Advancing credibility in longitudinal research by implementing open science practices: Opportunities, practical examples, and challenges

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Highlights

- Longitudinal studies provide unique insights into development, and are afforded a high degree of credibility
- Implementing open science practices (pre- and post-registration, Registered Reports, and data management) in longitudinal studies facilitates evaluation of their credibility
- I provide practical examples, and discuss the challenges, of implementing these open science practices in longitudinal developmental research

Abstract

Longitudinal studies provide unique opportunities to study dynamic developmental processes over time and are often afforded a high degree of credibility. Transparency facilitates evaluation of credibility, yet, research practices that can increase transparency, i.e. open science practices, do not appear to be widely implemented in longitudinal developmental research. In the current article I discuss three open science practices (pre- and post-registration, Registered Reports, and data management) and the opportunities they bring to facilitate enhanced credibility in longitudinal studies. Drawing on my own experiences of conducting longitudinal developmental research on adolescent mental health, I provide practical examples of how these open science practices can be implemented. Using open science practices in longitudinal research is also accompanied by challenges, and I specifically discuss the issue of evidencing prior knowledge of data in Registered Reports and some potential solutions to this challenge.

Longitudinal studies are uniquely placed to investigate dynamic developmental and mental health processes. They capture how individuals' behaviours and symptoms change over time (Anstey & Hofer, 2004; Rutter, 1994) and enable antecedents of these outcomes to be identified (Anstey & Hofer, 2004; Kievit, McCormick, Fuhrmann, Deserno, & Orben, 2021), with some caveats regarding inference of causality (King et al., 2018). Furthermore, many longitudinal studies benefit from large, representative samples, increasing generalizability and statistical power to detect smaller effects. Together, these factors mean that longitudinal research is generally regarded as delivering high-quality scientific insights and is afforded a high degree of credibility within the developmental psychology field. However, credibility - defined by the *Oxford English Dictionary* as 'the quality of being trusted or believed in' - is not guaranteed by the importance of the research question, the study design, or sample size; the practices used to produce the research must be high quality (Vazire, Schiavone, & Bottesini, 2021), the research must be transparent *and* be able to stand up to the critical evaluation that accompanies such transparency (Vazire, 2017, 2019).[1]

The 'credibility revolution' (Angrist & Pischke, 2010; Vazire, 2018) in psychological science illuminated how certain research practices can threaten credibility. These include making data-dependent decisions, hypothesizing after the results are known (HARKing), repeating analyses until a statistically significant result is achieved (p-hacking), and underpowering (Munafò et al., 2017).

Even without researchers engaging in 'questionable research practices', such as HARKing and p-hacking, in every study, researchers make numerous decisions that take the

[1] Transparency alone is not sufficient for credibility. For a further discussion of the components of credibility, see Vazire et al., 2021.

study in a different direction. The dizzying array of options for, e.g. measures, inclusion/exclusion criteria, and analytic techniques, leaves researchers in a "garden of forking paths" (Gelman & Loken, 2013), where they are faced with many defensible options or 'paths' for a single decision. All of these decisions – sometimes referred to as 'researcher degrees of freedom' (Simmons, Nelson, & Simonsohn, 2011) - introduce unseen variability into studies, which may influence the interpretation and practical value of the results. When unseen, i.e. undocumented, this variability threatens the credibility of research because readers lack the information to evaluate whether a study is credible.

To tackle these issues, researchers are encouraged to conduct their work according to a set of scientific principles and practices, often referred to as 'Open Science' (Munafò et al., 2017; Simmons et al., 2011; Wicherts et al., 2016). Open science practices have already made their way into several areas of psychology (Nosek, 2019), but to the best of my knowledge, implementing open science practices in longitudinal research appears to be the exception (e.g. the ABCD study; (Karcher & Barch, 2021), rather than the rule. Given that researchers, clinicians, and policy-makers rely on high-quality, longitudinal studies to unravel complex developmental processes, ensuring the credibility of longitudinal research is vital. To this end, greater implementation of open science practices in longitudinal studies of development provides an unmissable opportunity to enhance credibility.

In the current article, I focus on three topics that I feel are major opportunities for longitudinal researchers to implement open science practices in their work: pre- and post-registration, Registered Reports, and data access management[2]. I then discuss a real-world

[2] I use the term 'data access management', to encompass open data, as well as other data management practices, including controlling and documenting data access.

example of implementing open science practices in a longitudinal study and one of the associated challenges. For a broader overview of open science practices and their benefits, I signpost readers to other literature on the topic (e.g. (Crüwell et al., 2019; Kathawalla, Silverstein, & Syed, 2021; Klein et al., 2018; Munafò et al., 2017; Tackett, Brandes, & Reardon, 2019; Turkyilmaz-van der Velden, Dintzner, & Teperek, 2020). My primary goal within this article is to further discussion and to make some suggestions for how open science practices can be implemented in longitudinal developmental studies.

