Open Science challenges, benefits and tips in early career and beyond

Chris Allen[1]* and David MA Mehler[1&2]*

*Authors made equal contribution

1. Cardiff University Brain Research Imaging Centre (CUBRIC), Wales, UK

2. Department of Psychiatry, University of Muenster, Germany

Abstract

The movement towards open science is an unavoidable consequence of seemingly pervasive failures to replicate previous research. This transition comes with great benefits but also significant challenges that are likely to afflict those who carry out the research, usually Early Career Researchers (ECRs). Here, we describe key benefits including reputational gains, increased chances of publication and a broader increase in the reliability of research. These are balanced by challenges that we have encountered, and which involve increased costs in terms of flexibility, time and issues with the current incentive structure, all of which seem to affect ECRs acutely. Although there are major obstacles to the early adoption of open science, overall open science practices should benefit both the ECR and improve the quality and plausibility of research. We review three benefits, three challenges and provide suggestions from the perspective of ECRs for moving towards open science practices.

Introduction

Pervasive failures to replicate published work have raised major concerns in psychology and other disciplines, which has been termed a 'crisis' (Chambers, 2017; Collaboration, 2015; Higginson & Munafò, 2016; Munafò et al., 2017). The potential causes are numerous, well documented and require a substantive change in how science is conducted (Button et al., 2013; Franco, Malhotra, & Simonovits, 2014; Munafò et al., 2017; Nosek, Spies, & Motyl, 2012; Ramsey & Scoggins, 2008; Rosenthal, 1979; Tomkins, Zhang, & Heavlin, 2017). Here we focus upon the practical responses to the replication crisis and the consequences for researchers.

The solution, it has been suggested, is a shift to open science methods (Chambers, 2017; Munafò et al., 2017; Nosek, Ebersole, DeHaven, & Mellor, 2018). These encompass a range of practices aimed at making science more reliable, including wider sharing and reanalysis of code, data and research materials (Munafò et al., 2017; Nosek et al., 2012), valuing replications and re-analyses (Open Science Collaboration, 2015; Munafò et al., 2017), changes in statistical approaches with regards to power (Algermissen & Mehler, 2018; Button et al., 2013) and how evidence is assessed (Dienes, 2008), the use of double-blind peer review (Tomkins et al., 2017) and the use of formats such as pre-prints and open access publishing. In addition, the change that we have found to most effect how science is conducted is the adoption of study pre-registration and registered reports (RRs). These approaches require hypotheses and analysis pipelines to be declared publicly before data collection (Chambers, 2013; Munafò et al., 2017; Nosek, Ebersole, DeHaven, & Mellor, 2018; Rosenthal, 1979). This makes the crucial distinction between confirmatory hypothesis testing and post-hoc exploratory analyses transparent. In the case of RRs, hypotheses and methods are peer-reviewed on the basis of scientific validity, statistical power and interest, and RRs can receive in-principal acceptance for publication before data is collected (Nosek, Ebersole, DeHaven, & Mellor, 2018). These approaches circumvent many of the factors that have contributed to the replication crisis (Chambers, 2017; Munafò et al., 2017). Pre-registering hypotheses and methods renders so called Hypothesizing After the Results are Known (HARKing; Kerr, 1998) impossible and prevents manipulation of researcher degrees of freedom or p-hacking.

There are promising and important reasons to implement and promote open science methods, and there are also career-motivated reasons (Markowetz, 2015; Wagenmakers & Dutilh, 2016). However, there are also major challenges that are underrepresented and particularly affect those who carry out the research, most commonly Early Carer Researchers (ECRs). Here, we review three areas of challenge posed by open science practices, which are balanced against three beneficial aspects, with a focus on ECRs working in quantitative life sciences or psychology. Both challenges and benefits are accompanied by suggestions, in the form of tips, which may help ECRs surmount these challenges and reap the rewards of open science. We conclude that overall, open science methods are inevitable to address the replication crisis, are increasingly expected and ECRs in particular can benefit from being involved early on.

