Organizational Behavior and Human Decision Processes 162 (2021) 218–223

Contents lists available at ScienceDirect

Organizational Behavior and Human Decision Processes

journal homepage: www.elsevier.com/locate/obhdp

Open science and reform practices in organizational behavior research over time (2011 to 2019)☆,☆☆

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ARTICLE INFO

Keywords:
Open science
Reform practices
Credibility revolution
Metascience

ABSTRACT

The "credibility revolution" has fueled a number of initiatives to help bring scientific practices more in line with scientific ideals. These initiatives include increasing the sample size of studies, making data and materials publicly available, pre-registering data collection and analysis plans, publishing replication attempts, and publishing null results. To what extent have these practices become the norm in quantitative Organizational Behavior research? In the current study, using computer algorithms and human coders, we coded the reported use of several open science and reform practices in articles published in four prominent journals (*Academy of Management Journal; Journal of Applied Psychology; Organizational Behavior and Human Decision Processes; and Organization Science*) from 2011 through 2019. We found that although the vast majority of articles did not use any open science practices, some practices we coded were on the rise, especially in the last two to three years. While there is much room for improvement, these results suggest the field could be on the brink of important and sustained change.

1. Introduction

Almost 10 years ago, a series of events laid bare methodological issues in social science research and energized a movement calling for greater accountability and accessibility to scientific knowledge (Nelson, Simmons, & Simonsohn, 2018; Spellman, 2015). The so-called Open Science "revolution" (aka the "credibility revolution") fueled a number of initiatives to help bring scientific practices more in line with scientific ideals. These initiatives include increasing the sample size or "statistical power" of studies to detect effects, posting data and materials on public repositories ("open data" and "open materials"), pre-registering analysis plans, publishing replication attempts, and publishing null results instead of burying them in a proverbial file drawer (Nosek et al., 2015; Vazire, 2017).

The field of Psychology has made headway in incorporating some of these reform practices into researchers' standard and expected workflows. Sample sizes have increased, and more and more researchers are making their data and materials freely available (Christensen et al., 2019). Some of the change has happened because the field's gatekeepers (e.g., reviewers and journal editors) successfully communicated that they value this type of rigor and changed the incentives. *Psychological Science,* as of 2014, awards up to three badges (i.e., places an icon) alongside papers if researchers post data, post materials, or pre-register a study (Eich, 2013). The badges have corresponded with an increase in these practices, possibly suggesting that they could be effective at motivating and changing behavior (Kidwell et al., 2016). Other journals are making it clear in their submission process that they value these practices via editorials, mission statements, calls for papers, submission criteria, etc., signaling that papers are more likely to get accepted if they follow these guidelines.

Many scientists in favor of these reforms have also begun doing the work of tracking scientific practices. This burgeoning field of metascience (or metaresearch) has provided a large and growing evidence base for evaluating the effectiveness and potential side-effects of reforms (for an overview, see Hardwicke et al., 2019). This *meta*-research can provide valuable information for evaluating scientific fields. For

☆ This article is an invited submission. It is part of the special issue "Best Practices in Open Science," Edited by Don Moore and Stefan Thau.
☆☆ Thanks to Alex Anderson, Julia Bottesini, William Shadley, and Kate Warnock for research assistance. This research was supported in part by a grant from the John Templeton Foundation (#60937) to Simine Vazire.
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https://doi.org/10.1016/j.obhdp.2020.10.015
Received 18 December 2019; Received in revised form 19 October 2020; Accepted 20 October 2020
Available online 4 February 2021
0749-5978/

example, a survey of researchers in four social science disciplines (Economics, Political Science, Psychology, and Sociology) found signs of increased adoption of open science practices over time. In 2017, open data was reported as the most common practice (73%), followed by open materials (44%) and pre-registration (20%). In all, over 80% of published authors in the sample reported using at least one open science practice by 2017, compared to just over 20% reporting having used these practices by 2005 (Christensen et al., 2019). It remains unclear whether these changes in practice also happened in the related field of Organizational Behavior. What are the norms in Organizational Behavior? How have these norms changed over time?