Open science practices

To bring typically unseen variability out of the shadows and enable more thorough evaluation of a study's credibility, researchers can store a locked, uneditable plan for their study called a preregistration (Nosek, Ebersole, DeHaven, & Mellor, 2018; Open Science, 2015) in an online repository, e.g. the Open Science Framework. The plan is created prior to data collection, details crucial study decisions, and generally includes the research questions, hypotheses, inclusion/exclusion criteria, variables, and analysis plan (Nosek et al., 2018).

Pre-registration may be challenging for longitudinal researchers because such studies often involve multiple researchers using a dataset to answer numerous different research questions, after data collection and initial analyses have been conducted. Post-registration - a form of pre-registration for studies using pre-existing/secondary data (Benning, Bachrach, Smith, Freeman, & Wright, 2019) – can provide a solution to this, whereby the plan is created following data collection, but prior to data access. Several registration templates and tutorials for post-registration have been developed (Mertens & Krypotos, 2019; van den Akker et al., 2019), including for intensive longitudinal studies (Kirtley, Lafit, Achterhof, Hiekkaranta, & Myin-Germeys, 2021).

Registered Reports (Chambers, 2013; Chambers & Tzavella, 2021; Nosek & Lakens, 2014) takes pre-registration one step further: journal peer-reviewers evaluate the plan and rationale for a study prior to data collection or access. In principle acceptance of the article is based on this plan, i.e. without the results of the study being known. Then, providing researchers conduct the study as specified in their accepted plan, the journal accepts the manuscript irrespective of the direction and significance of the results. This not only adds additional quality checking at a point where aspects of the study can be modified, but reduces the likelihood of publication bias due to the results-free nature of the initial peer-review (Chambers, 2013; Chambers & Tzavella, 2021).

At all stages of the study, good data management, e.g. documentation of data and data access, ensuring long-term preservation of data, and data sharing, is integral to conducting transparent and reproducible science (Gollwitzer et al., 2020; Weston, Ritchie, Rohrer, & Przybylski, 2019; Wilkinson et al., 2016). For example, sharing deidentified data in a public (e.g. Open Science Framework) or restricted access (e.g. the UK Data Service: https://ukdataservice.ac.uk/deposit-data/) repository enables other researchers to independently verify a study's results.

Practical example of implementing open science practices in longitudinal research: The SIGMA study

The SIGMA study (Kirtley, Achterhof, et al., 2021) – an accelerated longitudinal study of adolescent mental health and development in Flanders, Belgium - was a positive catalyst for developing an open science culture within our lab. In this section, I describe how we have implemented a data access system and post-registration for the SIGMA study.

Managing data access

Access to data brings knowledge of the data, which increases the likelihood of biased, data-dependent decisions (Weston et al., 2019). Post-registration and Registered Reports both aim to reduce data-dependent decision-making and, in the case of post-registration, to document researchers' knowledge of the data and be transparent about whether decisions were data-dependent (Mertens & Krypotos, 2019; van den Akker et al., 2019; Weston et al., 2019). Within a longitudinal study, we can minimize potential leakage of knowledge about a dataset by limiting data access using a data checkout system - akin to a library - where specific variables are 'checked out' to researchers, and a record of access is maintained (Scott & Kline, 2019). To facilitate post-registration and Registered Reports in SIGMA, we developed a data checkout system, Data cuRation for Open Science (DROPS; (Kirtley, Lafit, Wampers, & Myin-Germeys, 2020). The full dataset is available only to the data manager, and abstract submission and variable access requests operate via a series of linked questionnaires in REDCap (Harris et al., 2019; Harris et al., 2009).

All abstract and variable access requests are stored within REDCap, which documents every researcher's access to variables within the SIGMA dataset, facilitating disclosure of prior knowledge of the data in post-registrations and Registered Reports. Should researchers wish to publish their studies as Registered Reports, the data manager provides a statement at Stage 1 to confirm whether researchers have had prior access to the data (variables) in question. DROPS can also produce a time and date-stamped variable receipt to verify when researchers received data.

Whilst not all labs have a designated data manager, these examples could provide a starting point for developing other types of data curation systems. Going forward, data check-out systems will also need to develop methods of accommodating exploratory research, for example by using holdout data (Weston et al., 2019).

Post-registration

Post-registration is a requirement of accessing SIGMA data. This has worked well, as the research questions we have addressed so far have been primarily confirmatory. Lab members receive training and guidance on post-registration to scaffold development of this skill, for example, during specific training sessions in lab meetings, through published tutorial papers and templates (Kirtley, Lafit, et al., 2021; Lafit et al., 2021), and informal mentorship.