Three challenges

Challenge 1: Restrictions on flexibility

Statistical hypothesis testing is the predominant approach for addressing research questions in quantitative research, but a point often underemphasised is that a hypothesis can only be truly held before the data is looked at, usually before the data is collected. Open science methods respect this distinction and require separating exploratory analyses from planned confirmatory hypothesis testing. This distinction lies at the centre of RRs and pre-registrations (Nosek et al., 2018), where timelines are fixed, enforcing a true application of *hypothesis* testing, but also forcing researchers to stop developing an experiment and start collecting data. Once data collection has started, new learning about analysis techniques, subsequent publications and exploration of patterns in data cannot inform confirmatory hypotheses or the experimental design. This restriction can be exasperating because scientists do not tend to stop thinking about and therefore developing their experiments. Continuous learning during the course of an investigation is difficult to reconcile with a hard confirmatory/exploratory distinction, but may be the price of unbiased research (Chambers, 2017). Open science methods do not preclude the possibility of serendipitous discovery, but confirmation requires subsequent replication, which entails additional work. Exploratory analyses can be added after registration, however, they can and should have a lower evidential status than pre-registered tests. Closed orthodox science simply allows for the incorporation of new ideas more flexibly, if questionably.

Informing and formulating research questions based on data exploration is recommended. Being open to and guided by the data rather than mere opinions also has many merits. However, robust statistical inference requires that the time for it is restricted to the piloting (or learning) phase. Historically, ECRs have often been provided with existing data sets and learned data analyses through data exploration. Exploratory analyses and learning are desirable but are only acceptable if explicitly separated from planned confirmatory analyses (Nosek & Lakens, 2014). The common practice of maintaining ambiguity between the two can convey an advantage to the traditional researcher because failure to acknowledge the difference exploits the assumption that presented analyses are planned. Distinguishing explicitly between planned and exploratory analyses can therefore only disadvantage the open researcher, because denoting a sub-set of analyses as exploratory reduces their evidential status. We believe, however, that this apparent disadvantage is the scientifically correct approach and is increasingly viewed as a positive and necessary distinction (Chambers, 2017; Chambers, 2013; Munafò et al., 2017). The restriction on flexibility imposed by explicit differentiation between exploratory and confirmatory science represents a major systemic shift how science is understood, planned and conducted, the impact of which is often underestimated.

The more restrictive structures of open science can result in mistakes having greater ramifications than within a more closed approach. Open science increases error visibility and the flexibility to avoid acknowledging mistakes is lost. However, for science, unacknowledged or covered up mistakes are certainly problematic. We therefore support the view that mistakes should be handled openly, constructively and, perhaps most importantly, in a positive non-detrimental way (Bishop, 2017). Mistakes can and will happen, but by encouraging researchers to be open about them and not reprimanding others for them, open science can counter incentives to hide mistakes.

Besides higher visibility, mistakes can also have greater ramifications owing to the loss of flexibility in responding to them and the fixed timelines. When developing full *a priori* analysis pipelines anticipating all potential outcomes and contingencies should be attempted. It is rarely possible to anticipate *all* contingencies and the anticipation itself can lead to problems. For example, we have spent considerable time developing complex exhaustive analyses, which may never be used as registered preliminary assumption checks failed. Had a more flexible approach been adopted the unnecessary time investment would likely have never been made. Amendments to pre-registrations and RR’s are perfectly acceptable, as are iterative studies, but such changes and additions will also take time. These examples illustrate how open science researchers can pursue higher standards than closed science but can encounter difficulties because of doing so.

Tip: Collect and thoroughly explore pilot data. Pre-register hypotheses and methods. Make and expect a distinction between planned and exploratory analyses. Be open about mistakes and do no reprimand others for their mistakes, rather applaud honesty.

