Open Educational Science

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Abstract

Scientific progress is built on research that is reliable, accurate, and verifiable. The methods and evidential reasoning that underlie scientific claims must be available for scrutiny. Like other fields, educational science suffers from problems such as failure to replicate, validity and generalization issues, publication bias, and high costs of access to publications—all of which are symptoms of a closed and nontransparent approach to research. We discuss why and how each aspect of the scientific cycle—research design, data collection, analysis, and publication—can and should be made more transparent and accessible. Open approaches to science, such as pre-registration, data sharing, transparent analyses, and open access publication, provide us with practical tools to engage in Open Educational Science. Transparency and accessibility are functional imperatives that come with many benefits for the individual researcher, the scientific community, and society at large—Open Educational Science is the way forward.

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"Everyone has the right freely to [...] share in scientific advancement and its benefits." (Article 27 of the Universal Declaration of Human Rights, UN General Assembly, 1948).

Most doctoral students, at some point in their training, encounter the revelation that the short summaries of research methods provided in journal articles tidy over much of the complexity and messiness in educational research. These summaries often spare readers from dwelling on trivial details, but they can also—to varying degrees—misrepresent important elements of the research process. Research questions and hypotheses that are presented as a priori predictions may have been substantially altered after the start of an investigation. A report on a single study or finding may have been part of a series of other unmentioned or unpublished findings. For educational researchers, summarizing and reporting on how we conduct our investigations is among our most important professional responsibilities. Our mission is to provide practitioners, policymakers, and other researchers with data, theory, and explanations that illuminate educational systems and improve the work of teaching and learning. All of the stakeholders in educational systems need to be able to judge the quality and contextual relevance of research, and that judgment depends greatly upon how researchers choose to share the methods and processes behind their work.

Two converging forces are inspiring scholars from a wide variety of fields and disciplines to rethink how research and methods are shared. One the one hand, digital technologies offer new ways for researchers to communicate and make their work more accessible. The norms of educational research and publishing have been shaped by the constraints of the printed page, and the costs of sharing data, instruments, analytic tools, and findings have declined dramatically in our networked age. At the same time, the academic community is reckoning with potentially very serious problems in the norms, methods, and incentives of scholarly publishing. These problems include high failure rates of replication studies (Maker & Plucker, 2014; Open Science Collaboration, 2012, 2015), publication bias (Rosenthal, 1979), high rates of false-positives (Ioannidis, 2005; Simmons, Nelson, & Simonsohn, 2011), and cost barriers to accessing scientific research (Suber, 2004; Van Noorden, 2013). One of the foundational norms of science is that claims must be supported by a verifiable chain of evidence and reasoning. Scientific claims are to be met with systematic skepticism: a suspension of judgement until the methods and evidential reasoning have been evaluated and found to be commensurate with the claims being made. In unearthing some of the problems with contemporary research, we have all the more reason to reaffirm our professional commitment to rigorous investigation. With the global spread of networked technologies, we have more tools than ever to confront these challenges by making our evidential reasoning more transparent and accessible.

Open Science is a movement that seeks to leverage new practices and digital technologies to increase transparency and access in scholarly research. There is no single philosophy or unified solution advanced by Open Science advocates (Fecher and Friesike 2014), but rather a constellation of emerging ideas, norms, and practices being discussed in fields such as climate research (Muster, 2018), animal welfare (Wicherts, 2017), sex research (Sakaluk & Graham, in press), hardware development (Dosemagen, Liboiron, & Molloy, 2017), criminology (Pridemore, Makel, & Plucker, 2017), energy efficiency (Huebner et al., 2017), biomedicine (Page et al., 2018), information science (Sandy et al., 2017), neuroscience (Poupon, Seyller, & Rouleau, 2017), robotics (Mondada, 2017), high-energy physics (Hecker, 2017), and mass spectrometry (Schymanski & Williams, 2017).

In this article, we offer a framework for Open Educational Science: a set of practices designed to increase the transparency of evidentiary reasoning and access to scientific research in a domain characterized by diverse disciplinary traditions and a commitment to impact in policy and practice. One challenge in defining Open Educational Science is the great methodological diversity within the education fields, and our aim is to describe a framework for Open Educational Science that can be interpreted and implemented across qualitative, quantitative, and design research. For all the methodological variety in educational research, most studies proceed through four common phases that include design, data collection, analysis, and publication. In this article, at the invitation of the AERA Open editors, we synthesize approaches for increasing transparency and access in each of these four domains.

We want to be clear from the outset that we come to the topic of Open Educational Science as advocates. We do not necessarily agree with every aspect or suggested solution which is proposed under the umbrella term of Open Science, but we do believe educational research suffers from many of the problems associated with closed science, and the best way forward is to explicitly address these problems even when a definitive solution has yet to be determined. In what follows, we provide an overview of different approaches to Open Educational Science and arguments pro and contra. In the years ahead, as researchers experiment with and refine Open Science norms and techniques, some specific techniques will not improve research quality, will be unwieldy to implement, or will prove not to be cost effective. However, if educational researchers experiment with Open Science approaches, test and refine new techniques, and implement them at a wide scale, we believe the quality of our research and dialogue will improve and the public will have greater access to more robust educational science.

Rationales for Open Educational Science

In Robert Merton's canonical definition, the institution of science is organized around four norms: universalism, communalism, systematic skepticism, and disinterestedness (1973, 1996), as summarized in Table 1.

Table 1.

An Ethos for Modern Science, adapted from Merton (1996)

Norm	Meaning
Universalism	Scientific validity is independent of the sociopolitical status and other personal attributes of its participants. Free access to scientific pursuits is a functional imperative.
Academic Communalism	All scientists should have common ownership of scientific goods to promote collective collaboration. Scientific findings are a common heritage of a collective humanity, in which the equity of the individual producer is severely limited.
Systematic Skepticism	Scientific claims should be exposed to temporary suspension of judgement and detached critical scrutiny before being accepted: both in methodological and institutional codes of conduct.
Disinterestedness	Scientific personal and institutions act for the benefit of a common scientific enterprise, not for self-aggrandizement and/or exploitation.

These norms are imperfectly implemented through a set of practices: keeping lab notebooks, using published statistical formulas, developing coding schemes for interview data, publishing findings in journal articles, promoting faculty based on the number and impact of publications, and countless others. Most of these practices evolved during a period where information collection, storage, and dissemination were constrained by analog or mechanical technologies.

