Open Communication Science: A Primer on Why and Some Recommendations for How

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Abstract

Communication scientists devote large amounts of resources to conducting studies to improve our understanding of the social world, in hopes that our efforts contribute to improving people's life outcomes. Unfortunately, for a variety of reasons, the process by which our research is conducted is not always clear in journal articles or books reporting our research. This lack of *process-insight* (a) limits our ability to build on each other's research, (b) limits our holistic understanding of communication processes, and (c) limits the ability of consumers of our research to put it into practice. The current article discusses recent methodological advances designed to address these issues – advances in open science practices. I provide a brief primer on the philosophy behind open science and its relevance for communication research, then provide recommendations for both novice and expert researchers to implement open science practices at multiple steps of the research pipeline.

Keywords

Open science, methodology, reproducibility, philosophy of science

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Communication scientists devote much of our time to studying processes that are critically important for many domains of life – education, environmental sustainability, health, technology, to name just a few examples. The research we do is not only relevant for advancing our theories within the discipline, it also has the power to influence policies and practices throughout the world (Giner-Sorolla, 2019; Goroff, Lewis, Scheel, Scherer, & Tucker, 2018; Lewis, 2019). We study how the shows our children watch influence what they learn (e.g., Bonus & Mares, 2018; Ward, 2002), and the implications of those processes for practices like representation in the media (e.g., Dal Cin, Stoolmiller, & Sargent, 2013); how the way we frame messages about climate change affects the public's opinion about one of the most critical issues of our time (e.g., Schuldt, Enns, & Cavaliere, 2017); how and why health messages influence people's smoking decisions (e.g., Skurka et al., 2018); how the technology we use influences our abilities to communicate and collaborate effectively across cultures (e.g., Yuan, Liao, & Bazarova, 2019), and whether the use of different technologies have any consequences for our health and well-being (e.g., Bayer, Ellison, Schoenebeck, Brady, & Falk, 2018; Orben & Przybylski, 2019).

These studies that we conduct have great potential for advancing knowledge within and beyond the field of communication, but realizing that potential requires that we share information about the full process involved in conducting our studies. For others to build on our work and use that work to improve the world around us, they must understand how we got from idea conception to publication. At present, there is limited information in the literature about the full life cycle of studies in the field of communication (Elson & Przybylski, 2017) as well as in other disciplines. What we typically see is the final product – journal articles in which the bulk of statistical significance tests fall below the magical $p < .05$ threshold (Vermeulen, Beukeboom, Batenburg, Avramiea, Stoyanov, van de Velde, & Oegema, 2015) with scant information about how exactly it is that we got there (Matthes, Marquart, Naderer, Arendt, Schmuck, & Adam, 2015; Simmons, Nelson, & Simonsohn, 2011). There are numerous reasons for this which I will discuss later; for now, the important thing is that the gaps in insights about how communication science gets produced inhibits our ability to build cumulative knowledge internally within the field (Elson & Przybylski, 2017) and has vast implications for the public's perception of the field and its utility for the world (Przybylski & Weinstein, 2016).

For the reasons I just outlined (and others), methodologists and philosophers of science from multiple disciplines have spent the past two decades developing practices and tools for making research processes more transparent. Collectively, these developments have become known as “open science” practices. The goal of this article is to discuss some of the recent developments in open science and provide practical guidance on how to implement open science practices along multiple points of the research pipeline. Since I suspect readers will vary in their knowledge about and experience with open science, I have structured the article in a way that will hopefully be useful regardless of where you are on the (novice to expert) continuum. For readers completely new to open science, the first section (“Open Science: A Primer on Why”) provides a brief introduction of the history and philosophy behind open science and makes the case for why it may be worthwhile to add open science practices to your research workflow. Readers who are already convinced that open science is worthwhile but have not yet begun putting principles into practice can skip to section two (“Getting Started with Open Science”) which provides instructions and manual templates for implementing foundational open science practices into your research workflow. Readers who were early adopters and are already well-versed in the foundational open science practices can skip to section three (“Advanced Open Science Practices”); that section discusses a new(er) model of scientific publishing and new software for automating some open science practices. Finally, I will end with a discussion on the role of incentives that may guide researcher, institution, and field-wide behavior with respect to the adoption of open science practices which I hope will generate further discussions of ways to move the field forward.