Challenge 2: The time cost

There are theoretical reasons why open science methods could save time. For example, *a priori* analysis plans constrain the number of analyses, or reviewers may be less suspicious of demonstrably *a priori* hypothesis. However, in our experience these potential benefits rarely come to fruition in the current system. The additional requirements of open and reproducible sciences often consume more time: archiving, documenting and quality control of code and data takes time. Considerably more time consuming is the adoption of pre-registrations or RRs, as full analysis pipelines, piloting, manuscripts and peer-review (for RRs) must occur prior to data collection, which are only then followed by the more traditional, but still necessary, stages involved in publication such as developing (exploratory) analyses, writing the final manuscript, peer review etc. For comparison, it is usually easier and quicker (although questionable) to develop complex analyses on existing final data sets rather than on separate subsets of pilot data or simulated data, as required under pre-registration. In our experience, these additional requirements can easily double the duration of a project. Data collection also takes longer in open experiments, which invariably have higher power requirements (Button et al., 2013). The ECR who adopts open science methods will likely complete fewer projects within a fixed period in comparison to traditional peers. Therefore, very careful consideration needs to be given to the overall research strategy, as early as possible in projects, because resources are limited for ECRs within PhD programs and post-doctoral positions. Moves towards rewarding open science practices through longer periods of ECR employment and training, combined with less emphasis on moving between institutions than is currently the norm, may help alleviate these concerns, but are at present rare. The increased time cost, in our experience, presents the greatest challenge in conducting open science and acutely afflicts ECRs.

Tip: Run pre-registered, simple, well powered, experiments but expect them to take substantially longer than would otherwise be the case.

Challenge 3: Incentive structure isn't in place, yet

Open science is changing how science is conducted, but it is still developing and will take time to consolidate in the mainstream (Moher et al., 2018). Systems that reward open science practices are rare and researchers are assessed according to traditional standards. Some reviewers and editors at journals and funders remain to be convinced of the necessity or suitability of open methods. While many may view open science efforts neutrally or positively they rarely weigh the sacrifices made in terms of flexibility and productivity proportionally. For example, reviewers tend to apply the same critical lens irrespective of when tested hypotheses were declared.

High-profile journals tend to reward a good story with positive results, but loss of flexibility limits the extent to which articles can be finessed and it reduces the likelihood of positive results (see Benefit 2). The requirement for novelty can also countermand the motivation to perform replications, which as recent findings indicate are necessary (Open Science Collaboration, 2015). Some journals are taking a lead in combatting questionable research practices and have signed guidelines promoting open methods (Nosek et al., 2015; Picciotto, 2018). However, talk is cheap, and levels of adoption are highly variable. While many prestigious journals, institutions and senior researchers declare their support for open methods, as yet, few have published using them.

Within open science standards are still developing. At present, there is a lack of concessions over single-blind, double-blind and open peer review (Tomkins et al., 2017). Levels of pre-registration vary dramatically with some registrations only outlining hypotheses, without analysis plans. While this approach may guard against HARKing and be tactically advantageous for individuals, it does little to prevent p-hacking and may eventually diminish the perceived value of pre-registrations. There is also a practical concern around statistical power. High standards are admirable (e.g. Nature Human Behaviour requires *all* frequentist hypothesis tests in RRs be powered to at least 95%), but within limited ECR research contracts they run up against feasibility constraints, partially for resource-intensive (e.g. neuroimaging, clinical studies) or complex multi-level experiments that are likely to contain low-medium effect sizes. Such constraints might skew areas of investigation and raise new barriers specifically for ECRs trying to work openly. However, developments in the assessment of evidence might alleviate some of these concerns in the future (Algermissen & Mehler, 2018; Smith & Little, 2018).

