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Conducting a Meta-Analysis in the Age of Open Science: Tools, Tips, and Practical Recommendations

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Abstract

Psychology researchers are rapidly adopting open science practices, yet clear guidelines on how to apply these practices to meta-analysis remain lacking. In this tutorial, we describe why open science is important in the context of meta-analysis in psychology, and suggest how to adopt the 3 main components of open science: preregistration, open materials, and open data. We first describe how to make the preregistration as thorough as possible—and how to handle deviations from the plan. We then focus on creating easy-to-read materials (e.g., search syntax, R scripts) to facilitate reproducibility and bolster the impact of a meta-analysis. Finally, we suggest how to organize data (e.g., literature search results, data extracted from studies) that are easy to share, interpret, and update as new studies emerge. For each step of the meta-analysis, we provide example templates, accompanied by brief video tutorials, and show how to integrate these practices into the Open Science Framework (https://osf.io/q8stz/).

Translational Abstract

Open science practices are gaining traction in the psychological research ecosystem. A number of contributions have been published recently with the goal to facilitate open science practices in a number of research designs; however, clear guidelines about how to integrate these practices in the context of meta-analyses have been lacking. Here, we describe why and how open science practices can be applied in the context of meta-analysis. After highlighting the benefits of the three main components of open science (preregistration, open materials, and open data), we propose a series of nine templates and video tutorials to help researchers with all aspects of an open meta-analysis. These materials are designed to facilitate the evaluation of empirical findings and help increase the impact of a meta-analysis—both important steps toward robust and valid inferences in psychological science.

Keywords: metascience, preregistration, open data, reproducibility, replicability

Meta-analyses play a central role in synthesizing research findings. With a high value-to-cost ratio, especially in fields where studies are typically onerous or expensive (e.g., clinical trials, interventions, fMRI studies), meta-analyses can maximize information and reduce the influence of biased studies, often providing the basis for decisions or policies. Yet, despite the recent rise of open science across fields of investigation (Federer et al., 2018; Nosek & Lindsay, 2018; Popkin, 2019), clear and well-defined guidelines about how to integrate meta-analyses within the open science ecosystem remain lacking in psychology. This gap in the literature has important consequences, as it suggests that some—if not all—of these practices are not crucial in the context of meta-analyses, or that the specificities of meta-analyses do not warrant customized suggestions.

In this tutorial, we argue that open science practices are critical to ensure robust and reliable meta-analyses, and propose specific practical recommendations to facilitate preregistration, open materials and open data. For each component, we provide templates that can help standardization, while allowing the necessary flexibility for researchers to adapt them to a range of designs. With the many small decisions that go into a meta-analysis, careful planning and clear documentation of these decisions is critical for transparency. The templates provided help to facilitate this. For instance, registering the analysis script ensures consideration of statistical decisions in advance of the literature search; registering the data extraction file ensures early decision-making about which variables to extract from included studies. All templates—together with tips on how to best utilize them—are also illustrated with

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step-by-step video tutorials, in an effort to facilitate systematic implementation in psychology. Figure 1 shows the suggested workflow for all templates. Note that this article is not meant to be a comprehensive tutorial about learning meta-analysis from scratch; a number of excellent resources already exist for conducting meta-analysis more generally.[1] Rather, our goal is to offer a set of tools and recommendations to apply open science practices to meta-analysis.

Preregistration

While typical in clinical trials (Moher et al., 2010), and becoming mainstream in other experimental studies in psychology (Adam, 2019; Nosek, Ebersole, DeHaven, & Mellor, 2018), preregistration remains rare in the context of meta-analysis (Moher, Tetzlaff, Tricco, Sampson, & Altman, 2007; see also Figure 1), despite current recommendations (most notably, the Preferred Reporting Items of Systematic Reviews and Meta-Analyses Protocol, PRISMA-P; Shamseer et al., 2015). Not unlike other types of empirical studies, flexibility in meta-analyses is detrimental to theory falsifiability (Ledgerwood, 2018) and can lead to questionable research practices such as *p*-hacking (Head, Holman, Lanfear, Kahn, & Jennions, 2015; Simmons, Nelson, & Simonsohn, 2011) and HARKing (Kerr, 1998), particularly because dealing with average estimates pooled across multiple studies may give a false illusion of robustness (Higgins, Thompson, & Spiegelhalter, 2009; Moreau, in press; Moreau & Corballis, 2019). Meta-analyses include a vast number of decisions that can greatly influence overall estimates of effect sizes, their statistical significance, or subsequent subgroup analyses. For example, data inclusion decisions have been shown to greatly influence meta-analysis findings, often more than analytic choices (Goodyear-Smith, van Driel, Arroll, & Del Mar, 2012), whereas procedures to handle publication bias can have a sizable impact on study outcomes (Greco, Zangrillo, Biondi-Zoccai, & Landoni, 2013). The bias these decisions can introduce has been documented extensively in the meta-analytic literature, including quantitatively, with multiverse analyses (Voracek et al., 2019). Preregistering thus serves two related but distinct purposes: It helps safeguard oneself against questionable practices, and provides a record of the original plan for other researchers to access and compare against the final, published study (see Figure 2).