I. Open Science: A Primer on Why

Something peculiar happened in the field of medicine around the turn of the 21st century. Medical researchers, like researchers in many other fields, conducted their research in a traditional way: the researchers generated their questions, designed their studies, applied for funding, carried out the study, analyzed their data, and published beautiful reports of great new discoveries. How they made each decision along the way to those discoveries was not always clear – we (readers) just knew they

discovered something new that was supposed to change the way we think about and/or practice medicine.

That process changed in the year 2000 due to the FDA Modernization Act of 1997 which created the ClinicalTrials.gov registry (Food and Drug Administration, 1997; Zarin & Tse, 2008; Zarin, Tse, & Ide, 2005). That law required American¹ researchers conducting clinical trials to add a small step to their process: between the time they designed the study and the time they conducted it, they had to pre-register their methods and outcome measures in the ClinicalTrials.gov registry so that the research community (and broader world) could see exactly what the researchers *planned* to do before they actually did it. This law went into effect in the year 2000 providing an interesting ‘discontinuity’ in the research time series that allowed researchers to assess what effect, if any, making that research process open had on the research that was produced before vs. after the mandate.

Kaplan and Irvin (2015) investigated this exact question in the area of heart disease research; they examined whether the registry mandate made any difference in research on drug or dietary supplement trials for the treatment or prevention of cardiovascular disease. What they found was striking: Before the year 2000 (before clinical trial researchers were required to disclose their research plan prior to conducting trials), 57% of clinical trials published reported positive effects of treatments – they were successful in preventing or treating cardiovascular disease. After the year 2000 (after registration was required), that success rate plummeted to 8% (Kaplan & Irvin, 2015). That finding gave many researchers pause. If making methods transparent has no influence on the research process, there should be no noticeable difference between research that was published before and after the registration mandate. That there is such a large difference in outcomes suggests that researchers were (either intentionally or unintentionally) making decisions that have important consequences, but those decisions were not apparent to consumers of the research. More concretely: medical researchers were ostensibly discovering effective treatments for heart disease, but it was not fully clear to others how they made those discoveries, and somehow making the discovery process open – sharing the research plan ahead of time – made those discoveries all but disappear.

Heart disease is not the only literature that has suffered from ailments like the one I just described. Researchers have had difficulty reproducing findings in cancer biology (Baker & Dolgin, 2017), psychology (e.g., Klein et al., 2018; Open Science Collaboration, 2015) and other social sciences (Camerer et al., 2018), including the field of communication. One recent example comes from the area of communication technology. As young people adopted the use of digital technologies (e.g., smart phones), scientists and the broader public began to speculate and worry that regular technology use would negatively impact their psychological well-being (Twenge, 2017). This ballooned into public concerns about the so-called “iGeneration” that is supposedly less happy and unprepared for adulthood due to their technology use (Twenge, 2017). Surely, one can find evidence for such claims depending on how analyses are conducted. However, a recent large-scale specification curve analysis of datasets containing over 350,000 adolescents found that the association between digital technology use and adolescent well-being explains, at most, 0.4% of the variation in well-being, suggesting the effects are too small to warrant public panic and policy changes being discussed around the world (Orben & Przybylski, 2019).

Findings like the ones I discussed in the preceding paragraphs highlight the importance of open science in my mind. They reveal a critical, though often unacknowledged, feature of the scientific enterprise: science is conducted by humans who have a range of backgrounds and experiences that influence the questions we ask, the approaches that we take, and ultimately the discoveries that we make. To understand the science requires a window into the approaches taken by the scientists. This reality was recently underscored by a meta-scientific study entitled “Many Analysts: One Data Set” (Silberzahn et al., 2018). In that study the researchers sent 29 research teams the same dataset to answer the same research question: are soccer referees more likely to give red cards to dark-skinned players than to light-skinned players. Since the research question and dataset are identical, one might think all teams would converge on the same process and answer. That is not what Silberzahn and colleagues (2018) found. The 29 teams analyzed the data 21 different ways; 20 teams found a statistically significant and positive effect, 9 found no significant relationship, and effect sizes

¹ Because American publishers manage many of the medical journals and have adopted registration policies in line with the FDA Modernization Act, researchers from other countries occasionally register their studies to have the opportunity to publish in American journals.

found across teams ranged from 0.89 to 2.93 in odds-ratio units. Those differences are substantial; they suggest that the answer to the research question depends, in part, on which team happened to analyze the data.