In our view, Open Educational Science is fundamentally about working as a community to better live up to the norms Merton proposed. It is increasingly possible to make the full chain of our evidentiary reasoning publicly available for scrutiny—we can announce our hypotheses before testing them, share our data and instruments to facilitate replication and scrutiny, and iteratively publish our findings and reasoning to be improved through multiple rounds of public and private comment. We can also make our research more widely available than is currently supported by the infrastructure of paywalled journals that emerged as a response to 20th century technologies and market conditions. In our view, Open Educational Science is not a new set of values, but a new set of norms and practices to more fully adhere with well-established scientific values.

Problems Addressed by Open Educational Science

Another way to understand the motivations of Open Science advocates is to consider the kinds of problems that they are trying to solve. Here we briefly consider four: The Failure of Replication, The File Drawer Problem, Researcher Positionality and Degrees of Freedom, and The Cost of Access.

The Failure of Replication. Among the most urgent reasons for greater transparency in research methods is the growing belief that a substantial portion of research findings may be reports of false positives or over-estimates of effect sizes (Simmons, Nelson, & Simonsohn, 2011). In John Ioannidis's (2005) provocative article, "Why most published research findings are false," he described several problems in medical research that lead to false positive rates: underpowered studies, high degrees of flexibility in research design, a bias towards "positive" results, and an over-emphasis on single studies rather than the totality of findings in a domain. Many of the concerns that Ioannidis raised over a decade ago have been heightened by well-publicized failures to replicate previous findings. A large-scale effort to replicate 100 studies in the social sciences found that fewer than 50% of studies replicated (Open Science Collaboration, 2012, 2015; see also Etz & Vandekerckhove, 2016). In the educational sciences specifically, one study found that only about 54% of studies that are replicated by others are successful (Makel & Plucker, 2014). Several prominent lines of research within the educational sciences have been complicated by large-scale replication studies that fail to confirm the original findings in scope or direction, such as ego-depletion (Hagger, 2016), implicit bias (Forscher, Lai, Axt, Ebersole, & Herman, 2017), stereotype threat (Gibson, Losee, & Vitiello, 2014; Hanselman, Rozek, Grigg, & Borman, 2017), and growth mindset (Li & Bates, 2017). Calls for a stronger focus the replicability of educational research are not new. For example, James Shaver and Richard Norton argued in 1980 that "given the difficulties in sampling human subjects, replication would seem to be an especially appropriate strategy for educational and psychological researchers."

File Drawer Problem. Contemporary problematic norms of scholarly practice are shaped in part by problematic norms in scholarly publishing. Most scholarly journals, especially the most prominent ones, compete to publish the most "important" findings, which are typically those with large or surprising effect sizes or with unexpected descriptions of behavior. Publication Bias, or the so-called File Drawer Problem (Rosenthal, 1979; but see also Nelson, Simmons, & Simonsohn, 2018), describes cases where researchers only attempt to publish positive findings, leaving their null and inconclusive findings in the "file drawer." When researchers face results with null or inconclusive findings, they face the difficult choice of pursuing the difficult task of convincing a journal to publish such results or leaving the study unpublished. The resulting literature consists disproportionately of positive findings of large effect sizes, or striking qualitative findings (Petticrew et al., 2008), that are unrepresentative of the totality of research conducted. For example, when discussing why researchers and educators should not attribute learning benefits to specific media such as TV or computers, Richard Clark (1983) noted that the literature was distorted due to journal editors' preference for studies with more extreme claims. Accurate meta-analyses and syntheses of findings depend upon having access to all of these conducted studies.

Researcher Positionality and Degrees of Freedom. For many years, qualitative researchers have discussed the importance of stipulating researcher positioning and subjectivity in descriptions of methods and findings (Collier & Mahoney, 1996; Golafshani, 2003; Sandelowski, 1986). Readers of research need to understand what stances researchers take towards their investigation, and whether those stances were set a priori to an investigation or change during the course of a study, to better understand how the researcher crafts a representation of the reality they studied.

In quantitative domains, statisticians have come to similar conclusions that understanding when researchers make analytic decisions has major consequences for interpreting findings. It is increasingly clear that post-hoc analytic decision making, “postdiction” instead of prediction, and post-hoc hypothesizing all can lead to what Gelman and Loken (2013) called the Garden of Forking Paths. With enough researcher degrees of freedom in analytic decision-making, even in carefully constructed randomized experiments, researchers can make decisions about exclusion cases, construction of variables, inclusion of covariates, types of outcomes and other methodological choices until something is found to be statistically significant at the .05 level and hence eligible for publication in many journals (Simmons, Nelson, & Simonsohn, 2011; Gelman & Loken, 2013). When researchers report the handful of models that meet a particular alpha threshold without reporting all the other models tested that failed to meet such a threshold, the literature becomes overpopulated with biased results.

For both qualitative and quantitative research, interpretation of results depends on understanding what stances researchers adopted before an investigation and what analytic decisions were responsive to new findings. Public confidence in quantitative findings should be closely linked to the constraints that researchers placed around their analytic decisions before producing an analysis. Transparency in that analytic process is critical for determining how seriously practitioners or policymakers should consider a result.

Cost of Access. The effective use of research requires going beyond summaries of findings and into scrutiny of researchers’ methodological choices, scrutiny that we can conduct more rigorously now as we better understand some of the organizational and methodological problems facing social science and education research. This makes access to published original research of even greater importance, precisely at a time where the costs of access to traditional journals are growing beyond the means of universities and other public institutions. Harvard University, one of the world’s wealthiest, published a warning that the costs of journal subscriptions were growing at an unsustainable rate (Sample, 2012). One solution to this challenge is shifting from a toll access model of conventional scholarly publishing to an Open Access model, where digitally distributed research is made available free of charge to readers (Suber, 2004). Greater access to educational research will provide greater transparency for a wider audience of researchers, policymakers, and educators.

The four stages of the open research cycle

Educational research is diverse, complex, non-linear, and iterative, but we summarize the research cycle as having four key stages: 1) the design of research, 2) the collection of data, 3) the analyses of those data, and 4) the publication of findings. In every step of this research cycle, Open

Educational Science can play a role (see Figure 1). Open Design helps researchers to clarify the distinctions between exploratory and confirmatory analysis, between prediction and “postdiction”, and between the original design of research and what was actually conducted. Open Data makes it possible for analytic claims to be verified, for alternative explanations to be put forth, and for errors in calculation and analysis to be identified. Open Analysis allows for a stepwise evaluation of a researcher’s analytic process to support verification and replication. Open Access allows for faster and more transparent dialogue among scholars and wider consumption of research findings by a globally networked public.

