Tracing the Adoption and Effects of Open Science in Communication Research

David M. Markowitz¹, Hyunjin Song² & Samuel Hardman Taylor³

Positions and Affiliations:

¹ Assistant Professor, University of Oregon, School of Journalism and Communication, Eugene, Oregon (dmark@uoregon.edu)

² Assistant Professor, Yonsei University, Department of Communication, Seoul, South Korea (hyunjinsong@yonsei.ac.kr)

³ Assistant Professor, University of Illinois at Chicago, Department of Communication, Chicago, Illinois (samuelht@uic.edu)

This paper is currently in press at the *Journal of Communication* for the Special Issue of Open Communication Research. The final, copyedited version might differ slightly from this version.

Tracing the Adoption and Effects of Open Science in Communication Research

Abstract

A significant paradigm shift is underway in communication research as open science practices (e.g., preregistration, open materials) are becoming more prevalent. The current work identified how much the field has embraced such practices and evaluated their impact on authors (e.g., citation rates). We collected 10,517 papers across 26 journals from 2010-2020, observing that 5.1% of papers used or mentioned open science practices. Communication research has seen the rate of non-significant p -values ($ps > .055$) increasing with the adoption of open science over time, but p -values just below $p < .05$ have not reduced with open science adoption. Open science adoption was unrelated to citation rate at the article level; however, it was inversely related to the journals' h -index. Our results suggest communication organizations and scholars have important work ahead to make open science more mainstream. We close with suggestions to increase open science adoption for the field at large.

Keywords: *open science, open communication science, preregistration, replication, questionable research practices*

Authors' Note

DMM and SHT conceived the project. DMM performed the LIWC text analyses, extracted the article citations, and ran statistical tests for these data. DMM and SHT conducted validation studies for the open science and LIWC dictionaries. HS extracted the journal article metadata and texts, performed the p -value analyses, and created the reproducibility code. All authors contributed to the paper's writing and editing.

Tracing the Adoption and Effects of Open Science in Communication Research

Open science aims to increase the validity and credibility of scientific theory and empirical evidence thereof. Validity and credibility issues for theory and associated empirical evidence across social science fields largely began around 2012, as notable researchers were caught in data fraud (Levelt et al., 2012) and foundational effects failed to replicate (Open Science Collaboration, 2015). These events encouraged social scientists to self-reflect and recognize that common research practices (e.g., small sample sizes, a lack of data sharing) were systemic problems that required fixing (Nelson et al., 2018).

Communication research is unlikely to be immune to the problems that sparked the open science revolution (Lewis, 2020). For example, experimental communication research shows evidence of Questionable Research Practices (QRPs) such as the selective reporting and inflation of p -values just below the 5% significance threshold (Matthes et al., 2015). Further, while replications exist, they are infrequent (Keating & Totzkay, 2019). Based on these grounds, many papers advocate for open science practices in communication research (Bowman & Keene, 2018; Dienlin et al., 2021; Lewis, 2020; McEwan et al., 2018); however, the field still lacks empirical data to demonstrate the prevalence—in a descriptive sense—of open science practices in communication research and how their adoption matters for authors and the field as a whole. There have been limited evaluations demonstrating that reproducibility threats, facilitated by QRPs, are prevalent in the field, or that the open science revolution has alleviated these threats.

The current paper evaluates the problem of QRPs and solutions proposed by open science in communication. First, we measure the prevalence of open science in communication over the past decade. Second, we provide an empirical assessment of QRPs in the communication literature by evaluating the rate of p -values just below the 5% significance threshold, which have

the greatest potential to reflect the use of QRPs. Finally, we analyze whether adopting or mentioning open science is associated with reporting fewer p -values just below .05, greater certainty in the reporting of research, and more scholarly impact (e.g., citations). With this work, we provide an empirical history of open communication research over the past decade and demonstrate why embracing open science practices matters for the field.