The challenges described above mean that ECRs are likely to have fewer published papers by the time they are applying for their next career stage. Compounding this issue is the dilution of authorship caused by the move towards more collaborative work practices (although see Fontanarosa, Bauchner, & Flanagin, 2017). ECR career progression critically depends on the number of first and last author publications in high-profile journals

(Chambers, 2017; Higginson & Munafò, 2016; Nosek et al., 2012). These factors make it more difficult for ECRs to compete for jobs or funding with colleagues taking a more orthodox approach. Furthermore, although senior colleagues may find their previous work devalued by the replication crisis, they are likely to have already secured the benefits from quicker and less robust research practices. They may then expect and teach comparable levels of productivity, which has the potential to be a source of tension (Brecht, 2017).

The trade-off between quality and quantity appears to be tipped in favour of quantity in the current incentive structure. As long as open science efforts are not formally recognised, it seems ECRs who pursue open science are put at a disadvantage compared to ECRs who have not invested in open science (Flier, 2017; Moher et al., 2018). However, reproducible science is increasingly recognized and supported, as we will discuss in the next section. Overall, ECRs are likely to be the ones who put in the effort to implement open science practices and may thus be most afflicted by the described obstacles. We believe academics at all levels should take account of these difficulties because the move towards open and reproducible science may be unavoidable and can ultimately benefit the whole community and beyond (Nosek et al., 2015).

To summarise, ECRs currently face a situation where demands on them are increasing. However, the structures that might aid a move towards more open and robust practices are not widely implemented or valued, yet. We hope that one consequence of the replication crisis and the open science movement will be a shift in emphasis from an expectation of quantity to one of quality. This would include greater recognition and understanding of open science efforts, especially for replication attempts, broader adoption of pre-registration and RRs, expectation of explicit distinctions between confirmatory and exploratory analyses and longer ECR positions from which lower numbers of completed studies are expected.

Tip: Early adoption of open methods and high standards requires careful planning at an early stage of investigations but doing so should place ECRs ahead of the curve as practices evolve. Persevere, focus on quality rather than quantity, and when evaluating others’ work give credit for efforts made towards the common good.

Three benefits

Benefit 1: Greater faith in research

The fundamental aim of the open science movement is to make science more reliable. All the structures of open science are there to make this so. Sharing of protocols and data leads to replication, reproduction of analyses and greater scrutiny. This increased scrutiny can also be a great motivator to ensure good quality data and analyses. Sharing data and analyses is increasingly common and expected (Eglen et al., 2017), where soon we anticipate findings may only deemed fully credible if they are accompanied by accessible data and transparent analysis pathways (Editorial, 2018). Instead of relying on trust, open science allows verification through checking and transparent timelines. There is also an educational aspect to this: where code and data are available, one can reproduce results presented in papers, which also facilitates understanding. More fundamentally, replication of findings is core to open science and paramount in increasing reliability.

“Science is an ongoing race between our inventing ways to fool ourselves, and our inventing ways to avoid fooling ourselves.” (Nuzzo, 2015). A scientist might observe a difference between conditions in their data, think they thought something similar previously, apply a difference test (e.g. a t-test) and report a headline significant result. However, researchers rarely have perfect access to previous intentions and may have even forgotten thinking the opposite effect was plausible. Pre-registration prevents this form of, often unconscious, error by providing an explicit timeline and record, as well as guarding against other forms of questionable research practices (Nosek et al., 2018). ECRs are at a particularly high risk of committing such errors due to lack of experience (Fanelli, Costas, & Ioannidis, 2017). Pre-registration also forces researchers to gain a more complete understanding of analyses (including stopping plans and smallest effect sizes of interest), and to attempt to anticipate all potential outcomes of an experiment (Dienes, 2008). Hence, open science methods can improve the quality and reliability of scientific work.

Tip: Make your work as accessible as possible and pre-register experiments where suitable.

Benefit 2: New helpful systems

The structures developed around open and reproducible science are there to help researchers and promote collaboration (Moshontz et al., 2018). Practically around software, which aids code sharing, storage and version control (Biecek & Kosinski, 2017) and where open science follows in the wake of the open source movement. Software can also assist in the assessment of previous research (Nuijten, Hartgerink, van Assen, Epskamp, & Wicherts, 2016; Simonsohn, Nelson, & Simmons, 2013).