In the context of meta-analyses, however, preregistration might seem particularly challenging. How can one know what studies are relevant before running the search, for instance? Will five databases be comprehensive enough, or overkill? What moderator analyses will have enough statistical power? And what methods should be used to detect bias? To facilitate the process of preregistration, we provide a list of items to consider, together with a brief explanation for each, in Template 1 (see online supplemental material). The template is designed to enable flexible yet thorough preregistration, specifically in the context of meta-analyses in psychology. The items follow the PRISMA protocol, but also contain tips and examples specific to our field. We also provide a ready-to-populate flow diagram that adheres to the PRISMA protocol (Template 2). The flow diagram is a visual depiction of the search process in a meta-analysis, from the initial query to the final selection of studies, and including all steps in between. This component is key for transparency, as it provides a quick overview of the data collection process, and serves as a reference document to navigate possible intricacies of the design. We include the flow diagram in the preregistration section, as ideally this document is designed at the planning stage of the meta-analysis, and later updated when search results and data extracted are known.

Open Materials

Another fundamental aspect in ensuring transparency of a meta-analysis is creating clear materials that can be understood without knowing anything about the background of the research. By materials, here, we refer to the *input* of the meta-analysis—in short, what was done to extract the numbers? Many subsequent reuses of meta-analyses focus on assessing practices or developing new methods, and might thus have very little to do with the topic of interest itself; clear materials allow seamless evaluation of a meta-analysis even without prior knowledge of the specific study focus. Furthermore, clarity in the materials facilitates extensions of previous meta-analyses (Martone, Garcia-Castro, & VandenBos, 2018), thus increasing potential impact on individuals and policies. In this section, we provide three additional templates to facilitate open materials.

A central component of open material relates to sharing scripts for data wrangling and analyses (Gilmore, Lorenzo Kennedy, & Adolph, 2018). Here, we provide examples in R, given its appeal for reproducibility and its widespread use in psychology. We designed a generic script (Template 3) that requires minimal tailoring for each individual meta-analysis. Beyond typical packages used for data wrangling and data visualization (see Template 3 for a full list), the script relies heavily on the metafor package (Viechtbauer, 2010), designed for meta-analyses. In Figure 1, we present the analysis script as part of both preregistration and materials, as the script should be written before the search is performed, but will likely be updated to include changes in confirmatory analyses or additional exploratory analyses. These changes typically happen after search results are known and the data have been extracted. To promote reproducibility, it is also crucial to document the exact search syntax used for all databases. We provide a search syntax template that can accommodate different databases, and that has been prepopulated with an example from psychology (Template 4).

A thorough meta-analysis often includes articles or reports that were not directly available online. For example, a researcher might want to include a published article that does not provide open data with the publication, or she might want to include unpublished data, perhaps from a thesis or conference proceedings. This is an important step, as it helps correct for some of the overall publication bias. In the process of accessing all possible data, a researcher often has to contact authors directly, usually by e-mail. This can be daunting, especially when contacting senior scientists in the field. To facilitate these requests, we provide two e-mail templates that have been worded carefully to ensure the rationale of the request

[1] For a detailed introduction to meta-analytic techniques including theoretical background, see Borenstein, Hedges, Higgins, and Rothstein (2009). For a practical introduction to meta-analysis, see the Cochrane Training resources (e.g., https://training.cochrane.org/handbook/current/chapter-10) or Mavridis and Salanti (2013). Finally, see Viechtbauer (2010) or http://www.metafor-project.org/doku.php for a primer on using the metafor package in R.