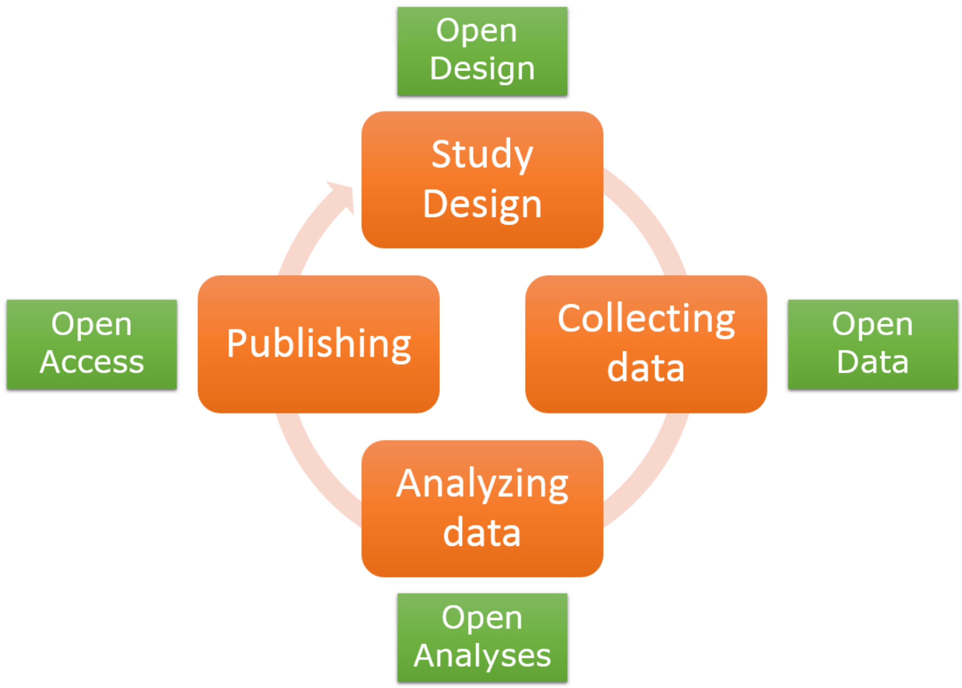

Figure 1. The open research cycle.

Within each of these four domains, researchers from different communities are experimenting with new techniques and norms that improve transparency and access. In what follows we examine each of the four stages of Open Educational Science—Open Design, Open Data, Open Analysis, and Open Access publication—and we describe the most important new techniques and norms proposed in each stage. We conclude with suggestions for how researchers in a diverse field can begin to adopt the practices of Open Educational Science, and our predictions for how the field will improve if we do.

Open Design and Pre-Registration

Research design is arguably the most important part of a study, as it dictates the scope and use of the study. The main aspects of this phase include formulating the key research question(s), designing methods to address these questions, and making many decisions about practical and technical aspects of the study. Typically, this entire phase is the private affair of a few involved researchers. In many studies, the hypotheses are obscured or even unspecified until the authors are preparing an article for publication. To what extent hypotheses and other aspects of the research design have changed over the course of a study remains unclear, as only the final version of the design will be part of a publication.

The opposite of this closed practice is Open Design, which includes creating and sharing the hypotheses and study plans before the study is actually conducted. This is better known as pre-registration, a practice for which many have called in the social sciences as well as in education research specifically (Gehlbach & Robinson, 2017; Nosek et al., 2015). Pre-registration is the practice of documenting and sharing the hypotheses, methodology, analytic plans, and other relevant aspects of a study before it is conducted.

As with all Open Educational Science practices, pre-registration is not a single approach, but comes in varying degrees, see Figure 2. One dimension of pre-registration is how much of the analytic strategy will be specified in advance. A form of 'pre-registration light' is stating only the hypotheses of a study before data collection takes place, either in a private format or in a public repository such as at the Open Science Framework (www.osf.io) or at www.AsPredicted.com. More complete forms of pre-registration include also stating the exact operationalization of these hypotheses, perhaps also with sampling procedures and explicit analysis plans—even including statistical code when the shape of the data is well understood. The practice of pre-registration is more developed among quantitative researchers, but qualitative researchers may find benefits from pre-registering statements about their hypotheses, positionality, coding schemes, or other analytic approaches. A second dimension of pre-registration involves when and how publicly materials will be shared. The most private form of pre-registration includes only making the (time-stamped) form available after the study has been published, but plans can be made public long before any data has been collected. Some pre-registration elements could be shared privately with collaborators, reviewers, or an ethic board early in a study, with more complete disclosure of pre-registration materials after publication.