That researchers have so much flexibility in how we can approach the design, procedure, and analyses of studies, and that the decisions we make at every step of the process can be so consequential for our conclusions is what motivated the creation of the open science practices I will describe in this article. There are many decisions that have to be made when conducting research (Gelman & Loken, 2013; Simmons et al., 2011) and as consumers of research it is critical to know what decisions researchers made in order to evaluate their inferences (Nosek, Spies, & Motyl, 2012), inferences that can be quite consequential for people's life outcomes (Giner-Sorolla, 2019; Lewis, 2019). Without all of the information about the process of knowledge generation, it becomes difficult to know...what exactly it is that we "know."

Addressing this gap in *process-insight* is critical for the advancement of science, and the advancement of practices and policies that result from scientific inquiry. Recent efforts to facilitate process-insight have been broadly categorized as "open science" efforts: "a collection of actions designed to make scientific processes more transparent and results more accessible" (Spellman, Gilbert, & Corker, in press). The emphasis on *actions* to facilitate people's understanding of the scientific *process* so that they can make sense of the *outcomes* of scientific studies is a useful framework for thinking about (open) science. It allows each researcher to think about different actions they can take to facilitate transparency in each of their projects, acknowledging that different actions may be differentially practical (and/or ethical) for different projects. For some projects a researcher will be able to implement all the strategies for increasing transparency, for other projects, they will be able to implement some open science practices but not others, and yes – there are even projects in which it will not be possible to implement any of the open science practices.

The goal of open science from this approach, is not to create one uniform box that all scientists must squeeze their research paradigms into. Science is a broad enterprise that benefits greatly from having a broad range of approaches; it would be to science's detriment to reduce diversity in approaches and methods. The goal of open science, in my view, is to make *explicit* the often-implicit decision-tree scientists use to arrive at their conclusions – to allow others to look at the process and make their own judgments about the conclusion rather than having to place full faith in the original scientists' conclusions. The practices described in the remaining sections are recent developments designed to help scientists achieve this broader goal.

II. Getting Started with Open Science

Although open science methods and practices continue to evolve, there are three sets of practices that the field seems to have reached consensus about, and thus are good practices for getting started. Those three are *preregistration*, *open materials*, and *open data*.

Preregistration is the practice I alluded to earlier when describing the clinical trials example in section one. It is the process of creating a public record of what the researchers' questions were, what method(s) they planned to use, and how they planned to analyze their data so that readers and other users of a study can have a better sense of how to interpret the findings (Nosek, Ebersole, DeHaven, & Mellor, 2018). Overall, preregistration "clarifies the distinction between planned and unplanned research by reducing unnoticed flexibility" in the research process (Nosek, Beck, Campbell, Flake, Hardwicke, Mellor, van't Veer, & Vazire, in press).

In practice, when preregistration occurs depends on the nature of the research project. For research projects that involve new data collection, preregistration occurs prior to data collection; for projects in which researchers are analyzing existing data, pre-registration occurs after the analysis plan is set but prior to analyzing the data (for specific recommendations for preregistering analyses of pre-existing datasets, see Weston, Ritchie, Rohrer, & Przybylski, 2018). Before writing a preregistration, the research team should have a discussion about the nature and goal of the project: is the goal to explore a new area, to conduct a confirmatory test of a specific theory or set of hypotheses, or some combination thereof (exploratory and confirmatory research are often described dichotomously, but projects often contain elements of both)? For projects that are more exploratory in nature, Ijzerman, Klein, and Neyroud (2018) created a publicly available research template (<https://osf.io/nc8ha/>) that outlines a workflow research teams can use to plan and make decisions about their project; the answers to the questions outlined in their template will be helpful for

creating a preregistration. For projects that are more confirmatory in nature, Izjerman and colleagues (2019) have also created a publicly available confirmatory template (<https://osf.io/qpdth/>) with questions and procedures to plan before data collection. Note that the Izjerman and colleagues (2018, 2019) templates were designed for quantitative researchers; for qualitative researchers, Hartman, Kern, and Mellor (2019) created a preregistration template (<https://osf.io/b6xmd/>) that was adapted from Kern & Gleditsch (2017).