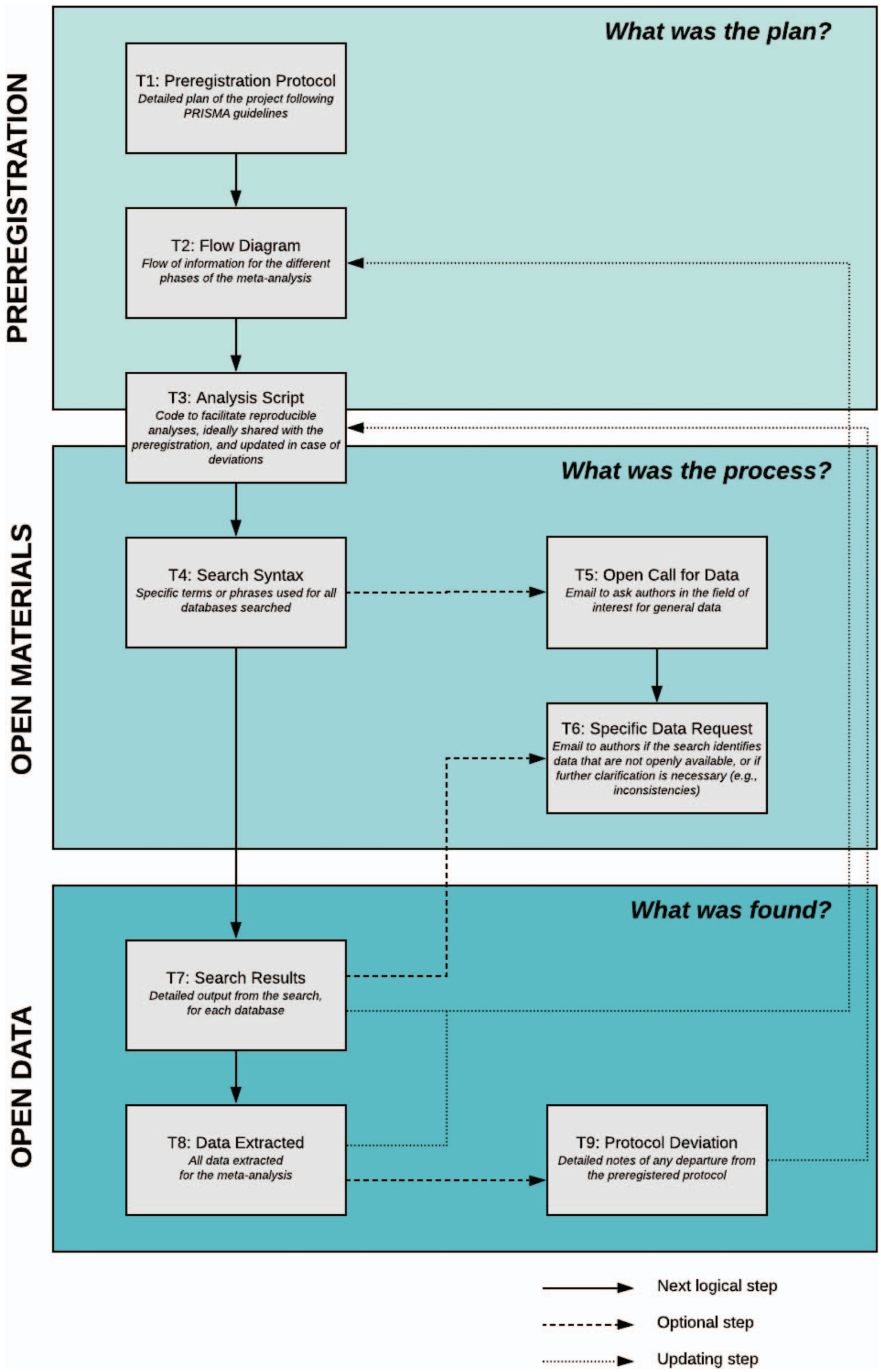

Figure 1. Flowchart describing all the provided templates for creating a transparent meta-analysis. We distinguish between what is intended before the meta-analysis (preregistration), the input for the research (open materials), and the output of the research (open data). Some templates may not always be required (see "Optional Steps") and other templates need to be updated following data collection (see "Updating Steps"). See the online article for the color version of this figure.