We do not limit post-registration according to prior data access; if a lab member has post-registered analysis using a particular set of SIGMA variables for one study, they are able to post-register analysis including those variables in another study. The lab member then documents their prior knowledge of the data in the post-registration for the new study. Data-dependent decision-making may occur here: for example, based on knowledge of missing data or variable multicollinearity gleaned from previous analysis of the same data. In such cases, we document the data-dependent nature of these decisions as thoroughly as possible in the post-registration and manuscript.

We use different templates for post-registration depending on the data: for time-invariant data, e.g. self-report questionnaires, we use the template for pre-registration of secondary data (van den Akker et al., 2019); and for time-variant data, e.g. experience sampling method data, we use the registration template for experience sampling method research (Kirtley, Lafit, et al., 2021). We upload the contents of the completed templates as open-ended registrations on the OSF. Each study using SIGMA data has a separate OSF project page connected to the relevant post-registration, and the post-registration link is provided in the manuscript. Deviations from the post-registration are reported in the manuscript and/or in the supplementary material, depending on word count restrictions. As masters students are generally new to using open science practices, we use the relatively low threshold 'As Predicted' (https://aspredicted.org/) registration template for their thesis projects using SIGMA data.

To date we have post-registered different types of studies using SIGMA data, including intensive longitudinal (Achterhof, Kirtley, Schneider, Hagemann, et al., 2021; Achterhof, Kirtley, Schneider, Lafit, et al., 2021) and longitudinal (Achterhof, Myin-Germeys, et al., 2021; Janssens et al., 2021) data. These studies may provide useful practical examples for longitudinal – and intensive longitudinal - researchers interested in introducing post-registration into their workflow.

Challenges of combining open science practices in longitudinal research and potential solutions

As mentioned previously, in longitudinal studies, multiple researchers may be actively using the same dataset simultaneously or one researcher may need to use overlapping sets of variables from a single dataset for different projects. As we have discovered, this creates some challenges when attempting to combine the three open science practices I have focused on in this article. Here, I discuss one challenge and some potential solutions in more detail.

Evidencing prior knowledge of data for different Registered Reports using overlapping variable sets

Relatively few journals offer Registered Reports for studies of pre-existing data, but those that do require proof that researchers have yet to access the study's data, e.g. a statement from a data manager. Registered Reports for longitudinal studies are especially challenging in terms of data access. Similar to other journals' policies, in the recent special issue call for *Infant and Child Development*, focusing on 'Registered Reports with Secondary Developmental Data', prior access to data precluded submission. Even in cases where data had yet to be accessed, researchers must agree not to access data until after Stage 1 manuscript acceptance (Davis-Kean, Ellis, & Syed, 2021).

The goal is highly worthwhile; to reduce data-dependent decision-making and researcher degrees of freedom (Simmons et al., 2011; Wicherts et al., 2016). However, this may unintentionally exclude longitudinal researchers from participating in Registered Reports initiatives, especially ECRs for whom 'quarantining' variables within a dataset for unpredictable amounts of time may negatively impact their research and progress.

An initial step in addressing these issues may be for journals to clarify what is meant by data access, e.g. would co-authorship without receiving data count as data access? In situations where a researcher cannot wait until Stage 1 acceptance to progress with another study using an overlapping variable set, journals could consider the Stage 1 submission for the first Registered Report as a time and date-stamped record of the researcher's knowledge of the variables for the second Registered Report. The researcher could then submit updated data knowledge statements during the Stage 1 review process for the second manuscript, allowing reviewers to compare subsequent manuscript revisions to the original, in light of the researcher's knowledge of the data at that moment. Any revisions that did not directly follow from reviewers' comments would need to be justified – as is the case for any manuscript - and transparently reported as to whether they were data-dependent. In the future, an alternative solution may be formal linkage of articles using overlapping datasets within a journal's submission system, enabling researchers to provide updates about their knowledge of the dataset, for multiple manuscripts simultaneously in a 'living' document.

In all cases, thorough documentation of data access is essential and implementing additional measures such as robustness checks could increase confidence in the findings (Weston et al., 2019). For an excellent, in-depth discussion of applying open science practices in the context of pre-existing data, see Weston et al., (2019).

Conclusions

Longitudinal studies provide unique insights into development. However, longitudinal research is also where the garden of forking paths may be most maze-like. A new frontier for longitudinal research is to justify its credibility by using open science practices to increase transparency, and allow critical evaluation. Pre- and post-registration, Registered Reports, and good data access management all bring opportunities for enhancing credibility in longitudinal developmental research. Whilst implementing these practices is not without challenges, ultimately, increasing credibility in longitudinal research will benefit numerous stakeholders.

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