When you click on the (Izjerman and colleagues, 2018, 2019) templates, you will notice that the confirmatory template asks for more information than the exploratory template. While the exploratory template mainly asks about the theoretical background and general methodological approach and procedures, the confirmatory template requests specific hypotheses, statistical power calculations (for a recent tutorial on this topic, see Giner-Sorolla et al., 2019), and a specific data analysis plan. This information is necessary to declare in advance when conducting confirmatory research to control for error related to inferential statistics used for confirmatory research (Spellman et al., in press).

After deciding on a plan of action for conducting the study, the next step is to choose a registry for sharing that plan. There are many registries available; which one you choose depends in part on the nature of the research and complexity of the research design and plan. For health communication researchers, for instance, if the study qualifies as a clinical trial, it may need to be registered with the Clinicaltrials.gov registry; for those studying communication processes related to education, it may be useful to register with the Society for Research on Educational Effectiveness registry (<https://sreereg.icpsr.umich.edu/>); for other topics, general registries like [AsPredicted.org](https://aspredicted.org) or the Open Science Framework (<https://osf.io/7zhkp/registrations>) will likely be sufficient.

The most straightforward preregistration form in my view is the AsPredicted form which asks researchers to answer nine simple questions: *data collection* (have any data been collected for this study already?), *hypothesis* (what's the main question being asked or hypotheses being tested in this study), *dependent variable* (describe the key dependent variable(s) specifying how they will be measured), *conditions* (how many and which conditions will participants be assigned to), *analyses* (specify exactly which analyses you will conduct to examine the main question/hypotheses), *outliers and exclusions* (describe exactly how outliers will be defined and handled, and your precise rule(s) for excluding observations), *sample size* (how many observations will be collected or what will determine sample size?), *other* (open box for anything else you wish to preregister), and a box to name the project. If that form is too simplistic for your study design, the Open Science Framework has 8 templates (<https://osf.io/7zhkp/registrations>) that you can use – choose your own adventure.

Once all collaborators on the research project approve of the preregistration plan, the registration is locked with a timestamp and serves as the recipe for conducting the study. When authors submit their manuscript for publication, they can get an anonymous link to their preregistration document to include in their manuscript submission so that reviewers can verify that the study was actually conducted in the manner originally planned by the authors, and if not, deviations are clearly articulated in the manuscript.

I would be remised if I did not take a moment to acknowledge and address some of the recent controversy in the literature around preregistration. One criticism of preregistration is that it is restrictive – it puts researchers in a box, limiting their ability to analyze data in new ways if they develop more insights. This is a misconception about preregistration; the preregistered plan is not the only thing that researchers are allowed to do – it is possible and in fact, probable, that you will deviate from the preregistration. That is perfectly acceptable. What the preregistration does is allow the reader to know what was planned in advance and what was done *post hoc*; we can certainly still learn a lot from *post hoc* decisions (see Fiedler, Kutzner, & Kreuger, 2012), but to calibrate our inferences correctly requires some knowledge about how and when those decisions were made (see Gelman & Loken, 2013; Simmons et al., 2011). One simple way to distinguish between preregistered results and non-preregistered results is to divide results sections in manuscripts in to “predicted results” and “exploratory results” sections; that will help readers to calibrate their interpretations.