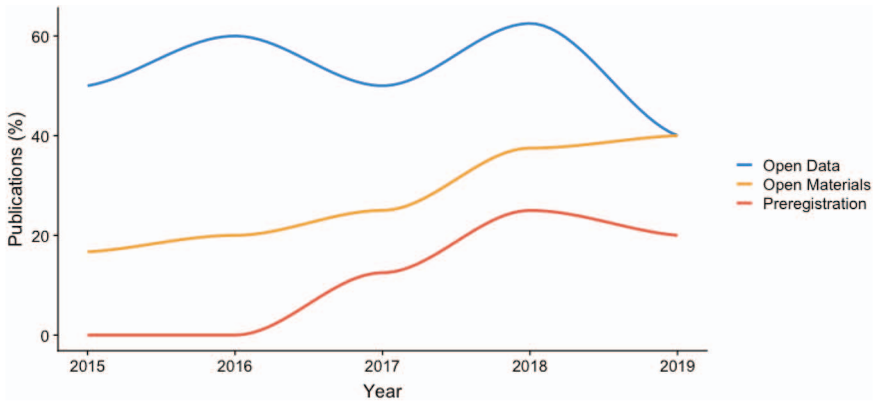

Figure 2. Open science in meta-analyses in the last 5 years. The plot shows the evolution of open science practices (preregistration, open materials, open data) for two psychology journals publishing meta-analyses (*Perspectives in Psychological Science* and *Psychological Science*) over the last 5 years. See the online article for the color version of this figure.

is clear and that authors understand what the project will entail. These templates include an open call for data, to e-mail authors in the field during the initial stage of the search (Template 5), and a specific data request, to e-mail authors of studies that appear to be relevant, but lack information or require clarification (Template 6).

Open Data

The third major component of open practices in meta-analyses relates to data sharing. By data, here, we refer to the *output* of the meta-analysis—what was extracted from the research. In a meta-analysis, perhaps more than in other types of studies, the data is the product. What we mean is, the contribution to the field is not in the novel way the data have been collected or analyzed—it is in the data themselves. Despite the fundamental importance of data sharing (Gilmore et al., 2018; Meyer, 2018), it remains relatively common for data to not be available with published meta-analyses (see Figure 1). This is problematic, as it prevents others from confirming or extending upon the findings.

The generic term *data* encompasses a range of information that can be useful to other researchers in the context of a meta-analysis. First, it is important to provide literature search results. Many databases allow downloading a record of the search, together with detailed outputs. Oftentimes, this includes the number of entries, all references, and abstracts. Template 7 has been designed to allow sharing all content relevant to the search results, thus increasing transparency and facilitating reproducibility. Information such as decisions to include or exclude a study, ambiguities, and the overall breakdown of articles across databases can be documented in this file. In addition, we provide a template to store all data extracted from the search, after it has been curated (Template 8). The template includes metadata about each reference, descriptive statistics, as well as notes and additional information for each study. These two templates allow structuring data sharing in a way that is clear and unambiguous to all parties interested in meta-analytic findings. Template 8 is also designed to be directly imported into the analysis script (Template 3).

Finally, regardless of how thoroughly planned a meta-analysis is, researchers will almost inevitably deviate from the original plan. Such deviations are extremely common; a recent study found that of 27 preregistered articles in *Psychological Science* from 2015 to 2017, *all* deviated from the plan in at least one aspect, and only one article successfully reported all deviations (Claesen, Gomes, Tuerlinckx, & Vanpaemel, 2019). It is therefore important to note that deviating from the preregistration is not a failure—deviations are often the consequence of detailed protocols, rather than a weakness in foresight. In this context, what is most problematic is not the presence of deviations themselves, but failing to make them transparent.

Keeping a record of all deviations from the original protocol is key to facilitate assessment by editors, reviewers, and readers. This record should include the specifics of what has been changed, and the extent of the change. For example, if one changes a preregistered criterion on outlier detection, perhaps because it appears too stringent, it is important to state the difference between the two criteria, as well as the extent to which this impacts the results and the interpretation of the findings. Deviations also need to be justified, that is, a rationale as to why the change was necessary or desired should be provided. As much as deviating from a preregistration is common, deviating opportunistically without any rationale is clearly problematic. Template 9 allows documenting and justifying deviations from planned protocols, and shows some fictional examples from psychology.