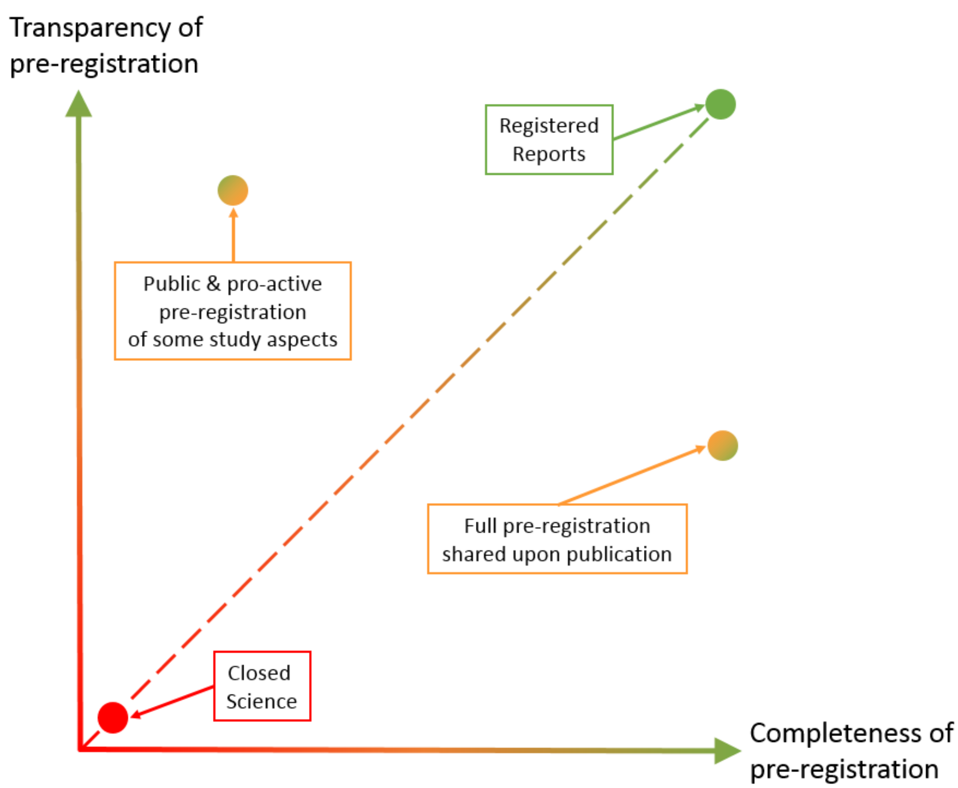

Figure 2. Various forms of pre-registration

As a general principle, it is better for pre-registrations to be as early, complete, and public as possible, but there are all kinds of circumstances where this isn't possible. As authors, we both conduct research in online learning systems where the shape and structure of data is well-established before we conduct many of our studies, and so pre-registration of analytic code, strategies for handling variable operationalization and outliers, and many other study elements can be registered in advance. Studies in new contexts, with new instruments, or asking new type questions will necessarily be less complete.

A variety of new technologies and systems are available for publishing pre-registrations, some of which are mentioned in Table 2. The Open Science Framework (www.osf.io) has one widely accessible system used across disciplines, and many other affinity groups are creating similar systems. The Institute of Educational Sciences maintained a Registry of Efficacy and Effectiveness studies, which is currently being re-established by the Society for Research in Educational Effectiveness (https://www.sree.org/pages/registry.php). There is currently no single widely-accepted way to publish a pre-registration, but as researchers try different kinds of approaches, there will be more examples to follow and eventually meta-research will follow to help establish best practices. We encourage individual researchers to experiment with these new systems, and we believe that journal editors, peer reviewers, program committees, and tenure and promotion committees should encourage and reward efforts towards pre-registration.

Table 2

Examples of tools and resources related to Open Design

Tools for Open Design	Examples
Pre-registration	Open Science Framework (www.OSF.io)
	AsPredicted (https://AsPredicted.org)
	Registered Reports (www.COS.io/rr)
Finding pre-registered studies	Registry of efficacy and effectiveness studies (https://www.SRRR.org/pages/registry.php)
	Registry of pre-registered studies and Registered Reports (https://www.Zotero.org/groups/479248/osf/items)

Arguments for and against Pre-Registration

One argument for pre-registration is that it increases the transparency of our research methods, and increased transparency allows for greater scientific scrutiny. In some research traditions, this transparency is essential for reproduction studies—using the same data as a study to get the same results—or replication studies—using the same methods with new samples. In other research traditions, this transparency is essential to alerting readers to the biases, positionality, and subjectivity of the researcher. Readers benefit from knowing what beliefs researchers bring to new questions, and how those beliefs may shape analytic decisions.

A second reason, is that the pre-registration of hypotheses is a functional imperative for valid hypothesis testing and preventing illusory results (Gehlbach & Robinson, 2017). At the heart of frequentist statistics, which still dominates the quantitative educational sciences, is the concept of long-term error control. While false positives will individually be reported, the long-term frequency of such this type of error is controlled and will never exceed the alpha value—commonly set at 5%. Relative frequencies depend on a denominator: the total amount of tests that have been (or even could have been) performed. If the hypotheses and analyses are not predesignated, and are thus exploratory, this denominator becomes unspecified and undefinable. In effect, it makes null-hypothesis tests lose their informative value and decisive nature. This problem was highlighted by De Groot back in 1956 (later translated to English, see De Groot, 2014), when he stated that:

> “If the processing of empirically obtained material has in any way an ‘exploratory character’, i.e. if the attempts to let the material speak leads to ad hoc decision in terms of processing [...], then this precludes the exact interpretability of possible outcomes of statistical tests.” (p. 191)

Whenever choices are made based on the data instead of being predesignated, there are so many possible ways to analyze the data that very often it will be possible to find one ‘path’ in this ‘garden of forking paths' which leads to a statistically significant result (Gelman & Loken, 2013). While this problem holds for studies of any size, it becomes more and more problematic with an increasing number of variables and/or samples (van der Sluis, van der Zee, & Ginn, 2017). In short, interpretable null-hypothesis testing depends upon pre-registration of hypotheses and all other decisions which affect the kind and number of statistical tests that might be run and/or reported. For confirmatory analyses, Tukey (1980) made the point very clearly: "1) RANDOMIZE! RANDOMIZE! RANDOMIZE! 2) Preplan THE main analysis)." The first of Tukey's points has been very widely adopted; the second much less so.

To summarize, pre-registration makes educational research more transparent and is a requirement of confirmatory analysis in a null-hypothesis testing perspective. There are, however, also some plausible criticisms of pre-registration, which we will consider below.

Pre-registration costs time and effort. Time is a valuable commodity, even more so in a 'publish or perish' culture. As such, any additional step that we have to take which costs time and effort is not incentivized. Adapting to a research cycle that includes pre-registration might take some time initially. However, once a researcher has grown used to pre-registration, it only changes the order of operations and does not require more time—in our own experience it actually saves time. That is, the final choice of which analyses will be performed and reported on will be decided prior to the data collection instead of afterwards. While this will require more forethought and some practice, it also saves researchers from performing a wide range of irrelevant post-hoc tests. Finally, even if pre-registration does require some more time and effort, this is a small investment which comes with substantial rewards in the form of statistical validity of the analyses and increased transparency.

Pre-registration does not fix 'X'. Does pre-registration prevent fraud, or remove all incentives to employ questionable research practices? It does not. However, this does not take away from the things it does do: increasing the validity of our statistical tests and the transparency of our research.

Does pre-registration limit creativity? Importantly, pre-registering the hypotheses and methods of a study does not place a limit on a scientist's creativity or ability to explore the data. That is, researchers can do everything in a pre-registered study that they could do in a non-pre-registered study. The difference is that in the former it will be made clear which decisions were based before the results were known, and which decisions are contingent on the results. As such, it requires making a distinction in publication between exploratory and confirmatory work, but it does not hinder or limit either (De Groot, 2014).