A second criticism of preregistrations is that they are not always precise enough to serve their intended purposes. Because researchers often have a general sense of study questions and hypotheses but cannot always anticipate in advance things like skew in data or outliers, preregistrations seem futile to some. For this criticism, I adopt the perspective of Nosek and colleagues (in press, pp. 3):

Preregistration requires research planning and it is hard, especially contingency planning. It takes practice to make design and analysis decisions in the abstract, and it takes experience to learn what contingencies are most important to anticipate. This might lead researchers to shy away from preregistration for worries about imperfection. Embrace incrementalism. Preregistration is a methodological skill that takes time to develop. Having some plans is better than having no plans, and sharing those plans in advance is better than not sharing them. With experience, planning will improve and the benefits will increase for oneself and for consumers of the research.

Open Materials is the second practice that has reached consensus in the ‘open science movement.’ Scientific articles and books are designed to communicate the process and outcomes of the studies in them – they should be the recipes for reproducing the research described within. Unfortunately, practical realities of the publication process over the years has limited the amount of details included in scientific reports. Journals have limited space and thus often impose page and word limits on their submitting authors to ensure that articles fit within those limits.

To address this issue, many of the registries I mentioned in the paragraphs on preregistration also have repositories for storing study materials. For instance, the Center for Open Science created the Open Science Framework (<https://osf.io>) which is a free repository for researchers to deposit study materials that are critical for readers to understand findings (Spies, 2013). To use the repository, researchers simply need to go to the website and sign up for an account using their email address.

Once an account has been created, researchers can create “project pages” to store materials related to their studies. For instance, if you return to the Ijzerman and colleagues (2018, 2019) templates I described earlier (exploratory template: <https://osf.io/nc8ha/>; confirmatory template: <https://osf.io/qpdth/>), you will notice that there are “Components” – effectively online sub-folders – for study materials. Those sub-folders allow research teams to easily drag-and-drop study material files to the OSF cloud storage server where the entire folder of materials and each file within it will get a unique hyperlink and DOI that can be used as links in manuscripts (and on CVs, websites, etc.) to direct people to the study’s materials. Research teams can upload their consent form, study instructions and protocol, materials and measures used in the study (assuming they are not proprietary), and anything else that would be helpful for readers to better understand how the research team conducted the study. This system allows researchers to share effectively limitless information about their studies, which can be helpful for consumers of the research, as well as original researchers themselves (e.g., the volume of emails requesting details about studies might decrease when supplemental materials are available for others to find the answers themselves).

Open Data is the third open science practice that has reached some consensus (though seemingly less consensus than the previous two). The main arguments in favor of open data are that open data: (a) allows others to verify the claims made in a paper, (b) facilitates efficiency in the scientific discovery process – we can use old data to ask new questions rather than having to collect new data every time, and (c) is in the public interest – open data allows the public to learn from the science they often directly or indirectly fund. The main (compelling) argument against open data that should be weighed against the arguments in favor is the issue of data privacy. In the modern age of sophisticated information aggregation techniques, it is increasingly tricky to share data in ways that can guarantee participant anonymity; it is increasingly easy to re-identify previously de-identified data. Research on data privacy, for instance, suggests that between 63% and 87% of the US population can be uniquely identified by having just three demographic variables: gender, ZIP code, and date of birth (Golle, 2006; Sweeney, 2000). That suggests, that even if researchers do not intend to, we can accidentally release identifiable data about our participants. If the data is innocuous that may not be a problem. But if, for instance, we are conducting health communication studies in which datasets contain (re)identifiable information about participants’ health, that can (unintentionally) increase risks to participants.

As you can see, there can be (ethical) tradeoffs involved with making data open, and thus I recommend giving careful thought to the decision for each research project. If you decide to make data open, I recommend reading Meyer’s (2018) tutorial on “Practical Tips for Ethical Data Sharing” which provides practical dos and don’ts for sharing data in effective, ethical, and legally compliant ways (from the perspective of the US Federal Policy for the Protection of Human Subjects). For researchers outside of the US, I recommend reviewing local regulations; for instance, the European Union’s General Data Protection Regulation (<https://eugdpr.org/>) outlines considerations for

researchers in the EU. For multi-institutional and international collaborations, institutional research ethics boards and legal counsel offices can provide specific case-by-case guidance.