It is worth noting that anticipation is key in this process—if the researcher can foresee what could force a deviation from the plan, this information can and should be part of the preregistration. For example, is the choice of an outlier detection method independent from the number of studies, or effect sizes, that would be discarded? If not, what proportion of effect sizes could lead to adjustments? Another example relates to coders for interreliability. What will be done if no consensus can emerge? Would one of the authors (e.g., lead, senior, etc.) make a final decision? Anticipating the decisions that might have to be made flexibly is the best way to solve problems before they arise, and provides a path forward determined a priori.

More generally, sharing data also enables dynamic meta-analyses that can be updated as new studies get published (Braver, Thoemmes, & Rosenthal, 2014). One of the exciting areas of research in this field relates to the automation of meta-analytic synthesis, whereby studies can be directly picked up from databases and added to a growing list of studies on which models can be run. Successful implementation of this type of project rests on two core pillars: data sharing for all studies, and standard templates to allow automatic processing. The former allows a complete, unbiased picture of the literature, while the latter helps minimize errors and human intervention, especially useful for large-scale analyses. These areas have seen promising developments in recent years, including community-augmented meta-analyses (Tsuji, Bergmann, & Cristia, 2014) and community-driven projects designed to expand the R ecosystem for meta-analysis such as R/metaverse (https://rmetaverse.github.io/). Importantly, standardization is not only good for error-detection and automation, it is also critical to ensure meta-analyses can be easily interpreted, not only by scientists and researchers but also by practitioners and policymakers (e.g., LeBel, McCarthy, Earp, Elson, & Vanpaemel, 2018).

Hurdles and Additional Considerations

There are numerous benefits associated with preregistration, open material, and data sharing in the context of meta-analyses. Yet, we acknowledge that some of the aspects aforementioned might, in specific instances, be impractical or challenging to implement (Houtkoop et al., 2018). For example, it can sometimes be difficult to lay out a meta-analysis plan ahead of time, especially if it involves students or trainees with limited time to dedicate to the project, perhaps due to their degree requirements. It is important to note that we are not commenting on what should be done, or giving instructions regarding best practices. Rather, we are merely providing resources to enable open practices, with the hope that these can be helpful to meta-analysts seeking options to better document and share their research projects.

Nonetheless, open practices often require very minimal change to the typical flow of a meta-analysis. For example, almost any meta-analysis requires many of the components of a standard preregistration (e.g., research question, intended search terms, moderators, focus of the analyses, etc.). In this sense, preregistration simply reorders the process so that these decisions are made *prior* to data collection. Using the necessary planning stage as a stepping stone to formal preregistration can help capitalize on work that typically has to be conducted anyway.

Hurdles in the way of sharing materials and data are perhaps more scarce. For alternate types of empirical studies, there might be factors that prevent researchers from embracing open science practices, even when they are willing to do so (Houtkoop et al., 2018). Institutional review boards might not allow open material and data, retroactive approval from participants or patients might be difficult to obtain, or sharing policies might in certain instances be harmful (e.g., clinical contexts). These factors are generally not relevant in the context of meta-analyses, as these rely on quantitative synthesis of data that have already been shared publicly. In cases where the data are not open, the e-mail templates we provided with this tutorial (Templates 5 and 6) help disclose intent related to data sharing to the researchers from whom data are requested. If issues remain with data sharing, other options can be explored; for example, researchers can generate data with the same descriptive properties (synthetic data), allowing reproducibility while protecting privacy rights. Even in contexts where one does not intrinsically care about open science, sharing data, and materials is still the most advantageous thing to do—easy-to-access data and materials increases future use of a meta-analysis, and thus impact and citations (McKiernan et al., 2016). Finally, one might assume that proficiency in a programming language such as R, Python, or Matlab is necessary to share materials. Although helpful, programming skills are not necessary for open materials: Syntax for analyses can be exported in a few clicks from GUIs such as JAMOVI or SAS, whereas all other types of information can be shared in standard formats. Following this rationale, we deliberately chose to design templates in commonly used and freely available formats (Open Document Format, .csv, .R) to facilitate wide and flexible use.