Open Science in Communication Research

The benefits of open science in communication have largely been addressed from a philosophy of science perspective (Lewis, 2020; McEwan et al., 2018). Dienlin and colleagues (2021) articulate why open science is necessary in communication research from the lens of replicability, or why some studies fail to produce a similar pattern of results compared to existing research. QRPs such as HARKing (e.g., “postdictions as predictions;” Dienlin et al., 2021, p. 5) and p -hacking (e.g., using flexible research decisions to obtain a significant effect just below the 5% level) reduce the probability that research findings will replicate in a different setting. Such QRPs are harmful to the reliability of scientific findings because the literature then rests on fluid, imprecise, and subjective research practices. For example, subjectively including (or dropping) covariates in a statistical model without clear rationales or disclosures to reach statistical significance (e.g., a form of p -hacking) represents an author “fishing” for a significant effect. To avoid QRPs, several guides exist for the communication researcher on how to implement open science into their work. Among them, three open science practices are discussed as mechanisms to increase the validity and credibility of published (quantitative) communication research: (1) *open science* via publishing research materials and data, (2) *preregistration*, and (3) conducting *replications*. We focused on these subcategories because they are the most dominant open

science practices discussed to improve communication research.¹

First, Bowman and Spence (2020) describe the importance of and best practices for making data and materials freely available without restrictions. The authors suggest such practices promote transparency in light of traditional journal constraints (e.g., page limits). Making research materials public can facilitate new discoveries by different research teams and even detect research misconduct (Simonsohn, 2013). Second, Lewis (2020) outlines the practice of preregistration (i.e., creating a transparent record of research questions, methods, and analytic plans), why it is an important planning mechanism before data collection, and how researchers can create their first preregistration document. Preregistration can also take the form of a registered report, which is peer reviewed before data collection (Nosek et al., 2018). The logic of preregistration is to limit a researcher's degrees of freedom in the analytic process and prevent QRPs. Third, replication generally refers to the repeating of previous research, and if successful, finding the same result (Nosek & Errington, 2020). Although quantitative communication research is—like all other post-positivist social science fields—based on the assumption of replications, the field historically conducts more conceptual replications than direct replications as the latter are typically undervalued as a contribution (McEwan et al., 2018).

Despite the promise of open science, its main rationale from a philosophy of science perspective has a few major constraints. This rationale relies on an untested assumption that all researchers understand and care about issues such as QRPs or replication, which are affecting communication and social science fields more broadly. Even if researchers care about these issues, they must have some level of intrinsic motivation to act upon and incorporate open

¹ There are more aspects of open science such as open access publishing, open peer review, among others. Among a full range of open-science practices, we strategically considered the three dominant categories of open science instead of less mainstream categories. See Dienlin et al. (2021) for a full review.

science research practices into their work because extrinsic motivators — journal publications, the academic job market, and tenure — are limited (McEwan et al., 2018). Therefore, researchers must believe open science is fundamentally valuable, as the costs or consequences of its practices are nontrivial. Preregistration adds an upfront cost for researchers whose resources are already constrained. Researchers who perform replications might struggle to have their work published because “conducting replications is viewed as lacking prestige, originality, or excitement” (Makel et al., 2012, p. 537). Publicly sharing study information requires additional work to make data and materials clear to a third party (Bowman & Spence, 2020), and other researchers might question the quality of public data (Washburn et al., 2018).

While we nevertheless believe the benefits of open science outweigh purported costs, we also understand why some communication researchers might be wary of open science practices: they are relatively new to the field with few institutional incentives for adoption, they require more labor for research and publishing, and open science training is scarce. Against this backdrop, we seek to identify how open science might be associated with benefits for authors, such as a more confident writing style and increased citation counts. These benefits, with more journal and institutional support for open science, might be pathways to encourage its uptake.

Taken together, the current paper has several aims to understand the adoption and outcomes of open science practices for communication research. First, we attempt to empirically survey the rate and prevalence of open science adoption in the communication field over time. We count the number of published studies that used or mentioned open science, preregistration, or replication from 2010-2020 across a diversity of journals to document how the field has responded to the open science revolution. Here, we are interested in three categories of open communication research outlined by Dienlin and colleagues (2021): (1) open science via

publishing materials and data, (2) preregistration, and (3) replications. We evaluate open science prevalence in journals indexed by the International Communication Association (ICA), National Communication Association (NCA), and other societies.

RQ1: How much has communication research adopted open science research practices and who tends to adopt open science practices?

