PUBLICATION NOTICE

This is a pre-publication version of the following article: Danka, M. N. (2024). Implementing ‘good practices’ in health psychology research: Reflections from an MSc project, The trap of ‘Publish or Perish’. *Health Psychology Update*, *33*(1). https://doi.org/10.53841/bpshpu.2024.33.1.23

Implementing 'Good Practices' in Health Psychology Research: Reflections from an MSc Project

Martin N. Danka

PhD Researcher

Centre for Longitudinal Studies, Social Research Institute, University College London

Email: martin.danka.21@ucl.ac.uk

Twitter: @MartinDanka

6 October 2023

The Trap of 'Publish or Perish'

Early in my undergraduate studies, I was offered to co-author my first research paper in health psychology. Thrilled and naïve, I assumed my experienced academic colleague would guide us towards producing high-quality work. I began realising something was 'off' when tasked with the analysis. I was instructed to run a few correlation tables, select variables that reached the 'magical' significance threshold, and then run regression models including all the 'significant variables'. I did raise the issue of data fishing but was told it was 'standard practice'. Conflicted and confused, I consulted several researchers about whether I should decline co-authoring the publication. They replied that even though the methodology was far from ideal, any publication would boost my career, regardless of its quality.

I never regretted my decision to refuse the co-authorship – I feel I acted in line with my values and maintained my sense of integrity. Having said that, my experience will likely not come across as surprising or even rare to anyone who has spent time working in academia. The 'publish or perish' mentality can be hard to avoid in many research areas. It is also considered one of the many reasons why people resort to using questionable research practices (QRPs), that may bias the evidence in favour of the authors' assertions, such as data fishing (Banks et al., 2016). Given that QRPs are common in psychology research (John et al., 2012), they can be challenging to navigate for both early career and more senior researchers.

Do We Know What Constitutes 'Good Practices'?

Fast forward a few years, I began working on my MSc research project, which I saw as the perfect opportunity to publish my first research paper. I had more research experience and was determined to do things the 'right way'. Despite my initial enthusiasm, I soon realised that it is much easier to spot QRPs than to incorporate good practices. Much of the literature on the replication crisis has focused on what went wrong. This is not to say that solutions and alternatives have been ignored. Collaborative efforts to promote open science and reduce bias are on the rise. However, many of these alternatives depend on idealised, simple examples and offer limited guidance for the messy reality of complex research questions and datasets. As a result, researchers may struggle to adopt these practices simply because they do not know how. In many cases, there is no consensus on what actually constitutes 'good practices'.

In my own thesis, I encountered several situations where, at first, it seemed as if anything you could possibly do might be wrong. I faced my first dilemma when pre-registering my analysis protocol. Such a task can be relatively straightforward with randomised controlled trials or smaller-scale studies. However, my project was a secondary analysis of a large cohort dataset. Whilst there are existing pre-registration templates for secondary data analysis (e.g., Akker et al., 2021), it was unclear to me how much detail one should provide. Realistically, with analyses of complex datasets, it is practically impossible to predict all that could 'go wrong' with your models. Researchers sometimes keep similar pre-registrations vague, which, however, defeats the purpose of limiting researcher degrees of freedom. On the other hand, if one wishes to anticipate all the potential issues, pre-registration can take an extraordinarily long time, to the point where it arguably becomes unfeasible.

Apart from pre-registration, some of the other issues relate to statistical inference. Statistical significance and the use of *p*-values are some of the particularly controversial topics. Some have proposed that we maintain thresholds but improve the ways in which they are used (Lakens et al., 2018). Others suggest that we abandon cut-offs (McShane et al., 2019; Wasserstein & Lazar, 2016). In most extreme cases, journals have gone as far as banning the use of *p*-values completely (Gill, 2018; Trafimow & Marks, 2015). In addition, plenty of alternative and supplementary metrics have also been developed (Wasserstein et al., 2019). The plurality of approaches can feel quite overwhelming, and researchers may, understandably, choose to adhere to the *status quo*.

Navigating Good Practices as a Student

I have not found the ultimate answer to any of these dilemmas. However, I was fortunate enough that my MSc supervisor had a strong background in research methods and was extremely open-minded. In the end, exploring these issues was not just a matter of searching for the best option available but of finding solutions that were feasible for my skillset and transparent enough to address various forms of bias, whilst providing the reader with tools to decide for themselves whether they deemed our solutions acceptable.

We kept our pre-registration more congruent with the nature of secondary data analysis. As some decisions required seeing the data beforehand, we openly stated the pre-registration was conducted after having obtained the data and noted which checks were done prior to designing the analysis protocol. We acknowledged the starting points for various analytical steps and noted where challenges and amendments were expected, aiming for flexibility without compromising transparency. This also helped us clarify some points in our analyses, which subsequently helped us proceed smoothly with the analysis itself.

Having read recent guidelines on statistical inference (Wasserstein et al., 2019; Wasserstein & Lazar, 2016), we wanted to address some of the limitations of null hypothesis testing, yet we did not want to completely change our metrics, as it would make our research less accessible to others. Whilst we deliberately avoided using the term 'statistically significant' and applying arbitrary thresholds, we still reported *p*-values as continuous quantities. Because *p*-values scale unintuitively, we also provided *s*-values to aid the interpretation of our findings. The *s*-value is a re-expression of the *p*-value as the number of heads in a fair coin toss. For instance, obtaining a $p = .03$ would be equally likely as obtaining about 5 heads in a row in a fair coin toss ($s = 5.1$; Greenland, 2019). We also followed the compatibility interval approach to interpreting confidence intervals, meaning all the effects within our confidence intervals were seen as highly compatible with our data (Amrhein et al., 2019). Additionally, we also ran sensitivity power calculations as a convenient option for secondary data analyses (Lakens, 2022).