In an effort to help answer these questions, the purpose of the current project is to conduct a review of open science and reform practices at four flagship journals in Organizational Behavior: *Academy of Management Journal (AMJ;* published by Academy of Management, Impact Factor 7.2); *Journal of Applied Psychology (JAP;* published by American Psychological Association, Impact Factor 5.1); *Organizational Behavior and Human Decision Processes (OBHDP;* published by Elsevier, Impact Factor 2.9)*; and Organization Science (Org Sci;* published by INFORMS, Impact Factor 3.3). These journals aim to publish papers that advance understanding of human behavior and thought in organizations and contribute to management practice. These journals were selected in consultation with the review team at *OBHDP*; while the list is not exhaustive nor is it representative of the entire field, it is meant to capture a snapshot of published research in Organizational Behavior from several leading journals.

We base our review on a trend analysis of quantitative empirical papers published from 2011 to 2019 (present day). We report all of the journals that we coded. The project's full analysis plan is pre-registered at: https://osf.io/n6hzy and https://osf.io/bmn9u.

2. The current study

We use a combination of computer algorithms and human coders to examine whether open science practices have changed from 2011 to 2019 at *AMJ, JAP, OBHDP,* and *Org Sci.* We focus on six indicators of scientific integrity and open science practices: sample size of studies, reports of open data, open materials, and pre-registration, whether the paper's central focus is replication, and whether any key findings are null results. Note that we did not verify the existence or usability of open data, open materials, or pre-registration—we simply evaluated the presence of authors' statements indicating that these are available. We use an estimation approach to make a judgment about whether the results are more consistent with the change hypothesis (that there is an increase in open science practices over time), null hypothesis (that there is no change in open science practices over time), or inconclusive.

By comparing procedural changes in empirical research articles published in these four journals over time from 2011 through 2019, we provide evidence about current and changing norms among Organizational Behavior researchers who use quantitative methods. Although we do not have a specific, ideal level of adoption of open science practices in mind, there are some levels that we think most will agree are problematically low and would signal a need for substantial improvement. However, if adoption is shown to be high or substantially increasing over time, this would indicate that Organizational Behavior is taking meaningful steps to advance and protect the integrity of published research.

3. Method

3.1. Sample of articles coded

Empirical quantitative articles ($N = 2{,}234$) were identified for years 2011 through 2019 at *AMJ* ($n = 643$)*, JAP* ($n = 731$)*, OBHDP* ($n = 494$), and *Org Sci* ($n = 366$). All 2019 articles available at the time of analysis were included (through December for all except *OBHDP*, which was through September).

In line with the pre-registered analysis plan, *meta*-analyses, editorials, calls for papers, reviews, errata, commentaries, and qualitative studies (as flagged by our algorithm) were excluded from analyses in each journal.[1]

3.2. Coding sample sizes

Sample sizes of studies were coded by human coders, only for years 2011 and 2019. All empirical articles in our sample published at *OBHDP* ($n = 103$) and *Org Sci* ($n = 85$) for both years were included in analyses. Fifty articles per year for each of the two years were randomly selected to be included at *AMJ* ($n = 100$) and *JAP* ($n = 100$).

For each article, two coders independently recorded the sample size of each study following the coding guidelines in Fraley and Vazire (2014).[2] For example, according to the guidelines, coders recorded sample sizes prior to exclusions (e.g., any participants excluded due to outliers or failures of participants to follow instructions were still counted in the total sample size coded). For longitudinal studies, coders used the sample size at the first wave of data collection, unless the analysis depended on all intervals (e.g., difference scores). For studies in which the unit of analysis was not individuals, coders used the sample size at the unit level of analysis (e.g., dyads, groups). Coders achieved 85.3% agreement, recorded across all journals. Any discrepancies were resolved by discussion between coders. The sample size of each article was calculated as the median sample size of all eligible studies in an article, then aggregated at the issue level, again as the median of all articles in that issue.

3.3. Coding all other variables

A computer script identified and flagged articles for the occurrence of keywords relating to the dependent variables listed below. The full list of keywords used in the algorithms can be found at https://osf.io/cgujm. All flagged articles were checked by a member of the research team to verify whether or not the flagged article actually met the criteria for that variable, and coded the variable as present/not present at the article level. We then aggregated scores for each article within issue to obtain a percentage of articles in each issue that were scored as "present."