Incentivizing pre-registration through Registered Reports

The role that pre-registration will start to play with the educational sciences will depend, to a large degree, on the willingness of individual researchers to experiment with it, and the extent to which the scientific community at large rewards and incentivizes pre-registration. One compelling approach to incentivizing pre-registration is for journals to adopt a new format of empirical research article called a Registered Report (Chambers, Dienes, McIntosh, Rothtein, & Willmes, 2015; Nosek & Lakens, 2014). In a Registered Report, researchers initially submit an introduction, literature review, and methods section for peer review in advance of conducting a study or collecting data. Peer reviewers provide critical feedback, and editors can then conditionally accept this "stage 1 article" on the basis of the importance of the questions and the rigor of proposed methods. The researchers then complete the study, and if they adhere to their initially-stated protocols, the editors agree to accept the publication irrespective of the magnitude or direction of findings. Registered Reports embed pre-registration in the publishing process, while addressing one of the main sources of the File Drawer problem, the publishing bias against null and inconclusive results.

Open Data

Open Data typically refers to pro-actively sharing the data set underlying a study on a public repository such as the Open Science Framework (www.osf.io), or others mentioned in Table 3. However, Open Data is also an umbrella term which is often used to refer to sharing not only data, but also materials, analysis code, and any other relevant elements which underlie a paper. Here we will focus primarily on research data, but it is important to note that 'data' does not just refer to quantitative data sets, but also includes texts, visual stimuli, interview transcripts, log data, diaries, and any other materials which were used or produced in a study.

Table 3

Examples of tools and resources related to Open Data

Tools for Open Data	**Examples**
Public data sharing	Open Science Framework (www.OSF.io)
	DANS (https://dans.knaw.nl/en)
	Qualitative Data Repository (https://qdr.syr.edu)
	Repository of data archiving websites (www.re3data.org)
Publishing datasets	Nature Scientific Data (https://www.nature.com/sdata/)
	Research Data Journal for the Humanities and Social Sciences (http://www.brill.com/products/online-resources/research-data-journal-humanities-and-social-sciences)
	Journal of Open Psychology Data (https://openpsychologydata.metajnl.com)
Asking for data sharing	Reviewer's Openness Initiative (https://OpennessInitiative.org)

Anonymization	Named entity-based Text Anonymization for Open Science (https://osf.io/w9nhb/) ARX (http://arx.deidentifier.org) Amnesia (https://amnesia.openaire.eu/index.html)
Privacy standards and regulations	U.S. Department of Health & Human Services (https://www.hhs.gov/hipaa/for-professionals/privacy/special-topics/de-identification/index.html#standard) Australian National Data Service (https://www.ands.org.au/working-with-data/sensitive-data/de-identifying-data) European Commission (https://ec.europa.eu/info/law/law-topic/data-protection_en)

In the arms race for rapid publication, the reproducibility of a study is an easy victim. Current publication requirements and cultural incentives emphasize results over methods. This is partly reflected in the fact that how we are expected to share in great detail *what* we have found, but typically not asked to share the means to verify *how* we found it. Without access to the data underlying a scientific publication—whether these are qualitative or quantitative data—the ability for peers to verify the veracity of scholarly work is threatened, or even nullified. In line with the statement that scholarly work should be verifiable, Open Data is the philosophy that authors should make all the relevant data publicly available so they can be inspected, verified, re-used, and further built on. The US National Research Council stated that "*Freedom of inquiry, the full and open availability of scientific data on an international basis, and the open publication of results are cornerstones of basic research [...].*" (1997). Open Data comes with many benefits, including increased citation rates (Piwowar, Day, & Fridsma, 2007), maximizing the public utility of data collection efforts, and widening the benefits of scientific work to all of society.

Research data includes all data that are collected or generated during scientific research, and these include materials from quantitative and qualitative studies. Secondary analysis of quantitative data is more common than that of qualitative data, but this may be a function of the fact that quantitative data are currently shared more often. Long-term and discoverable storage is advisable for data that is unique (i.e., can be produced just once) and/or involved a considerable amount of resources to generate. These features are often true for qualitative and quantitative data alike. The fact that data are unique is often cited as a reason for restricting access to them (to avoid scooping, to maintain exclusive benefit from the data collected), but the more unique and hard-won the data set, the more potential value there is in sharing it. Elman and Kapiszewski (2014) wrote an informative guide to sharing qualitative data, which we recommend to qualitative researchers.

Purposes of sharing data

Like the other forms of transparency, Open Data is not a dichotomous issue but a multidimensional one. Researchers have to decide what data they want to share, with whom, and when, as shown in the data sharing worksheet (adapted from Carlson, 2010) in Table 4.

One dimension of Open Data regards the question of *which* data should be open, which is typically a question of *for which purpose* data should be shared. For published papers this could be only the data which are necessary to replicate the findings as reported in the paper but nothing more. On the other side of the spectrum is the principle of making open all the data which have been collected, including data which were not used in any publication.

Another aspect of Open Data concerns the *method of sharing*. For example, many journals already require that authors make the data available to other scientists upon request, but this does not appear to be an effective strategy. After the authors of over 140 papers published in a journal which required authors to share data upon request were contacted, only 25.7% of these data sets were actually shared (Wicherts, Borsboom, Kats, & Molenaar, 2006). What is even more worrisome is that reluctance to share data is associated with weaker evidence and a higher prevalence of apparent errors in the reporting of statistical results (Wicherts, Bakker, & Molenaar, 2011). As such, we advocate for a more complete form of transparency in which data is shared pro-actively on a publicly accessible repository.

Table 4.

Data sharing worksheet, adapted from Carlson (2010)

	Would not share with anyone	Would share with my immediate collaborators	Would share with others in my research centre or at my institution	Would share with scientists in my field	Would share with scientists outside of my field
Immediately after the data have been generated					
After the data have been normalized and/or corrected for errors					
After the data have been processed for analysis					
After the data have been analysed					
Immediately before publication					
Immediately after the findings derived from this data have been published					

Open Data for a better peer-review process. At the most basic level, Open Data asks researchers to share their data with the reviewers. The pragmatic reason to do this is straightforward: Reviewers should have direct access to the data so they can verify the veracity of the manuscript. As it is the prime purpose of peer-review to assess the scientific worthiness and accuracy of a paper, it stands to reason that reviewers ought to be able to access the data itself. The norm is that any and all empirical claims in a paper should be evidenced, either by the presented study or studies, or by referencing studies in other papers. Without access to the data underlying a paper that is to be reviewed, peer reviewers are substantially hindered in their ability to assess the evidential value of the claims. Furthermore, giving reviewers access to the data in a way that allows them to check the veracity of a manuscript should have a positive effect on reducing the number of calculation errors, unsupported claims, and erroneous descriptive statistics which are later found in the published literature (e.g., van der Zee, Anaya, & Brown, 2017). Sharing data for the purpose of enhancing the peer-review system can be simply done through email, or through the same platform that is used for the submission and reviewing process. Alternatively, data can also be shared not only with the peer reviewers but also with the wider community of readers of scientific work, an aspect which will be discussed in the subsequent sections.