Second, we evaluate the rate of p -values just below the 5% mark in quantitative communication research and assess how adopting or mentioning open science practices impact their prevalence. QRPs such as p -hacking lead “researchers to quit conducting analyses upon obtaining a statistically significant finding,” producing a high rate of p -values just below .05 in published articles (Simonsohn et al., 2014, p. 670). Thus, a high frequency of p -values just below .05 signals the potential of false-positive research (see Simmons et al., 2011), a trend investigated in experimental communication research by Matthes and colleagues (2015), who had human coders count p -values between $.04 \leq p < .05$ across articles from four communication journals (1980-2013). Our work extends this research by making inferences about p -value prevalence at the field level before and after the open science revolution, showcasing how communication research findings have shifted on a macro-level in response to the credibility threats uncovered by the replication crisis. We explore how adopting open science practices associates with the prevalence of p -values between $.045 < p \leq .05$ at the article level.²

RQ2: To what extent does the rate of p -values just below the 5% threshold associate with an article’s year of publication and connect to open science adoption?

Our third aim seeks to address how adopting open science practices relates to positive

² While Matthes et al. (2015) evaluated p -values between $.04 \leq p < .05$, we evaluate p -values between $.045 < p \leq .05$ as a more conservative test of our research question. We included $p = .05$ because research suggests most social scientists consider $p = .05$ to be statistically significant (Nuijten et al., 2016).

outcomes for the researcher. We consider positive outcomes across two domains: verbal certainty and research impact. In terms of verbal certainty, research suggests people, including scientists, who use more words from a particular language category (e.g., emotion) tend to reveal their mental focus on the corresponding category (Pennebaker, 2011). This “words as attention” model has been successfully applied to hundreds of research studies in the social sciences (Boyd & Schwartz, 2021). Based on this idea, we investigate how open science practices relate to an increased psychological focus on certainty in scientists’ writing, which can expand the rationales for adopting open science in communication beyond preventing QRPs.

Verbal certainty is a category of cognitive processing words (Boyd et al., 2020), which reflect an increased sense of conviction, confidence, or authority in an idea (Cheatham & Tormala, 2015). While research outcomes are rarely as clear as one might hope, communicating the outcome in a clear, confident manner—not only including what a researcher knows, but also including what they do not know from the results of a study—is likely a beneficial practice in science communication, and potentially benefits individual researchers for their transparency throughout their scientific process. Drawing on this framework, prior research suggests an increased focus on certainty terms, and therefore increased evidence of a researcher’s confidence in their work, is associated with tangible outcomes for scientists. An analysis of nearly 20,000 National Science Foundation (NSF) grant abstracts revealed that authors who attended to more verbal certainty (e.g., using terms such as *absolute* and *clear*) tended to receive more money from the NSF (Markowitz, 2019). This result is consistent with research on confidence heuristics: people who project a confident and certain disposition are often viewed as more credible than those who project a less confident and certain disposition (Price & Stone, 2004).

The replication crisis undermined the confidence in the validity of social science (Nosek

et al., 2018). Steps taken to reduce QRPs and improve the validity of empirical claims should therefore change how authors write about their science. An increased focus on preregistration should lead to more certainty in science articles because with fewer ways to conduct research when it is preregistered, researchers should feel more confident and certain in their work when they remain consistent with their preregistered empirical and analytic plans. In science, “openness promotes confidence and trust, whereas secrecy breeds distrust and suspicion” (Cook et al., 2018, p. 112). As Cottey (2010) also argues, openness and confidence tend to increase together in scientific research. We expect an increased focus on open science practices will be positively associated with an increased focus on certainty and confidence in the research process.

H₁: Adopting or mentioning open science in research articles is positively associated with rates of verbal certainty.

We also test how adopting or mentioning open science practices relate to scholarly impact at the article level, as indicated by citations. We expect open science practices will be positively associated with citation rate because open science provides reasons to cite an article beyond its content (e.g., open data, open materials). For example, prior work observed papers that link to data in an open repository tend to receive more citations, on average (Colavizza et al., 2020). Openness in different aspects of the scientific process (e.g., making papers publicly available, without a paywall) tends to offer citation benefits to researchers (Wang et al., 2015).

H₂: Adopting or mentioning open science in research articles is positively associated with citation counts.

Method

We collected a dataset of full article texts and their metadata across a range of scholarly papers from major communication journals. Our preregistered hypotheses and analytic plans are

located on the Open Science Framework (OSF: <https://osf.io/58jyf/>). Deviations from our preregistrations are noted in the online supplement. Our code and data are also publicly available on the OSF, but raw text files are excluded due to possible copyright concerns. The data have been deidentified, given the potentially sensitive topics discussed in the paper and because our primary interest is in field-level trends, not author-level trends.