Open materials. The computer algorithm searched the entire article for keywords or phrases related to making stimuli materials freely available (e.g., posted/available/provided/shared/accessible materials/stimuli/measures/video). A human coder then confirmed that the article claimed to post materials for at least one study.

Open data. The computer algorithm searched the entire article for keywords or phrases related to making data freely available (e.g., posted/available/provided/shared/accessible data). A human coder then confirmed that the article claimed to post data for at least one study.

Pre-registration. The computer algorithm searched the entire article for various tenses and spellings of the following words and phrases related to pre-registration: pre-registered, pre-analysis plan, hypothesis registry, and registered report. A human coder then confirmed that the article claimed to pre-register at least one study.

Replication. The computer algorithm searched in the abstract of the article for various tenses and spellings of the following words: replication and reproducibility. A human coder then confirmed that the article claimed to replicate at least one study. Only claims of direct replication (of a study in the same article or of an original study published elsewhere) counted, so conceptual replications were not included. Only the

[1] Exclusions were as follows: *AMJ* ($n = 65$)*, JAP* ($n = 61$)*, OBHDP* ($n = 90$), and *Org Sci* ($n = 406$). The algorithm to identify qualitative papers can be found at https://osf.io/cgujm.

[2] These guidelines are one way to code for sample size. Other ways are possible and equally likely to be valid.

abstract was searched because we were interested in replications that were reported as a main objective of the research.[3]

Null results. The computer algorithm searched in the abstract of the article for various tenses and spellings of words and phrases related to obtaining null results (e.g., did not affect; no evidence; zero relationship). A human coder then confirmed that the article claimed to report null results for at least one study. To be counted, articles needed to report a non-statistically-significant finding as one of its main findings and interpret this as evidence of the absence of an effect. Only the abstract was searched because we were interested in null results that were reported as a key finding.

4. Results

See Figs. 1 and 2 and Table 2 for a summary of the results. The data and code are available at https://osf.io/cgujm.

4.1. Sample size

An independent-samples *t*-test compared sample sizes of studies published in 2011 and 2019 in each of the journals. Each journal had an increase in median sample size of published studies; increases for two of the four journals were statistically significant (without corrections for multiple comparisons). See Table 1 and Fig. 1.

Although the pre-registered analysis plan was to conduct *t*-tests as reported in Table 1, it is worth exploring other analyses combining data across the journals ($Median_{2011} = 189.0$, $SD_{2011} = 364.48$; $Median_{2019} = 310.63$, $SD_{2019} = 613.75$). We ran a mixed model with year (2011 vs. 2019) predicting median sample size, aggregated at the issue level, with random by-journal intercepts to capture the variance due to journal. The results reveal an increase in sample size over time which reaches statistical significance at the 0.05 threshold, though it does not meet stricter thresholds recommended for exploratory analyses (e.g., $\alpha = 0.005$; Benjamin et al., 2018), and the 95% confidence interval comes close to including 0 ($b = 36.87$, $t(47.08) = 2.53$, $p = .015$, 95% CI = [7.53, 66.21]).

4.2. Open materials

We found 46 instances of authors claiming to have open materials, representing 2% of published studies across the four journals (see Fig. 2 and Table 2). There were no instances prior to 2014, and most instances occurred in 2018 and 2019. In 2018, 17 articles (7% of articles published that year) had open materials, and in 2019, 15 articles (7% of articles published that year) did. The correlation between open materials and time (operationalized as issue number) at the four journals ranged from close to zero (*JAP*) to positive and large (*OBHDP*): *AMJ*, $r = 0.38$, 95% CI = [0.10, 0.54], *JAP*, $r = 0.12$, 95% CI = [-0.09, 0.29], *OBHDP*, $r = 0.65$ 95% CI = [0.44, 0.87], and *Org Sci*, $r = 0.38$, 95% CI = [0.16, 0.83]. Thus, results show that although most articles do not have open materials, this practice has generally increased over the time period examined.