Putting ethical and legal issues aside for the moment, making data open from a practical perspective is similar to the other two practices we have already discussed. Again, revisiting the Izjerman and colleagues (2018, 2019) templates on the Open Science Framework (exploratory template: <https://osf.io/nc8ha/>; confirmatory template: <https://osf.io/qpdth/>) for example, in addition to components for open materials, you will notice that there are also components for data and code. Again, researchers can drag-and-drop (or upload) their labeled dataset and analysis scripts, and if warranted, a document explaining the scripts and deviations from plans (if plans were preregistered in advance). Once the data and scripts are uploaded, just like the preregistration and open materials, it will get a hyperlink or DOI that can be included in manuscripts so that others can easily find it.

One thing to consider is the format of the data that is uploaded. Researchers use a variety of software packages (e.g., R, SPSS, MPlus, etc) to analyze data, and the formats that are native to one package may not be accessible to others. For instance, researchers who use IBM's SPSS to analyze their data typically have .sav files. If they were to upload those files to the Open Science Framework, then only others who also have (expensive) SPSS licenses would be able to open them, meaning that data is "less open" to those without the resources for SPSS subscriptions². One alternative to solve this problem is to save open datasets in (more) common formats such as .csv files which can be read by a broader range of packages. This is of course not always possible, but it is something to consider and check before uploading datasets to ensure that they are open for a broader range of people.

The three practices that I just outlined – preregistration, open materials, and open data, are practices that many researchers will be able to start implementing immediately. They generally do not require any additional resources or specialized training or skills beyond what we learn in research methods courses. That is not to say they will be quick to implement; like anything else, the first time you implement them it may take some time to orient and get used to the repository that you choose to use (e.g., Open Science Framework, Github, etc.). But after the initial "startup time", that early investment can pay off over time; as Nosek and colleagues (in press) recently noted, it can be hard at first, but is ultimately worthwhile.

III. Advanced Open Science Practices

After getting used to preregistration and making materials and data open, there are a few additional practices researchers may consider to further facilitate transparency in their research process. These practices extend the three discussed in the previous section.

Registered Reports are a publishing model that extends the preregistration idea introduced earlier in section two. When I introduced preregistration, I introduced it as a time-stamped public record of the researcher's plans for conducting the study (Nosek et al., 2018). Although the methodological details of the study plans are time-stamped, with traditional preregistration as I described above, there is no record of whether the study conducted maps onto the theory ostensibly being tested; for the most part, preregistration focuses on methods and ignores theory (except for a short question about the research question and hypotheses). This can create a problem because in communication, papers are published not only for having rigorous methods, but also for making interesting and important advances to theory (Shapiro, 2002; Slater & Gleason, 2012). If a paper is methodologically rigorous but not theoretically interesting (see Davis, 1971), it is unlikely to be published. Therefore, it is possible for preregistered studies to be rejected for being uninteresting, incentivizing researchers to re-write their manuscripts to create an interesting theoretical story that maps onto the preregistered results they found...therefore recreating one of the problems preregistration was designed to solve (see also Kerr, 1998).

Registered reports address this issue directly by enabling reviewers and editors to make a holistic evaluation of the potential theoretical contribution of the research, the rigor of the methods, and whether those methods are actually good tests of the theory outlined in the paper *before* the authors conduct the study (Chambers, Feredoes, Muthukamaraswamy, & Etchells, 2014). The registered report model integrates preregistration into the publishing process through a two-stage process. At stage 1, authors write an introduction, method section with hypotheses, design, and analysis plans for their proposed study; they can also include any pilot data they have to support their study

² For R users, the package haven can be used to read some proprietary data formats like SPSS (.sav) into R for analysis.

proposal. Once they have written that proposal, they can submit it as a manuscript to one of the 208 participating journals that accepts registered reports (the list of participating journals can be found here: <https://cos.io/rr/>; some participating communication journals include *Communication Research Reports*, *Computational Communication Research*, and the *Journal of Media Psychology*). At that stage the manuscript is sent out for peer review and reviewers can provide suggestions on things to change to the design, other theoretical insights the authors should consider, etc. – the usual recommendations reviewers typically make; the only difference is that they are now making those recommendations prior to seeing results.