Data Collection

We retrieved empirical research articles from all ICA and NCA journals, other top-ranked communication journals indexed by the ISI Web of Science Journal Citation Report (see Song et al., 2020), and journals with special interests in open science topics (see Dienlin et al., 2021). However, according to our preregistration plan, we excluded journals that did not have text in HTML format, journals whose articles mainly focus on qualitative research,³ and articles from journals that did not contain open science terms from our first iteration of the *open science dictionary* (see below). We proceeded with journals containing at least one article that mentioned open science topics and whose focus broadly reflects the field or major subdisciplines of quantitative communication science. From each journal, we collected published papers (including online first articles) between January 2010 and July 2020 (depending on publication cycles of the target journals) to cover before and after the open science revolution around 2012.

Duplicates ($n = 497$) and non-research articles (e.g., book reviews, announcements, corrections, and other irrelevant articles; $n = 1,643$) from the remaining journals were excluded. Since we were primarily interested in empirical research papers, and labels for such article types might differ across journals, two of the authors went journal-by-journal to isolate the relevant article types to be retained in the analysis (see Supplementary Table S1). The final dataset with

³ We tested this assumption by searching for open science terms (see Open Science Dictionary section) in each qualitative communication journal and no terms appeared.

10,517 papers from 26 journals contained 63,105,729 words (see Table 1 for descriptive data).

All analyses and computations were performed in R (version 4.0.2).

Data Extraction and Measures

We extracted ten metadata dimensions from each publication: Digital Object Identifier, journal name, volume, issue, date of publication, article section, article title, first author, last author, and total number of authors per paper. We also extracted the article's full text from the first main section of the paper (e.g., Introduction) to its final main section (e.g., Discussion) depending on the journal. The abstract, (sub)headings, and references were not extracted.

***P*-value prevalence just below 5%.** To evaluate RQ₂, we used the R package *statcheck* to automatically extract statistical tests from each paper's main text (Epskamp & Nuijten, 2018). *Statcheck* is often used to detect reporting errors in APA-formatted statistical tests, though we used the package to count the number of statistical tests reported in each paper just below or equal to the 5% significance level (i.e., p -values between $.045 < p \leq .05$), which would indicate a greater possibility of QRPs such as p -hacking (Head et al., 2015; Matthes et al., 2015). *Statcheck*'s extraction accuracy has been validated against human coding and is thus equated to a "spellcheck" for statistics (Nuijten et al., 2016, 2017). If a test statistic exists in APA style, *statcheck* will extract it and categorize inconsistencies with an accuracy between 96.2% and 99.9%. A similar automated extraction approach of p -values has also been applied to communication science articles to assess biased significance reporting (Vermeulen et al., 2015).

We calculated a conservative estimate of per-paper p -value prevalence by dividing the number of p -values between $.045 < p \leq .05$ by the total number of p -values reported in each paper. We evaluated reporting trends over time and assessed if open science practices reduce the rate of p -values between $.045 < p \leq .05$. Should the number of p -values per paper reduce within

the range of $.045 < p \leq .05$, we would also expect a complementary result where open science practices normalize and expect the reporting of more non-significant results as well ($p > .055$).⁴ Therefore, we investigated how open science practices link to a potential reduction in p -values just below statistical significance and an increase in p -values that are not statistically significant.

Importantly, statistical tests with p -values are not reported consistently across journals and reporting errors are more common in social science papers than one would expect (Nuijten et al., 2016). Recall, *statcheck* offers the ability to recompute exact p -values when test statistics (such as χ^2 , t , F , Z , or Q values) are in APA style. Any p -values extracted using this method are henceforth referred to as *recomputed p-values* since *statcheck* recomputes significance values from provided test statistics. *Statcheck* can also extract p -values as authors reported them in the main text of a paper (without recomputation). We collected such p -values, independent of formatting (APA or not), which are henceforth referred to as *reported p-values* because they rely on authors' significance reporting. These are important p -values because they are the statistical results that readers interpret in a paper (e.g., most readers, on average, are unlikely to recompute or detect errors when reading an article).

We assigned reported p -values to the QRP-suspected category when they were reported exactly (e.g., $p = .046$). If they were reported inexactly (e.g., $p < .05$) without test statistics, we excluded such p -values because it would be impossible for us to determine whether the reported p -values belonged to a QRP-suspected range or not. The last three columns of Table 1 report the final sample sizes per journal that were retained in the p -value analyses by p -value type.