Open science in the context of meta-analysis is rapidly evolving, with more researchers preregistering their studies, and sharing materials and data each year. Yet challenges remain. One example is with Registered Reports; that is, contributions accepted for publication prior to data collection on the merit of their rationale and design (see e.g., Hardwicke & Ioannidis, 2018). To our knowledge, there is currently no outlet among the main psychology journals that proposes Registered Reports specifically for meta-analysis. One of the potential concerns about the suitability of meta-analyses in this context relates to the fact that the literature is often known, at least partly, by the analyst, which means that the outcome of a meta-analysis might be easily predicted ahead of data collection. This is not entirely accurate, however, as meta-analyses typically include a large number of parameters, many of which play an important role in the final outcome (e.g., inclusion criteria, search strategy, and correction for publication bias). Together with the large number of papers processed in the course of the search, it is often very difficult to predict the outcome of a meta-analysis before it has been performed.

In addition, very strong predictions could be made for studies that are not meta-analyses, perhaps following a well-powered pilot. In such situations, one could argue that the outcome of the replication is known a priori, and yet very few researchers would argue that this makes experimental studies inadequate for Registered Reports. In our view, the same rationale applies to meta-analyses—if predictions are well-informed by previous literature, this is an additional strength of the meta-analysis rather than a limitation. Finally, and perhaps more importantly, the advantages associated with the Registered Reports format—most notably the possibility to get feedback on a research project early on and the peace of mind associated with producing a study for which publication does not depend on the outcome but is judged on the merit of the project beforehand—in our view trump the potential downsides, especially given the time commitment required to synthesize the literature on a research question.

Conclusion

In this tutorial, we presented a rationale for open science practices in the context of meta-analysis, specifically focused on preregistration, open materials, and open data. In an effort to facilitate broad impact and readability, we provided nine standardized templates with tips and recommendations. Finally, we discussed current directions at the intersection of open science and meta-analysis, such as the potential for Registered Reports in the context of meta-analysis, or with respect to dynamic meta-analyses, either curated or automated, to enable up-to-date evidence in real time. These are exciting developments for meta-analysts—and critical steps toward stronger, more valid inferences in psychological science.

In-Detail Boxes

Box 1. Preregistering a Meta-Analysis: OSF or PROSPERO?

There are various repositories available to preregister meta-analyses. Among these, PROSPERO is perhaps the most popular, covering research "relevant to health and social care, welfare, public health, education, crime, justice, and international development, where there is a health related outcome" (https://www.crd.york.ac.uk/prospero/). On the other hand, the Open Science Framework (OSF; https://osf.io/) has established itself as a strong, reliable platform in psychology, with capabilities that go well beyond preregistration. So, which option should you choose? Here, we can differentiate between three main scenarios:

- If your meta-analysis does not have implications for health, we suggest registering it on OSF (see Soderberg, 2018, for a step-by-step guide);
- If your meta-analysis is related to health in any way, we recommend registering on PROSPERO. This is because the repository acts as a database, with scientists interested in meta-analyses regularly searching for ongoing or finished projects, before they get published;
- If you would like to increase visibility, registering on both platforms is an option, but keep in mind that the two preregistrations need to be identical, otherwise this might seem like an attempt to accommodate flexibility in future analyses by logging multiple preregistrations.

Alternatives exist (e.g., aspredicted.org), but they are often less thorough and less visited than the two main options we discussed here.

Box 2. Using Version Control to Facilitate Workflow and Collaboration

Meta-analyses are often substantial projects that involve countless hours of work often shared across several collaborators. In this context, it is helpful to create a version-controlled workflow that guarantees automatic archiving for all successive versions and facilitates parallel contributions across collaborators. Among version control systems, Git is very popular and integrates seamlessly with RStudio (see for a brief tutorial Vuorre & Curley, 2018). Here, we provide a step-by-step guide to set up a version-controlled meta-analysis project in RStudio.

1. Sign into your github account. If you do not have an account, you can create a free one at github.com
2. Once signed in, create a new repository: github.com/new
3. After your new repository has been created, click on the green button "Clone or download," and copy the link
4. Open RStudio
5. Click on "New Project" then select "Version Control" and "Git"
6. Paste the link to the new repository, and click on "Create Project"; your new project is now Git-controlled
7. Create a new R script, or R Markdown file, drag it onto your github repository, and click on "Commit changes"
8. In R Studio, click on "Git" then "Pull Branches"
9. Open your R script, make changes, then click on "Git", "Commit"
10. Click on "Push"; changes are now visible and accessible by all collaborators.

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