Recommendations

Implementing new methodological and statistical approaches into my project was an invaluable experience, but it was also a journey filled with uncertainty and trial and error. From this journey, I have learnt a few principles worth sharing:

1. **Advocate for good practices:** Unless your research group is heavily focused on research methods, it is likely that you will need to take the initiative and advocate for implementing new practices. This presents an excellent opportunity to start a dialogue about current methods and set an example.
2. **Prioritise transparency over perfection:** In the real world of research, the perfect study is a mirage. Transparency allows others to learn from your experiences, both positive and negative, and it provides the foundation for replication and extension of your work. If you face difficult decisions, report a sensitivity analysis showing alternative outcomes. If your plans change, admit what you have changed and explain why.
3. **Aim for accessibility:** The reach of your research is dramatically extended when it is easily comprehensible and accessible. Ensure that the language in your work is as jargon-free as possible and provide supplementary materials that help explain complex methods or analyses.
4. **Adapt good practices to your project:** Recommendations about good practices come from various backgrounds, and authors do not always consider how this may have influenced their views. Make sure you understand how any given recommendations relate to your own project.
5. **Aim for balance between what might be best versus feasible:** There is an often-unacknowledged tension between ideal research practices and the practical limitations of time, skillset, and resources. Striving for the 'best' should be balanced with what is actually 'doable' within these constraints.

My Main Takeaway

Receiving the DHP award for Outstanding MSc Health Psychology Research Project and presenting my MSc project at the annual conference was not only a great honour but also an opportunity to share the broader challenges in advancing good research practices in health psychology. Between submitting my dissertation and finalising the project for publication, I started a PhD and developed a passion for causal inference methodologies. This has led me to reconsider some of my previous choices once again. After initially worrying that I should have known better, I have come to realise that this is a positive indicator of learning—an ongoing process, even for experienced researchers. This is perhaps the most valuable lesson I have learnt: although we should strive for research excellence, ultimately, we must also be supportive and kind to one another and ourselves to facilitate progress.

Acknowledgments

Thank you to Ellie Iob, my MSc project supervisor, for her unwavering support throughout the project and shared passion for research methods.

References

Akker, O. R. van den, Weston, S., Campbell, L., Chopik, B., Damian, R., Davis-Kean, P., Hall, A., Kosie, J., Kruse, E., Olsen, J., Ritchie, S., Valentine, K. D., Veer, A. van 't, & Bakker, M. (2021). Preregistration of secondary data analysis: A template and tutorial. *Meta-Psychology*, *5*. https://doi.org/10.15626/MP.2020.2625

Amrhein, V., Trafimow, D., & Greenland, S. (2019). Inferential Statistics as Descriptive Statistics: There Is No Replication Crisis if We Don't Expect Replication. *The American Statistician*, *73*(sup1), 262–270. https://doi.org/10.1080/00031305.2018.1543137

Banks, G. C., O'Boyle, E. H., Pollack, J. M., White, C. D., Batchelor, J. H., Whelpley, C. E., Abston, K. A., Bennett, A. A., & Adkins, C. L. (2016). Questions About Questionable Research Practices in the Field of Management: A Guest Commentary. *Journal of Management*, *42*(1), 5–20. https://doi.org/10.1177/0149206315619011

Gill, J. (2018). Comments from the New Editor. *Political Analysis*, *26*(1), 1–2. https://doi.org/10.1017/pan.2017.41

Greenland, S. (2019). Valid *P*-Values Behave Exactly as They Should: Some Misleading Criticisms of *P*-Values and Their Resolution With *S*-Values. *The American Statistician*, *73*(sup1), 106–114. https://doi.org/10.1080/00031305.2018.1529625

John, L. K., Loewenstein, G., & Prelec, D. (2012). Measuring the Prevalence of Questionable Research Practices With Incentives for Truth Telling. *Psychological Science*, *23*(5), 524–532. https://doi.org/10.1177/0956797611430953

Lakens, D. (2022). Sample Size Justification. *Collabra: Psychology*, *8*(1), 33267. https://doi.org/10.1525/collabra.33267

Lakens, D., Adolfi, F. G., Albers, C. J., Anvari, F., Apps, M. A. J., Argamon, S. E., Baguley, T., Becker, R. B., Benning, S. D., Bradford, D. E., Buchanan, E. M., Caldwell, A. R., Van Calster, B., Carlsson, R., Chen, S.-C., Chung, B., Colling, L. J., Collins, G. S., Crook, Z., … Zwaan, R. A. (2018). Justify your alpha. *Nature Human Behaviour*, *2*(3), Article 3. https://doi.org/10.1038/s41562-018-0311-x

McShane, B. B., Gal, D., Gelman, A., Robert, C., & Tackett, J. L. (2019). Abandon Statistical Significance. *The American Statistician*, *73*(sup1), 235–245. https://doi.org/10.1080/00031305.2018.1527253

Trafimow, D., & Marks, M. (2015). Editorial. *Basic and Applied Social Psychology*, *37*(1), 1–2. https://doi.org/10.1080/01973533.2015.1012991

Wasserstein, R. L., & Lazar, N. A. (2016). The ASA Statement on p-Values: Context, Process, and Purpose. *The American Statistician*, *70*(2), 129–133. https://doi.org/10.1080/00031305.2016.1154108

Wasserstein, R. L., Schirm, A. L., & Lazar, N. A. (2019). Moving to a World Beyond “$p < 0.05$”. *The American Statistician*, *73*(sup1), 1–19. https://doi.org/10.1080/00031305.2019.1583913