RRs do not only guard against questionable practices, but can also increase the chances of publication as they offer a path to publication irrespective of null findings. In well designed and adequately powered experiments null findings are often informative (Dienes 2008). Furthermore, if the current incentive structure has skewed the literature toward positive findings a higher prevalence of null findings is likely to be a better reflection of scientific enquiry. If this were the case, then we would expect more null findings in RRs and pre-registrations than in the rest of the literature. To test this, we surveyed a list of 127 published bio-medical and psychological science RRs compiled (September 2018) by the Open Science Framework (https://osf.io/d9m6e/). We assessed the percentage of hypotheses that were not supported and compared it to percentages previously reported within the wider literature. 61% of the studies we surveyed did not support their hypothesis (https://osf.io/wy2ek/), which is in stark contrast to the estimated 5-20% of null findings in the traditional literature (Cristea & Ioannidis, 2018; Fanelli, 2012). Even compared to a liberal estimate of 30% published null results, a substantially larger proportion of hypotheses was not supported among RRs (61% vs. test value 30%, 95% Confidence Interval [55-66%], $p < 0.001$; Bayes Factor = 2.025×10^{24}). Moreover, the percentage of unsupported hypotheses was similar, if not slightly higher for replication attempts (66% [58-74%]) compared to novel research (55% [46-63%]) amongst the RRs surveyed. These exploratory analyses suggest that RRs increase the chances for publishing null findings. Further, the difference between the incidences of null findings in RRs and that of the wider literature can be interpreted as an estimate of the file drawer problem. Since RRs guarantee the publication of work irrespective of their statistical significance, the ECR publishes irrespective of the study's outcome.

There is a spectrum of open science practices and tools at researchers' disposal. These range from making data publicly available right through to fully open RRs. Generally, researchers should be encouraged to adopt as much as possible, but one should not let the perfect be the enemy of the good. Some research questions are exploratory, may be data driven or are iterative, which may be less well suited to pre-registration. Pre-registration also presents problems for complex experiments, as it can be difficult to anticipate all potential outcomes. There are also often constraints on when and if data can be made available, such as anonymization. Dilemmas also arise when elegant experimental designs are capable of probing both confirmatory and exploratory questions, where it is recommended that only confirmatory aspects are pre-registered. Researchers should be encouraged to adopt open practices, but select the methods that fit their research question with feasibility in mind.

Tip: Make use of new tools that facilitate sharing and documenting your work efficiently and publicly. Do not be afraid of null results but design and power experiments such that null results can be informative and register them to raise the chances of publication.

Benefit 3: Investment in the future

Putting more of your work and data in the public domain is central to open science and increases the opportunities for acknowledgment, exchange, collaboration and advancement (Modjarrad et al., 2016). Reuse of open data can lead to publications, which may not have happen under closed science (Open Science Collaboration, 2015; Lowndes et al., 2017). Data, pre-prints and pre-registrations are citable and appear to increase citation rates (McKiernan et al., 2016). Openness in science can also promote equality by making resource-costly data or rarely available observations accessible to a wider range of communities. Data sharing can also increase the longevity and therefore utility of data, whereas in closed science data usability declines drastically over time (Vines et al., 2014). In short, open science should improve the quality of work and get you recognised for your efforts.