To further promote pro-active data sharing, scholars can sign the "Peer Reviewers' Openness Initiative" or PRO (https://opennessinitiative.org). This initiative suggests that reviewers will only provide their intellectual labor when the authors of a study either make their data and materials openly available, or state a reason why this is not possible or desirable.

Open Data to enable second-hand analyses. Gathering data can be a lengthy and costly process. This makes it economically wasteful to not share this valuable commodity but keep it hidden. A prime example is secondary analyses which require direct access to the data and cannot be performed using only the summary statistics typically presented in a paper. In this way, Open Data is a research accelerator which can speed up the process of establishing new, important findings (Pisani et al., 2016; Woelfle, Olliaro, & Todd, 2011). For example, in the educational sciences existing data sets can be used as an initial test for new ideas and/or to acquire parameter values necessary for informed power analyses. While there will always be a need for new data, not using existing data sets is economically wasteful and counterproductive.

In addition to researcher-driven efforts to increase proactive data sharing, journals can play an even bigger role. An increasing number of journals have started to award special badges that will be shown on a paper that is accompanied by publically available data in an Open Access repository (https://osf.io/tvyxz/wiki/5.%20Adoptions%20and%20Endorsements/). Journal policies can have a dramatic positive effect on the prevalence of Open Data (Nuijten, Borghuis, Veldkamp, Alvarez, van Assen, & Wicherts, 2017). Authors who want to pro-actively share their data are recommended to not exclusively rely on their personal websites, but to make use of any of the popular data repositories to further guarantee that the data will remain available.

Societal benefits. Society benefits when data is used to answer research questions; but the content or value of a data set does not diminish when it is reused. As such, using data only once is an economic waste, as society only stands to gain from more use. Furthermore, many researchers, especially those in low to middle income countries, struggle with accessing and making use of research data and outcomes (Papin-Ramcharan & Dawe, 2006). This contrary to the spirit of the Universal Declaration on Bioethics and Human Rights, article 15, which states that "Benefits resulting from any scientific research and its applications should be shared with society as a whole and within the international community, in particular with developing countries” (UNESCO, 2005). However, authors should remain vigilant in deciding if, and which, (openly available) datasets they want to use, and carefully assess the quality and the relevance of the data.

Privacy concerns. Perhaps the strongest objection to Open Data sharing concerns issues of privacy protection. When you make your data open, whether these are mostly qualitative or mostly quantitative, there are always concerns that you are (inadvertently) sharing personally identifiable information. Sharing data is not a binary decision, and there is a growing body of research around differential privacy that suggests a variegated approach to data sharing (Daries, 2016; Gaboardi et al.,2016; Wood et al., 2014). Even when a data set cannot be shared publicly in its entirety, it may be possible to share de-identified data or, as a minimum, information about the shape and structure of the data. Daries et al (2016) provided one case study of a de-identified data set from MOOC learners, which could not be used for accurately estimating distributions or correlations about the population—because the de-identification process require blurring and deleting data—but it could provide useful insights about the structure of the data set and opportunities for hypothesis generation. For textual data, such as transcripts from interviews and other forms of qualitative research, there are tools which allow researchers to quickly and effectively de-identify large bodies of texts, such as NETANOS (Kleinberg, Mozes, & van der Toolen, 2017), or with other tools mentioned in Table 3. Even when a whole data set cannot be shared, subsets might be sharable to provide more insight into coding techniques or other analytic approaches. Privacy concerns should absolutely shape decisions about what researchers choose to share, but research into differential privacy gives some indication about how openness and privacy can be balanced in thoughtful ways.

Scooping and parasitic data re-use. Not all researchers unequivocally agree that sharing data is a good thing. For example, in an editorial in the *New England Journal of Medicine*, Longo and Drazen (2016) stated that: “There is concern among some front-line researchers that the system will be taken over by what some researchers have characterized as ‘research parasites’” (para. 3). Specifically, these authors were concerned that scholars might “parasitically” use data gathered by others; they suggested that data should, instead, be shared “symbiotically”, for example by demanding that the original researchers will be given co-author status on all papers which use data gathered by them. This editorial, and especially the framing of scholars as “parasites” for re-using valuable data, sparked considerable discussion, which for example resulted in the ironically called “Research Parasite Award” for rigorous secondary analysis (http://researchparasite.com/). Here we see not necessarily a clash of values, as none seem to have directly argued against benefits of sharing data, but instead a debate about *how* we should go about data sharing. Another fear expressed by some researchers is that proactively sharing data in a public repository will lead other researchers to use their data, and potentially ‘scoop’ potential research ideas and publications.

Towards Open Data

We find it difficult to find strong arguments against re-using data, as it is only logical and economical to do so whenever appropriate. *"The value of data lies in their use. Full and open access to scientific data should be adopted as the international norm for the exchange of scientific data derived from publicly funded research."* (US National Research Council, 1997, p. 10). A more realistic problem could be that the original researchers who collected the data are not always properly credited for their work. It is vital that data sets are publicly shared together with persistent identifiers, such that they can be properly cited by whoever has reused the data. As such, the data collectors continue to benefit from sharing their data, as they will be repeatedly cited and they have proof of how their data have been fundamental to others' research. Other institutional actors could play a role in elevating the status of Open Data; for example, journals could publish new article types which are descriptions of new data sets, promotion and tenure committees could consider data contributions as part of promotion packages, and scholarly societies like AERA could create new awards for the contribution of valuable data sets in education research.

Open Analyses

The combination of Open Design and Open Data sharing makes possible new frontiers in Open Analysis—the systematic reproduction of analytic methods conducted by other researchers. Replication is central to scientific progress, as any individual study is generally insufficient to make robust or generalizable claims. It is only after ideas are tested and replicated in various conditions and contexts and results meta-analyzed across studies that more durable scientific principles and precepts can be established. While Open Design and Open Data are increasingly well-established practices, in this section on Open Analysis, we speculate on new approaches that could be taken to enable transparency in analytic methods.