4.3. Open data

We found 56 instances of authors claiming to have open data, representing 2.5% of published studies across the four journals (see Fig. 2 and Table 2).[4] Like open materials, most instances occurred in recent years. In 2017, 12 articles (4.5% of articles published that year) had open data, with that number increasing to 15 (6% of articles published that year) in 2018, and to 19 (8% of articles published that year) in 2019. The relationship between open data and time at the four journals ranged from close to zero (*AMJ* and *JAP*) to positive and large (*OBHDP*): *AMJ*, $r = 0.09$, 95% CI = [-0.22, 0.40], *JAP*, $r = 0.08$, 95% CI = [-0.12, 0.25], *OBHDP*, $r = 0.71$, 95% CI = [0.51, 0.91], and *Org Sci*, $r = 0.46$, 95% CI = [0.23, 0.79]. Thus, results show that although most articles do not report having open data, this practice has increased at two of the journals over the time period examined.

4.4. Pre-registration

We found 18 instances of authors claiming to use pre-registration, representing 0.8% of published studies across these four journals (see Fig. 2 and Table 2), and 14 of the instances were in just one journal (*OBHDP*). Like open materials and open data, when it did occur, most instances occurred recently. In 2018, only 5 articles used pre-registration (2% of articles published that year) and in 2019, 11 did (5% of articles published that year). There was a moderately strong, positive correlation between instances of pre-registration and time at *OBHDP*, $r = 0.53$, 95% CI = [0.29, 0.77]. The correlations were positive but weak at *AMJ*, $r = 0.15$, 95% CI = [-0.08, 0.27] and *JAP*, $r = 0.19$, 95% CI = [-0.05, 0.60]. No instances of pre-registration were observed at *Org Sci*. Thus, results show that although most articles do not use pre-registration, in the journal where most instances occurred, this practice increased over the time period examined.

4.5. Replication and null results

We found 7 instances of replication and 13 instances of null results across the four journals (less than 1% occurrence of each practice per journal; see Fig. 2 and Table 2). We found no instances of replication at *AMJ*. The correlation between replication and time at *JAP*, $r = 0.08$, 95% CI = [-0.17, 0.38], *OBHDP*, $r = -0.02$, 95% CI = [-0.30, 0.26], and *Org Sci*, $r = 0.05$, 95% CI = [-0.26, 0.38] were close to zero. Likewise, the correlation between null results and time at *AMJ*, $r = -0.05$, 95% CI = [-0.18, 0.12], *JAP*, $r = -0.23$, 95% CI = [-0.46, -0.01], *OBHDP*, $r = -0.22$, 95% CI = [-0.50, 0.05], and *Org Sci*, $r = 0.01$, 95% CI = [-0.35, 0.38] were weak, and most were negative. These results suggest that replication as the main objective of a study and reporting of null results as a key finding occur rarely, and these practices have not increased over the time period examined.

5. Discussion

The aims of the reform movement are varied, but center around two broad goals: transparency and quality control. By evaluating changes in variables relating to these factors in four leading journals in Organizational Behavior, this study helps assess current open science norms and their evolution over time. Of the practices we coded, open materials, open data, and pre-registration fall under the umbrella of transparency, whereas sample size, null results, and replications fall under the umbrella of quality control. Although findings from our study show infrequent use of any of these practices in any of the journals we coded, there were traces of an increasing adoption over the years across all transparency-related practices, especially at *OBHDP*. However, quality control practices showed evidence of improvement on only one metric (sample size), and we found almost no articles that focused on

[3] We attempted to have the algorithm search the entire article, per a reviewer's suggestion, but testing revealed that human coding would be too labor intensive for the scope of the current project.

[4] We also coded articles that the algorithm flagged as having open data using 3 human coders for instances when data was publicly available, without having been posted by the authors themselves. We found 13 instances like this. These instances are included in the current analyses.