After the authors have revised the manuscript to address all of the reviewer and editor concerns, the editor can offer an “in principle acceptance” to the authors. In principle acceptance means that the journal virtually guarantees publication of the article as long as the authors conduct the study exactly as they promised to do in the manuscript proposal. The outcome of the study (significant/non-significant) does not affect publication – the journal has to publish it either way, as long as the authors followed the agreed upon process. This in principle accepted manuscript in effect becomes a time-stamped preregistration of the theoretical test proposed and study protocol and analysis plan. After the authors finish collecting the data they submit their “Stage 2” manuscript (which in practice looks like a typical manuscript) with the results and the discussion interpreting those results, and the journal simply checks to ensure that the authors carried out the procedure they promised to, and if so, accepts the manuscript for publication (Chambers et al., 2014; see Elson & Przybylski, 2017 for examples specific to the field of communication recently published in a special issue of the *Journal of Media Psychology*).

This registered report process aligns the incentives of all parties. Authors receive assurances that if they do the study as promised their efforts will be rewarded with a publication – reviewers do not get to change their minds and ask the authors to run a different study if they do not like the results. Reviewers get to provide input into the study before the authors run the study rather than waiting until after it is over to provide counterfactual advice about what they should have done. Journals get greater assurances about the rigor of the studies they are publishing, as experts provide their critiques and recommendations in advance, leading the research team to have better strategies for conducting thorough tests of theories the field deems interesting and worthy of exploring regardless of specific outcomes.

Automated Data Documentation is a new technique that extends the earlier discussions of both open materials and open data. While there have been some increases in open materials and open data in recent years (e.g., Kidwell et al., 2016), meta-scientists have noticed that those materials and data are not always well documented, making them difficult for others to use (Arslan, in press). That is, because documentation can be tedious and there are not clear norms or standards of how to do it well, researchers often just upload files that might make sense to them (since they are the ones who created them) but may not make sense to others who lack the ability to read the mind of the original researchers.

To address this problem – to make open materials and data more understandable, Arslan (in press) generated an R package and web app entitled *codebook*. The package uses metadata from existing sources and automates tasks such as documenting scales and reliabilities, summarizes descriptive statistics, and identifies patterns of missingness in the data within minutes. As Arslan (in press) notes, this approach creates codebooks that generate high-level summaries of data and provides meaningful labels making it easier for users to clean and use datasets more efficiently and reproducibly. Once researchers download the codebook package (Arslan, 2018), they can generate easy to share codebooks in PDFs, HTML websites, R data frames, and some proprietary dataset formats such as SPSS and Stata. These codebooks can then be shared in research project folders in the repositories discussed earlier in the article (e.g., Open Science Framework). A step-by-step tutorial for using codebook is available in Arslan (in press).

Writing Manuscripts with R Markdown is the final practice I will introduce that can facilitate transparency and reduce reporting errors in papers (provided that you are proficient in the R programming environment). A few years ago, Nuijten and colleagues (2016) discovered via their “Statcheck” (Epskamp & Nuijten, 2016) software, that in a sample of 250,000 *p*-values reported in eight major psychology journals from 1985 to 2013, half of all papers contained at least one *p*-value that was inconsistent with its test statistic and degrees of freedom, and one in eight papers contained a grossly inconsistent *p*-value that would have affected the statistical conclusion of the paper. In the media psychology area of communication, Elson and Przybylski (2017) conducted a similar analysis

and found 12.5% inconsistency in the sample of articles they analyzed from the *Journal of Media Psychology*. Inconsistencies can occur for many reasons including simple human error, for example, from reading a number in the statistical output and typing it incorrectly in the manuscript word processor.