Early adoption of open and reproducible methods is an investment in the future and can put researchers ahead of the curve. In the wake of the replication crisis, employers and grant funders increasingly see open and reproducible science as part of necessary requirements and heavily encourage their adoption (Flier, 2017, Kiley, Peatfield, Hansen, & Reddington, 2017). Recently funders have also offered funding specifically for replications (e.g. the Netherlands Organisation for Scientific Research). Open access publishing has seen a rapid increase in uptake, rising by the factor of 4-5 between 2006 and 2016 (McKiernan et al., 2016), with several journals rewarding open science efforts (Kidwell et al., 2016). Initiatives by leading scientific bodies demonstrate that the need for an open science culture is starting to be recognized, increasingly desired, and will become the norm (Nosek et al., 2015; Nosek et al., 2012). Therefore, adoption of open science practices is likely to have career benefits and to grow, especially as it is a one-way street: once adopted it is very hard to revert to a traditional approach. For example, once the confirmatory/exploratory distinction is understood and implemented it is difficult to un-know (Chambers, 2017).

Tip: Early adoption of open science practices, which can be evidenced, will likely confer career advantages in the future.

Conclusion

Overall, we believe open methods are worthwhile, positive, necessary and inevitable, but can come at a cost that ECRs would do well to consider. We have summarised three main benefits that the ECR can gain when working with open science methods and, perhaps more importantly, how open science methods allow us to place greater faith in scientific work. We also emphasize that there are obstacles, particularly for the ECR. The adoption of open practices requires a change in attitude and productivity expectations. Yet, taken together, we think that capitalising on the benefits is a good investment for both the ECR and science and should be encouraged where possible. A response to the replication crisis makes the transition to open science methods necessary and, despite the challenges, early adoption of open practices will likely pay off for both the individual and science.

References

Algermissen, J., & Mehler, D. M. A. (2018). May the power be with you: Are there highly powered studies in neuroscience, and how can we get more of them? *Journal of Neurophysiology*, (119), 2114–2117. https://doi.org/10.1152/jn.00765.2017

Biecek, P., & Kosinski, M. (2017). archivist: An R Package for Managing, Recording and Restoring Data Analysis Results, *VV*(Ii). https://doi.org/10.18637/jss.v082.i11

Bishop, D. V. M. (2017). Fallibility in science: Responding to errors in the work of oneself and others. *Advances in Methods and Practices in Psychological Science*, 1–9. https://doi.org/10.7287/peerj.preprints.3486v1

Brecht, K. (2017). “Bullied Into Bad Science”: An Interview with Corina Logan – JEPS Bulletin. Retrieved from http://blog.efpsa.org/2017/10/23/meet-corina-logan-from-the-bullied-into-bad-science-campaign/

Button, K. S., Ioannidis, J. P. A., Mokrysz, C., Nosek, B. A., Flint, J., Robinson, E. S. J., & Munafò, M. R. (2013). Power failure: why small sample size undermines the reliability of neuroscience. *Nature Reviews Neuroscience*, *14*(5), 365–376. https://doi.org/10.1038/nrn3475

Chambers, C. (2017). *The seven deadly sins of psychology: A manifesto for reforming the culture of scientific practice*. Princeton university Press.

Chambers, C. D. (2013). Registered Reports: A new publishing initiative at Cortex. *Cortex*, *49*(3), 609–610. https://doi.org/10.1016/j.cortex.2012.12.016

Cristea, I. A., & Ioannidis, J. P. A. (2018). P values in display items are ubiquitous and almost invariably significant : A survey of top science journals. *PLOS ONE*, 1–15. https://doi.org/10.1371/journal.pone.0197440

Dienes, Z. (2008). *Understanding psychology as a science: An introduction to scientific and statistical inference*. Palgrave Macmillan.

