459058>
- Nuijten, M. B., Hartgerink, C. H., van Assen, M. A., Epskamp, S., Wicherts, J. M. (2016). The prevalence of statistical reporting errors in psychology (1985–2013). *Behavior Research Methods*, 48, 1205–1226. <http://doi/10.3758/s13428-015-0664-2>
- Paul-Hus, A., Desrochers, N., De Rijcke, S., & Rushforth, A. D. (2017). The reward system of science. *Aslib Journal of Information Management*, 69, 478-485.
<https://doi.org/10.1108/AJIM-07-2017-0168>
- Robinson, D. H., Levin, J. R., Schraw, G., Patall, E. A., & Hunt, E. B. (2013). On going (way) beyond one's data: A proposal to restrict recommendations for practice in primary educational research journals. *Educational Psychology Review*, 25, 291-302.
<https://doi.org/10.1007/s10648-013-9223-5>
- Rosenthal, R. (1979). The file drawer problem and tolerance for null results. *Psychological Bulletin*, 86, 638-641. <http://dx.doi.org/10.1037/0033-2909.86.3.638>
- Schmidt, S. (2009). Shall we really do it again? The powerful concept of replication is neglected in the social sciences. *Review of General Psychology*, 13, 90-100.
<http://dx.doi.org/10.1037/a0015108>
- Simons, S. J., Shoda, Y., & Lindsay, D. S. (2017). Constraints on Generality (COG): A proposed addition to all empirical papers. *Perspectives on Psychological Science*, 12, 1123-1128.
<https://doi.org/10.1177/1745691617708630>

Simmons, J. P., Nelson, L. D., Simonsohn, U. (2011). False-positive psychology: Undisclosed flexibility in data collection and analysis allows presenting anything as significant.

Psychological Science, 22, 1359–1366. <http://doi/10.1177/0956797611417632>

van der Zee, T., & Reich, J. (2018). Open education science. *AERA Open*, 4(3),

2332858418787466. <https://doi.org/10.1177/2332858418787466>

Vazire, S. (2018). Implications of the credibility revolution for productivity, creativity, and progress. *Perspectives on Psychological Science*, 13, 411-417.

<https://doi.org/10.1177%2F1745691617751884>

Wilner, S., Wood, K., & Simons, D. J. (2018, July 14). Complete recovery of values in

Diophantine systems (CORVIDS). <https://doi.org/10.31234/osf.io/7shr8>

Yarkoni, T., & Westfall, J. (2017). Choosing prediction over explanation in psychology: Lessons from machine learning. *Perspectives on Psychological Science*, 12, 1100-1122.

<https://doi.org/10.1177/1745691617693393>