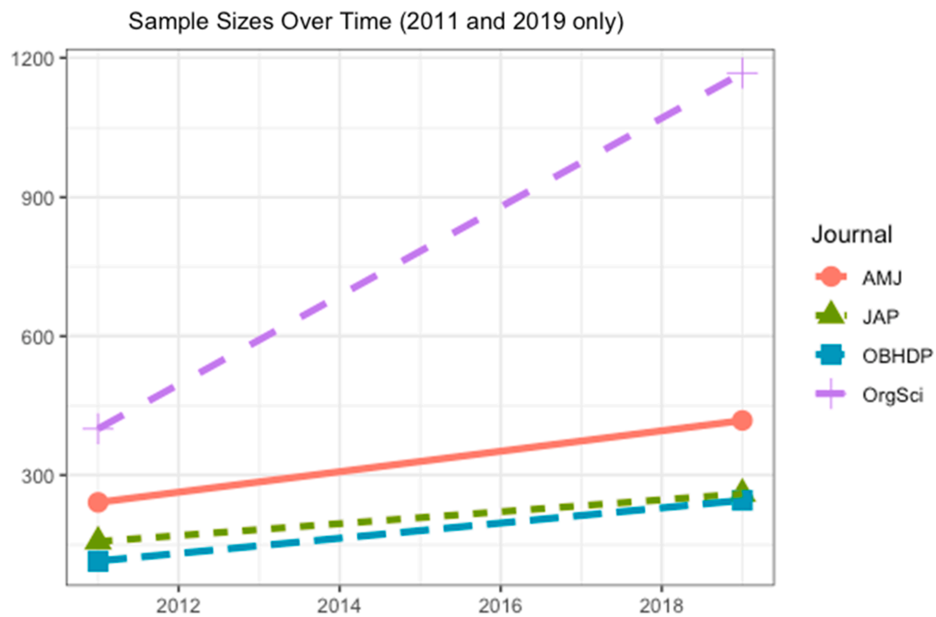

Fig. 1. Median sample size, aggregated at the issue level, by journal.

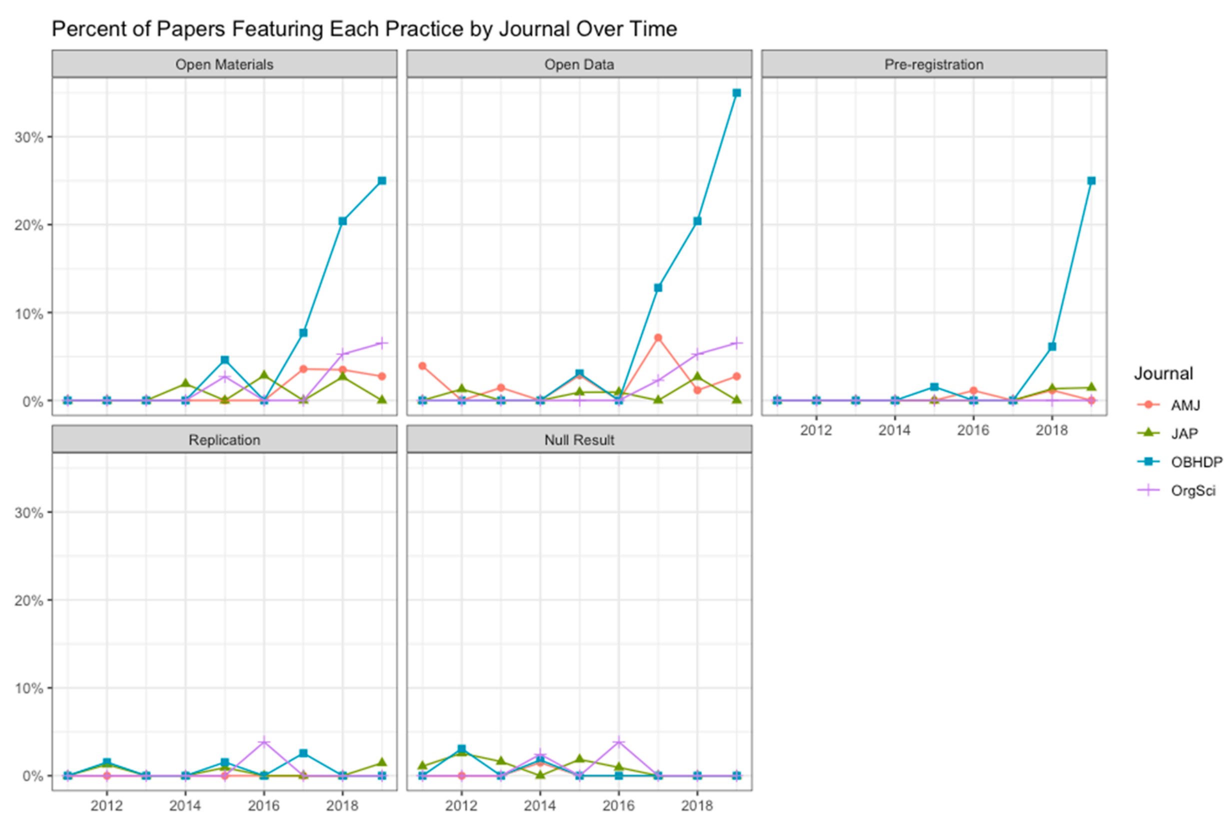

Fig. 2. Percent of papers using each practice by journal over time (2011 through 2019).

replication or null results, even in recent years.