Together, we compare our results across extraction methods of *recomputed* (APA-only), *reported* ("as is" p -values without recomputing), and *pooled p-values* (*recomputed p-values*

⁴ We considered non-significant p -values to be $p > .055$ since any p -value between $.05 < p < .055$, if rounded down by authors, might be considered statistically significant at $p = .05$.

augmented with remaining *reported p-values*).

Language patterns of research articles. We quantified language patterns of research articles using the automated text analysis tool, Linguistic Inquiry and Word Count (LIWC: Pennebaker et al., 2015). LIWC's dictionary of nearly 6,400 words increments social (e.g., words related to friends), psychological (e.g., emotion words, words related to motivation), and part of speech categories (e.g., pronouns, articles). LIWC counts words as a percent of the total word count per text. For example, "The results of this study reached a clear conclusion," contains 9 words and increments LIWC categories such as insight terms (e.g., *conclusion*; 11.11% of the total word count), causal words (e.g., *results*; 11.11%), and articles (e.g., *the, a*; 22.22%).

LIWC word collections were developed by human judges who decided on the terms to retain if a majority of raters agreed that they fit each conceptual category. Base-rate tests and reliability analyses then ensured the words formed uniform and coherent categories. Therefore, each category in the LIWC dictionary has been vetted for psychometric properties across diverse settings (e.g., formal writing, informal writing, natural speech; Pennebaker et al., 2015). To ensure that our primary LIWC measure, verbal certainty, was a valid dimension for our collection of communication science articles, we revalidated terms in this dictionary. Indeed, humans rated sentences from our database with certainty words as more certain, confident, and unquestioned than control sentences (see Supplementary Materials for details).

Open science dictionary: Construction, reliability, and validation. We also used LIWC to count words in our *open science dictionary*, which identified how much a research project focused on, used, or mentioned open science practices across three subcategories (Dienlin et al., 2021): (1) open science via open materials and data, (2) preregistration, and (3) replication.

Our original dictionary began with 26 terms (see Supplementary Materials), collected by

the authors after consulting other public collections⁵, which signal open science practices in our subcategories. This process allowed us to start with an initial collection of face-valid concepts that indicated open science terms. From this list, we identified how the concepts might manifest in everyday practice. Open data, for example, might occur when a researcher posts their data to a public repository and we therefore included a list of common open data repositories.

Following this term-collection process, we randomly selected a batch of articles from our database ($n = 172$; slightly less than 2% of papers) to measure the reliability of the open science dictionary, using procedures outlined by Pennebaker and colleagues (2015). Zero variance terms were dropped, and 16 terms reached a level of acceptable reliability using standardized items (Cronbach's $\alpha = .75$). This reliability level is also consistent with that of other LIWC dictionaries (Pennebaker et al., 2015). We spot-checked our dictionary to ensure terms were incremented appropriately, which revealed that our *open code* item identified a concept different from its intended meaning (e.g., open statistical or programming code). Instead, many qualitative studies mentioned creating an open code for grounded theory research. Since this differed from our aim, we removed this term from the dictionary. In the iterative process of refining the dictionary, we also added several terms to be more inclusive (e.g., *github*, *power analyses*, *replication study*), and reliability was stable.⁶ Table 2 contains the final 18 terms in our statistically reliable *open science dictionary*, separated by subcategories.

We also validated our open science dictionary in two ways. First, the lead and third authors hand-coded 100 articles for all open science dictionary terms to ensure they were incremented and used correctly (see Supplementary Materials). Coders were highly reliable

⁵ <https://osf.io/t84kh/>

⁶ Using the full sample of articles ($N = 10,517$), items from the open science dictionary were still highly reliable for assessments of language patterns (Cronbach's $\alpha = .60$ using standardized values).

across categories (average Krippendorff's α s = .944, $ps < .001$). Classification statistics (e.g., precision, recall, F1-measure) were also above an acceptable range, on average, supporting the idea that the human and automated coding of our dictionary were well-calibrated. Second, we performed an out-of-sample validation of our dictionary using 1,253 articles from *Psychological Science* (2010-2020), whose open science badges provide ground truth for papers using open science practices or not (see Supplementary Materials). Papers with open science badges contained greater scores on the open science dictionary than those without badges ($0.81 < \text{Cohen's } d < 1.91$). Taken together, our dictionary is a valid and reliable collection of terms to indicate how much research articles focus on, use, or mention open science subcategories.