One form of replication is a reproduction study, where researchers attempt to faithfully reproduce the results of a study using the same data sources and analytic techniques. Such studies are only possible through a combination of Open Data and Open Design, so that replication researchers can use the same methodological techniques, but also the same exclusion criteria, coding schemes, and other analytic steps that allow for faithful replication. In recent years, perhaps the most famous reproduction study was by Thomas Herndon, a graduate student at UMass Amherst who discovered that two Harvard economists, Carmen Reinhart and Kenneth Rogoff (R/R), had failed to include five columns in an averaging operation in an Excel spreadsheet (The Data Team, 2016). After averaging across the full data set, the claims in the R/R study had a much weaker empirical basis. Much to R/R's credit, the reproduction, correction, and ensuing debate was possible because R/R shared with Herndon the Excel file which made the scholarly dialogue and refinement possible.

In quantitative research, where statistical code is central to conducting analyses, the sharing of that code is one way to make analytic methods more transparent. GitHub and similar repositories (see Table 5) allow researchers to store code, track revisions, and share with others. At a minimum, they allow researchers to publicly post analytic code in a transferable, machine-readable platform. Used more fully, GitHub repositories can allow researchers to share pre-registered code-bases that present a proposed implementation of hypotheses, final code as used in publication, and all of the changes in between. These records would allow reviewers and the public to better understand the magnitude of post-hoc decision making that was conducted, the variations between initial plan and execution, and the distinction between prediction and postdiction.

Table 5

Examples of tools and resources related to Open Analyses

Tools for Open Analyses	**Examples**
Code sharing	Juypter Notebook (http:/Jupyter.org)
	Docker (https://www.docker.com)
	GitHub (www.GitHub.com)
	Open Science Framework (www.OSF.io)
	RMarkDown (https://rmarkdown.rstudio.com)
Examples of code sharing	Gallery of Jupyter Notebooks (https://GitHub.com/jupyter/jupyter/wiki/A-gallery-of-interesting-jupyter-notebooks)
Documentation guidelines	DRESS Protocol standards for documentation (https://www.projecttier.org/tier-protocol/dress-protocol/)
	OECD Principles and Guidelines for Access to Research Data from Public Funding (https://www.oecd.org/sti/sci-tech/38500813.pdf)

As with data, making code "available upon request" will not be as powerful as creating additional mechanisms that encourage researchers to proactively share their analytic code: as a requirement for journal or conference submissions, as an option within study pre-registrations, as supplementary materials in journal publications and pre-prints, or in other venues. Reinhart and Rogoff's politically consequential error might have been discovered much sooner if their analyses had been made available along with publication, rather than after the idiosyncratic query of an individual researcher.

Even when code is available, differences across software versions, operating systems, or other technological systems can still cause errors and differences. A powerful new tool for Open Analysis is available in the form of Jupyter notebooks (Kluyver et al., 2016). Jupyter is an open-source web application that allows publication of data, code, and additional notation in a web format. Jupyter notebooks can be constructed to present the generation of tables and figures in stepwise fashion, so a block of text description is followed by a working code snippet, which is followed by the generation of a table or figure. A sequence of these segments can then be used to demonstrate the generation of a full set of figures and tables for a publication. Users can then copy and fork these notebooks to reproduce analyses, test additional boundary conditions, and understand how each section of a paper is generated from the data. Jupityr notebooks point the way towards an alternative future of supplementary materials or publications, where publications provide complete, transparent demonstrations of how analyses are conducted, rather than the summaries of the findings of these analyses.

Replications and reproducibility are quality criteria that do not hold only for quantitative research, but are just as relevant and vital for many qualitative approaches (Anderson, 2010). Qualitative data analysis software, such as Dedoose and Nvivo, present new opportunities for sharing qualitative data. At present, most research articles based on qualitative data indicate that the research process included multiple iterative steps, but the final research article presents only a summary of top level themes with selected evidence. With unlimited storage space for supplementary materials in articles, qualitative researches could provide greater transparency in their analyses by making publicly available more of the underlying data, coding schemes, examples of coded data, analytic memos, examples of reconciled disagreements among coders, and other important pieces that describe the underlying analytic work leading to conclusions. At present, much of this material could be made publicly available by selectively releasing project files that can be exported from Dedoose, Nvivo, Atlas.ti, and other tools. Privacy concerns will prevent certain kinds of resources from being shared, but virtually every qualitative project has selections of data that can de-identified to provide at least examples of the kinds of analytic steps taken to reach conclusions. Just as various new forms of open source software have made it increasingly possible for quantitative researchers to more widely share tools, data, and analyses, hopefully the next generation of qualitative data analysis software will also make qualitative research processes more transparent.

Strong claims require strong evidence. Robust claims in learning science and education research should be based on rigorous data collection, appropriately-chosen methods, and multiple studies across contexts that demonstrate the robustness of a principal, finding or claim (Koole & Lakens, 2012). Ideally, as education research grows stronger and more methodologically sound in the decades ahead, our community will increasingly see analytic transparency as a crucial element of the strength of prominent lines of research, and scholarly communities, practitioners, and policymakers will put the greatest weight on claims that result from transparent research practices.

Open Publication

Open Access (OA) literature is digital, online, available to read free of charge, and free of most copyright and licensing restrictions (Suber, 2004). Most for-profit publishers obtain all the rights to a scholarly work and give back limited rights to the authors. With Open Access, the authors retain copyright for their article and allow anyone to download and reprint provided that the authors and source are cited, for example under a Creative Commons Attribution License (CC BY 4.0). Of the 1.35 million scientific papers published in 2006, about 8% were Open Access immediately or after an embargo period, and 11.3% could be freely accessed in a repository or on an author's personal website (Björk, Roos, & Lauri, 2009). A more recent analysis of Open Access publishing shows that of the articles published in 2015 a total of 45% were openly available. Evidentially, Open Access publishing is on the rise and has become mainstream. The most compelling reason to enable global and unrestricted access to scholarly work is that it is a functional imperative. In the words of Merton (1973): "The institutional conception of science as part of the public domain is linked with the imperative for communication of findings" (p. 274). As many scientists lack access to relevant publications, scientific progress itself is hindered—restricting access to knowledge is counterproductive. There is also a range of 'selfish' reasons to open up one's publications. Scholarly work that is openly accessible, such as pre-prints and Open Access manuscripts, are cited earlier and more frequently (Craig, Plume, McVeigh, Pringle, & Amin, 2007; Lawrence, 2001). Sharing a publicly accessible pre-print can also be used to receive comments and feedback from fellow scientists; a form of informal peer-review. We discuss two of the most important approaches to Open Access publishing: pre-print repositories (sometimes called Green OA) and Open Access journals (sometimes called Gold OA).