Editorial. (2018). Referees’ rights. Peer reviewers should not feel pressured to produce a

report if key data are missing. *Nature*, *560*, 409. https://doi.org/doi: 10.1038/d41586-018-06006-y
Eglen, S. J., Marwick, B., Halchenko, Y. O., Hanke, M., Sufi, S., Gleeson, P., … Poline, J. B. (2017). Toward standard practices for sharing computer code and programs in neuroscience. *Nature Neuroscience*, *20*(6), 770–773. https://doi.org/10.1038/nn.4550
Fanelli, D. (2012). Negative results are disappearing from most disciplines and countries. *Scientometrics*, *90*(3), 891–904. https://doi.org/10.1007/s11192-011-0494-7
Fanelli, D., Costas, R., & Ioannidis, J. P. A. (2017). Meta-assessment of bias in science. *Proceedings of the National Academy of Sciences*, *114*(14), 3714–3719. https://doi.org/10.1073/pnas.1618569114
Flier, J. (2017). Faculty promotion must assess reproducibility. *Nature*, *549*(7671), 133–133. https://doi.org/10.1038/549133a
Fontanarosa, P., Bauchner, H., & Flanagin, A. (2017). Authorship and Team Science. *JAMA*, *318*(24), 2433. https://doi.org/10.1001/jama.2017.19341
Franco, A., Malhotra, N., & Simonovits, G. (2014). Social science. Publication bias in the social sciences: unlocking the file drawer. *Science (New York, N.Y.)*, *345*(6203), 1502–1505. https://doi.org/10.1126/science.1255484
Higginson, A. D., & Munafò, M. R. (2016). Current Incentives for Scientists Lead to Underpowered Studies with Erroneous Conclusions. *PLOS Biology*, *14*(11), e2000995. https://doi.org/10.1371/journal.pbio.2000995
Kerr, N. L. (1998). HARKing: Hypothesng After the Results are Known. *Personality and Social Psychology Review*, *2*(3), 196–217. https://doi.org/10.1207/s15327957pspr0203
Kidwell, M. C., Lazarević, L. B., Baranski, E., Hardwicke, T. E., Piechowski, S., Falkenberg, L.-S., … Nosek, B. A. (2016). Badges to Acknowledge Open Practices: A Simple, Low-Cost, Effective Method for Increasing Transparency. *PLOS Biology*, *14*(5), e1002456. https://doi.org/10.1371/journal.pbio.1002456
Kiley, R., Peatfield, T., Hansen, J., & Reddington, F. (2017). Data Sharing from Clinical Trials — A Research Funder's Perspective. *New England Journal of Medicine*, *377*(20), 1990–1992. https://doi.org/10.1056/NEJMsb1708278
Lowndes, J. S. S., Best, B. D., Scarborough, C., Afflerbach, J. C., Frazier, M. R., O'Hara, C. C., … Halpern, B. S. (2017). Our path to better science in less time using open data science tools. *Nature Ecology & Evolution*, *1*(6), 0160. https://doi.org/10.1038/s41559-017-0160
Markowetz, F. (2015). Five selfish reasons to work reproducibly. *Genome Biology*, *16*(1), 274. https://doi.org/10.1186/s13059-015-0850-7
McKiernan, E. C., Bourne, P. E., Brown, C. T., Buck, S., Kenall, A., Lin, J., … Yarkoni, T. (2016). How open science helps researchers succeed. *ELife*, *5*(JULY), 1–19. https://doi.org/10.7554/eLife.16800
Modjarrad, K., Moorthy, V. S., Millett, P., Gsell, P.-S., Roth, C., & Kieny, M.-P. (2016). Developing Global Norms for Sharing Data and Results during Public Health Emergencies. *PLOS Medicine*, *13*(1), e1001935. https://doi.org/10.1371/journal.pmed.1001935
Moher, D., Naudet, F., Cristea, I. A., Miedema, F., Ioannidis, J. P. A., & Goodman, S. N. (2018). Assessing scientists for hiring, promotion, and tenure. *PLoS Biology*, *16*(3), 1–20. https://doi.org/10.1371/journal.pbio.2004089
Moshontz, H., Campbell, L., Ebersole, C. R., IJzerman, H., Urry, H. L., Forscher, P. S., … Chartier, C. R. (2018). The Psychological Science Accelerator: Advancing Psychology through a Distributed Collaborative Network. *Advances in Methods and Practices in Psychological Science*. https://doi.org/10.31234/OSF.IO/785QU
Munafò, M., Nosek, B., Bishop, D., Button, K., Chambers, C., Percie du Sert, N., … Ioannidis, J. (2017). A manifesto for reproducible science. *Nature Human Behaviour*, *1*(1), 0021. https://doi.org/10.1038/s41562-016-0021
Nosek, B. A., Alter, G., Banks, G. C., Borsboom, D., Bowman, S. D., Breckler, S. J., … Yarkoni, T. (2015). Promoting an open research culture. *Science*, *348*(6242). Retrieved from http://science.sciencemag.org/content/348/6242/1422