Why might some practices (i.e., some transparency-related practices) be gaining traction at a slightly higher rate than others (quality control practices)? The frequency of using these practices seems to track inversely with their costs in terms of resource intensiveness (e.g., time and effort to implement). Having open materials and open data—which we saw in 2% and 2.5% of articles, respectively, over the time period we examined—has become relatively easy, and authors can implement these late in the research process, after confirming that data collection was successful and further action is worthwhile. These practices occurred the most in our sample. Pre-registration, which we saw in less than 1% of articles, is arguably costlier than those two in that it requires planning and action ahead of full data analysis. Pre-registration also inhibits questionable research practices such as HARKing—hypothesizing after results are known—(Kupferschmidt, 2018), which could make it more difficult to publish if not offset by its added value. From a resource perspective, pre-registration should occur less frequently than open materials and open data, which we saw. Likewise, we found almost

Table 1

Sample Size	2011			2019			Independent samples *t*-test				
	Median per article	Mean†	SD	Median per article	Mean†	SD	df	t	p-value	Confidence Interval	
										Lower Bound	Upper Bound
AMJ	241	264.00	119.94	418	576.54	320.23	10	−2.24	0.049	−623.59	−1.49
JAP	156.5	183.79	90.93	259.5	364.84	384.01	16	−1.21	0.243	−497.41	135.30
OBHDP	114.5	117.13	19.35	245.5	256.85	55.84	4.8	−5.34	0.004	−207.90	−71.55
ORG SCI	400	714.50	665.22	1167	1318.17	880.52	9	−1.26	0.240	−1688.67	481.34

Note. † Mean of the median aggregated at the issue level. OBHDP's *t*-test results are with equal variances not assumed (results do not substantively change with equal variances assumed).

Table 2

Practices at Four Journals Over Time

	2011	2012	2013	2014	2015	2016	2017	2018	2019	**Total**
AMj										
Sample Size	241	–	–	–	–	–	–	–	418	
Open Materials	0	0	0	0	0	0	3	3	2	**8**
Open Data	2	0	1	0	2	0	6	1	2	**14**
Pre-Registration	0	0	0	0	0	1	0	1	0	**2**
Replication	0	0	0	0	0	0	0	0	0	**0**
Null Results	0	0	0	1	0	0	0	0	0	**1**
Articles	51	55	69	67	70	88	84	86	73	**643**
JAP										
Sample Size	156.5	–	–	–	–	–	–	–	259.5	
Open Materials	0	0	0	1	0	3	0	2	0	**6**
Open Data	0	1	0	0	1	1	0	2	0	**5**
Pre-Registration	0	0	0	0	0	0	0	1	1	**2**
Replication	0	1	0	0	1	0	0	0	1	**3**
Null Results	1	2	1	0	2	1	0	0	0	**7**
Articles	89	78	62	52	107	102	97	75	69	**731**
OBHDP										
Sample Size	114.5	–	–	–	–	–	–	–	245.5	
Open Materials	0	0	0	0	3	0	3	10	10	**26**
Open Data	0	0	0	0	2	0	5	10	14	**31**
Pre-Registration	0	0	0	0	1	0	0	3	10	**14**
Replication	0	1	0	0	1	0	1	0	0	**3**
Null Results	0	2	0	1	0	0	0	0	0	**3**
Articles	63	65	71	56	65	46	39	49	40	**494**
Org Sci										
Sample Size	400	–	–	–	–	–	–	–	1167	
Open Materials	0	0	0	0	1	0	0	2	3	**6**
Open Data	0	0	0	0	0	0	1	2	3	**6**
Pre-Registration	0	0	0	0	0	0	0	0	0	**0**
Replication	0	0	0	0	0	1	0	0	0	**1**
Null Results	0	0	0	1	0	1	0	0	0	**2**
Articles	39	51	44	41	37	26	44	38	46	**366**
Four Journals Combined										
Sample Size	189.0	–	–	–	–	–	–	–	310.6	
Open Materials	0	0	0	1	4	3	6	17	15	**46**
Open Data	2	1	1	0	5	1	12	15	19	**56**
Pre-Registration	0	0	0	0	1	1	0	5	11	**18**
Replication	0	2	0	0	2	1	1	0	1	**7**
Null Results	1	4	1	3	2	2	0	0	0	**13**
Articles	242	249	246	216	279	262	264	248	228	**2234**