Pre-prints

Pre-prints are publicly-shared manuscripts which have not (yet) been peer-reviewed. In some instances, an author might share the pre-print of a manuscript that is undergoing peer-review, or that (s)he intends to submit to a peer-reviewed outlet. Alternatively, authors might not have any intention to submit their work to a journal or conference proceedings, but do want to make the result of their research publicly available.

An important reason for authors to share a manuscript as a pre-print is to make the products of their work available earlier and speed up the dissemination of new knowledge. A variety of peer-reviewed journals acknowledge the benefits of pre-prints. For example, the Journal of Learning Analytics states that "[a]uthors are permitted and encouraged to post their work online (e.g., in institutional repositories or on their website) *prior to* and during the submission process, as it can lead to productive exchanges, as well as earlier and greater citation of published work" (emphasis added; http://learning-analytics.info/journals/index.php/JLA/about/submissions). Economists have embraced this approach for many years, through the NBER Working Paper series, and the openness of economics research magnifies its public impact (Fox, 2016). Across the physical and computer sciences, repositories such as ArXiv have dramatically changed publication practices and instituted a new form of public peer review across blogs and social media. In the social sciences, SSRN and SocArXiv offer additional repositories for pre-prints and white papers. While, historically, peer review has been considered a major advantage over these forms of non-reviewed publishing, the limited amount of available evidence suggests that the typically closed peer-review process has no to limited benefits (Bruce, Chauvin, Trinquart, Ravaud, & Boutron, 2016; Jefferson, Alderson, Wager, & Davidoff, 2002) which opens alternative pathways for scholarly scrutiny without or alongside peer review. For an overview of relevant tools and websites, see Table 6.

Table 6

Examples of tools and resources related to Open Access publication

Tools for Open Access	**Examples**
Pre-print servers	Social Science Research Network (https://www.ssrn.com/en/)
	PsyArXiv (https://psyarxiv.com)
	F1000 (https://f1000research.com)
	PeerJ (https://PeerJ.com)
Open Access journals	Directory of Open Access Journals (https://doaj.org)
Checking the copyright licenses of a journal or publisher	Sherpa/Romeo (http://www.sherpa.ac.uk/romeo/index.php)
Post-publication peer-review	PubPeer (https://PubPeer.com)
	ResearchGate (www.ResearchGate.com)
	F1000 (https://f1000research.com)

Open Access Journals

Most research is still published by a publisher that charges an access fee. This so-called ‘paywall’ is the main source of income for most publishers. As publishers essentially rely on free labor from scholars—they do not pay the people who write the manuscripts, conduct the reviews, and perform much of the editorial work – this raises the question of why society has to pay twice for research: first to have it done, and then to gain access to it. At a university level, each institution produces the research itself, verifies its quality, and subsequently purchase a license to be able to gain access to their own work.

The alternative infrastructure under development is Open Access, whereby readers get access to read scholarly literature for free. In addition, this literature is sometimes made available with only minimal restrictions around copying, remixing, and republishing. Most Open Access journals are online only, and so they avoid the costs of printing and publication. Many Open Access journals use article processing charges to cover the costs—and often, profits—of publishing. These article processing fees vary between 8 and 3900 USD, with international publishers and journals with high impact factors charging the most (Solomon & Björk, 2012). Additionally, journals published by societies, universities, and scholars charge less than journals from large publishers. Several solutions and scenarios have been proposed to change the for-profit nature of scholarly publishing into one that is more aligned with the norms and values of the scientific method (e.g., Björk & Hedlund, 2009).

Not everyone is enthusiastic about Open Access journals. For example, Romesburg (2016) argues that Open Access journals are of lower quality, pollute science with false findings, reduces the popularity of society journals, and should be actively opposed (note that this paper used to be pay-to-access but is now Open Access itself). Such criticisms of Open Access tend to be based on false assumptions about the various Open Access models and their scholarly qualities (Bolick, Emmett, Greenberg, Rosenblum, & Peterson, 2017). However, a more pertinent concern is the existence of so-called ‘predatory journals’ or ‘pseudo journals’ (Clark & Smith, 2015). These journals have few to no concerns about the quality of the papers they publish, but typically solely seek financial gains by charging publication fees. Scholars who publish in these journals are either fooled by the appearance of legitimacy, or are looking for an easy way to boost their publication list—a tendency which has been attributed to the increasing pressure to publish or perish (Moher & Srivastava, 2015). Predatory journals have rapidly increased in number; from 2010 to 2014 the number of papers published in predatory journals rose from 53,000 to 420,000 (Shen & Björk, 2015). Predatory publishing is an important issue that scholarly communities need to address, but the real force behind predatory publishing is not the expansion of Open Access business models but the publish or perish culture of academia.

Evidence-based educational policymaking and practice depend on access to evidence. So long as educational publishing is primarily routed through for-profit publishers, a substantial portion of the key stakeholders of educational research will have limited access to the tools they need to realized evidence-based teaching and learning.

The future of Open Educational Science

In the decades ahead, we hope that Open Educational Science will simply become synonymous with good research practice. All of the constituencies that educational researchers seek to serve—our fellow scholars, policymakers, school leaders, teachers, and learners—benefit when our scientific practices are transparent and when the fruits of our labors are distributed widely. Many of the limits to openness in education research are the results of norms, policies, and practices that emerged in an analog age with high costs of information storage, retrieval, and transfer. As those costs have dramatically declined, it behooves all of us—the first generation of educational researchers in the networked age—to rethink our practices, and to imagine new ways of promoting transparency and access through Open Design, Open Data, Open Analysis, and Open Access publishing.

Making the educational sciences more open is not an abstract process at the system level, but one that occurs in the daily life of individual researchers. The path towards Open Educational Science is a flexible one, and does not require rapid or dramatic changes; rather, with each new study, with each student or apprentice, with each new publication, researchers and teams can take one step at a time towards more open practice. It will take experimentation, time, and dialogue for new practices to emerge, and there will be new technologies to try and ongoing assessment of how new practices are affecting the quality of research produced in our field. Researchers who adopt these new practices will be able to find support from new scholarly societies, like the Society for the Improvement of Psychological Science and fellow researchers trying to find ways to improve upon the methodological traditions of our different fields and disciplines. Parts of this process will be difficult and contentious, as with all changes in norms and practices. But with a courageous spirit to reexamine past practices and to imagine a more rigorous future, Open Educational Science will lead to better research that serves the common good.

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