Nosek, B. A., Ebersole, C. R., DeHaven, A. C., & Mellor, D. T. (2018). The preregistration revolution. *Proceedings of the National Academy of Sciences*, *2017*(15), 201708274. https://doi.org/10.1073/pnas.1708274114
Nosek, B. A., & Lakens, D. (2014). Registered reports: A method to increase the credibility of published results. *Social Psychology*, *45*(3), 137–141. https://doi.org/10.1027/1864-9335/a000192
Nosek, B., Spies, J., & Motyl, M. (2012). Scientific Utopia. *Perspectives on Psychological Science*, *7*(6), 615–631. https://doi.org/10.1177/1745691612459058
Nuijten, M. B., Hartgerink, C. H. J., van Assen, M. A. L. M., Epskamp, S., & Wicherts, J. M. (2016). The prevalence of statistical reporting errors in psychology (1985–2013). *Behavior Research Methods*, *48*(4), 1205–1226. https://doi.org/10.3758/s13428-015-0664-2
Nuzzo, R. (2015). How scientists fool themselves – and how they can stop. *Nature*, *526*(7572), 182–185. https://doi.org/10.1038/526182a
Open Science Collaboration (2015). Estimating the reproducibility of psychological science. *Science*, *349*(6251), aac4716-aac4716. https://doi.org/10.1126/science.aac4716
Picciotto, M. (2018). Analytical Transparency and Reproducibility in Human Neuroimaging Studies. *Journal of Neuroscience*, *38*(14), 3375–3376. https://doi.org/10.1523/JNEUROSCI.0424-18.2018
Ramsey, S., & Scoggins, J. (2008). Practicing on the Tip of an Information Iceberg? Evidence of Underpublication of Registered Clinical Trials in Oncology. *The Oncologist*, *13*(9), 925. https://doi.org/10.1634/theoncologist.2008-0133
Rosenthal, R. (1979). The file drawer problem and tolerance for null results. *Psychological Bulletin*, *86*(3), 638–641. https://doi.org/10.1037/0033-2909.86.3.638
Simonsohn, U., Nelson, L. D., & Simmons, J. P. (2013). P-Curve: A Key to the File Drawer. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2256237
Smith, P. L., & Little, D. R. (2018). Small is beautiful: In defense of the small-N design. https://doi.org/10.3758/s13423-018-1451-8
Tomkins, A., Zhang, M., & Heavlin, W. D. (2017). Reviewer bias in single- versus double-blind peer review. *Proceedings of the National Academy of Sciences of the United States of America*, *114*(48), 12708–12713. https://doi.org/10.1073/pnas.1707323114
Vines, T. H., Albert, A. Y. K., Andrew, R. L., Dé, F., Bock, D. G., Franklin, M. T., … Rennison, D. J. (2014). Report The Availability of Research Data Declines Rapidly with Article Age. https://doi.org/10.1016/j.cub.2013.11.014
Wagenmakers, E. J., & Dutilh, G. (2016). Seven Selfish Reasons for Preregistration. *APS Observer*, *29*(9).

Acknowledgments

We would like to thank the Wellcome Trust (104943/Z/14/Z) and Health and Care Research Wales (HS/14/20) for their financial support and the following people for their helpful input: Rhian Barrance, Chris Chambers, Emily Hammond and Robert Thibault.