One way to reduce such errors is to merge the analysis and writing processes into one ‘environment’ so that as one portion (analysis) is done, the other (manuscript) is automatically updated with all of the correct information. This is what R Markdown enables one to do (Frank & Hartgerink, 2017; Knowles, 2018). With R Markdown, it becomes easy to integrate data directly into other documents without copying and pasting errors, and also integrate other features required for manuscripts like reference management to autogenerate bibliographies. Researchers can create a document within R, and that document can have text portions (e.g., to write your introduction, methods, discussion) as well as R code chunks that run data analysis, generates figures and tables, etc. In the end, one can “knit” all of the elements together to export the manuscript as an HTML, PDF, or Word document which can be uploaded to the journal and or open science repository along with the R Markdown file that generated everything. The Knowles (2018) tutorial is helpful for working through this procedure step-by-step.

The second set of practices I just outlined – registered reports, automated coding, and writing manuscripts in R Markdown – are practices that may take more time to adjust to than the practices outlined in section two; they require different approaches (in the case of registered reports) and skills (automated coding and R Markdown) than many of us learned in research methods courses, so that may make them inherently more difficult. Over time however, the difficulty involved with learning them can pay off by increasing efficiency and transparency at multiple points in the research process.

IV. Incentivizing Open Science

Now that I have provided a primer on open science and its importance and provided some strategies that both novices and experts can put into practice, I think it is worth considering how the sociology of communication science and the incentives within it may influence the likelihood of uptake of the practices just outlined.

The majority of the article outlined strategies that individual researchers or research teams can put into practice to make their research more open and transparent, but I think it is important to remember and acknowledge that individuals are embedded in broader research contexts that influence their behavior. The likelihood of individual researchers implementing these practices depends, at least in part, on the institutional structures and cultures surrounding researchers. Graduate students and postdoctoral fellows are unlikely to adopt open science practices without support from their advisors and programs, untenured junior faculty are unlikely to adopt these practices if their senior colleagues (who ultimately decide if they keep their jobs) do not support these efforts. If institutions wish for their scientists to do more careful and open science, they should consider whether their institutional norms and policies incentivize that behavior, and if not, make changes accordingly (see also Nelson, Simmons, & Simonsohn, 2012).

It is also important to acknowledge the role of the broader field, as individual institutions do not operate in vacuums – they respond to the perceived norms and guidelines from peers across the discipline. Field-wide signals, such as the editorial policies of the flagship journals can have cascading effects on the adoption of practices. One compelling example of this occurred in the field of psychology. In January 2014, the journal *Psychological Science* began giving authors the opportunity to earn open science badges for their articles if they preregistered their study, made their study materials available, and/or made their data available – one badge for each behavior. Two years after this policy change, Kidwell and colleagues (2016) examined the effects of the badge policy by comparing open practices in articles published in *Psychological Science* before and after the availability of badges. Before badges, less than 3% of *Psychological Science* articles reported open data. After badges, 23% reported open data, a trend that continues to increase at an accelerating rate – by the first half of 2015, that number was up to 39% (Kidwell et al., 2016). The journal has also seen comparable increases in preregistration and open materials since making these badges available.

Badges surely are not perfect, and certainly there are great articles published that simply are not eligible for badges (e.g., important exploratory research on protected populations that if data were made available might pose a risk to the participants), but they are an example of how key actors in

a field can signal the value of researchers taking the time to engage in open science practices. Those institutional normative signals can change the behavior of researchers in the field (see also Tankard & Paluck, 2016).

V. Conclusion

Communication scientists spend a great deal of time, resources, and attention examining processes that are critical for understanding and changing a variety of important outcomes in our social world – how students learn and how to improve our education systems, why people do or do not pay attention to health messages and thus how practitioners can use that knowledge to improve message design, how people make sense of environmental information and what that means for their motivation to behave sustainably – to name just a few. Examining these processes in the ways that we do provides us with rich opportunities to expand our understanding of how the social world works and enables us to simultaneously use that knowledge to improve that world.

We can only capitalize on that opportunity however, if we have clear insights into the processes underlying the knowledge we spend so much effort generating. The open science strategies described above are a few ways to *begin* providing our fellow researchers and practitioners with the *process-insight* necessary to build on and use the research that we generate. My hope is that this article will serve as the beginning of a conversation on ways that we, as communication scientists, can make our science more open to both producers and consumers of communication research. That together, we can use these practices as starting points to improve our collective knowledge of how and why people communicate.

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