Note. Sample size is the median of the median sample size of each article. Sample size data were not collected in 2012 through 2018. All other numbers (besides years) are count data.

no instances of articles featuring studies with null results or replication—practices which require conducting entire studies or writing up entire manuscripts that do not fit the traditional mold are certainly resource intensive.

But resources alone are perhaps too simplistic an explanation of adoption; there could also be a misfit with the norms of what is seen as worthwhile to investigate or publish. If these practices were rewarded, then we should see researchers willing to invest in them, at least in the journals with the highest impact factors, with arguably more prestige in the field, because it would be worth spending more resources to get a manuscript accepted at those journals. Instead, we saw that *OBHDP* led the others in use of these practices, and it also has the lowest impact factor of the four journals. There are many reasons why this could be the case, and we can only speculate about these reasons. We suspect that incentives and norms may play a role. As others have pointed out, this may reflect the fact that the field of Organizational Behavior, like many other fields, privileges novelty (rather than replication) and discovery *of something* rather than the absence of something.

If journals want to see an increase in open science and reform practices, they could tackle both resource barriers and norms and incentives. First, journals could simply make these practices a factor in the review process (instruct reviewers to weigh them in their evaluation), and make it clear to authors that they encourage these practices. A bigger step would be to offer badges for papers that engage in these practices, as badges provide a reward of sorts (e.g., public acknowledgement). Journals can also use and advertise metrics besides Impact Factor—such as how they score on transparency and reproducibility policies (e.g., the TOP Factor; https://topfactor.org/), and emphasize open science practices when they communicate with researchers via calls for research and in editorial decisions. These moves would all help to clarify to researchers what the journal values, which could change the norms. Of course, journals should only do this if they will, in fact, count these practices in authors' favor (even if it means the results are less likely to be attention-grabbing).

Why should journals value these practices (among others)? Transparency makes it possible to verify the claims made in scientific papers. To conduct research transparently is to give your critics ammunition—the underlying data and code to check reproducibility and robustness, details about the materials and procedures to identify potential design problems and conduct replications, the pre-registration for readers to calibrate their conclusions based on what was planned and what was not, etc. However, transparency does not guarantee quality or credibility. Transparently-reported research can still produce many false positives and other errors. The purpose of transparency is to make it possible to evaluate the credibility of one's claims (Vazire, 2017). Actually evaluating the quality of transparently-reported work requires that someone do the verification work. As Vonnegut famously observed, "Another flaw in the human character is that everyone wants to build and nobody wants to do maintenance," (p.167). Thus, a second crucial piece of credibility is increasing the prevalence of verification and correction efforts. Without this component, transparency will not make our research more accurate or credible.

One important aspect of verification and correction is valuing null results and replication studies. These two practices were almost absent according to our measures, and there was no evidence that they were on the rise, indicating that these practices still lag behind other open science practices. Regarding steps to ensure quality control in particular, there is a great deal of room for improvement.

Overall, the results suggest that, although the vast majority of articles in these four Organizational Behavior journals do not use any open science practices, some practices we coded for were on the rise, especially those that increase transparency, and especially in the last two years. While current rates of adoption are low, an optimistic interpretation of our results suggests that the field could be on the brink of important and sustained improvements.

CRediT authorship contribution statement

Elizabeth R. Tenney: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing - original draft, Writing - review & editing, Visualization, Supervision. **Elaine Costa:** Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing - original draft, Writing - review & editing, Visualization, Supervision. **Aurélien Allard:** Conceptualization, Methodology, Software, Validation, Investigation, Data curation, Writing - review & editing. **Simine Vazire:** Conceptualization, Methodology, Writing - original draft, Writing - review & editing, Visualization.

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