Citation rate. To examine the scholarly impact of adopting or mentioning open science, we extracted paper citations with the R package *rcrossref* (Chamberlain et al., 2020). Since older articles might naturally have more citations than recent articles, we calculated the number of days between the article's publication and citation extraction date using the following formula: [Citation Extraction Date – Article Publication Date]. We divided each article's citation count by the date difference and high scores indicate more citations per day relative to low scores. See Supplementary Table S2 and S3 for descriptive data about our key variables.

Results

The Adoption of Open Science in Communication

Overall rates of open science adoption were relatively low in communication research compared to other disciplines (Kidwell et al., 2016), and lower than the perceived prevalence of open science practices within the field as self-reported by communication scholars (Bakker et al., 2021). Approximately 5.1% of papers (536/10517) had at least one mention of open science from our dictionary over a ten-year period. The first notable increase in open science adoption

occurred for papers published in 2016 (top of Figure 1). Preregistration was the most popular subcategory (2.50%; 263/10517), specifically *power analysis* or *power analyses* (232/10517), followed by open science (2.31%; 243/10517) and replication (0.97%; 102/10517). About 12% of papers with open science terms ($n = 66$ of 536) incremented subcategories simultaneously.⁷

Rates of open science adoption have slightly increased over time (Supplementary Table S2). We also assessed open science adoption in specific journals (see Supplementary Table S4 and Supplementary Figure S1). The bottom panel of Figure 1 suggests *Journal of Media Psychology*, *Political Communication*, and *Communication Research Reports* have had the strongest increase in open science over time.

Do high impact journals adopt open science at a different rate than low impact journals? We obtained h-index scores (i.e., h articles in a journal have received at least h citations) from *Scimago*; high h-index scores indicate a more productive and impactful journal than low scores. H-index scores predicted scores on the open science dictionary using a mixed effects regression, controlling for year (continuous) and the number of authors per paper (continuous) as fixed effects, plus first and last authors of each paper as random intercepts.⁸ All confidence intervals in this paper are computed using percentile-based bootstraps ($N = 5,000$).

H-index scores negatively predicted rates of the open science dictionary [$B = -3.099\text{e-}05$, $SE = 8.116\text{e-}06$, $t = -3.82$, $p < .001$, 95% CI $[-4.69\text{e-}05, -1.51\text{e-}05]$, $R^2c = 0.04$].⁹ Specifically, h-index scores negatively predicted open science ($p < .001$), but the relationship was not significant for preregistration ($p = .662$) nor replication ($p = .232$). Papers from lower-impact journals, on

⁷ It is important to note that communication scholars also publish in journals of neighboring fields and general interest outlets. Therefore, communication researchers might be adopting open science at higher rates if they are publishing in fields where such practices are more normative and expected.

⁸ We did not include journal as a control in this analysis since it is naturally collinear with h-index scores and we used h-index instead of impact factor because it was reported more consistently across journals.

⁹ R^2c = variance explained by fixed and random effects using the MuMIn package in R (Bartoń, 2020).

average, tend to contain more open science than papers from higher-impact journals.

The Effects of Open Science in Communication

***P*-value prevalence just below 5%.** Among 3,303 papers, we collected 29,009 statistical tests and associated *p*-values in APA-format ($n = 2,202$ errors reported and recomputed). Among 5,707 papers, we collected 53,239 reported *p*-values. Finally, for the pooled analysis, in addition to the 29,009 *p*-values values with errors recomputed, we extracted 27,124 *reported p-values* from 2,769 papers without test statistics. Therefore, for the pooled analysis, we excluded 4,445 papers from the full database without any *p*-values identified by *statcheck* (final $N = 6,072$).

To predict the rate of *p*-values between $.045 < p \leq .05$ per paper as a function of open science dictionary scores, we used a mixed effects logistic regression. This model type is well-suited to predict proportional outcomes with a known count (i.e., the rate of *p*-values between $.045 < p \leq .05$ over the total number of *p*-values per paper). Our model contained *year since 2013* (continuous) and the number of authors per paper (continuous) as fixed effects.¹⁰ Random intercepts included first author and last author for each paper to account for author-specific variations in using open science. See Supplementary Tables S5-S10 for all model details.

We failed to find a significant relationship between the open science dictionary (nor any subcategory) and the rate of *p*-values between $.045 < p \leq .05$ per paper when using pooled *p*-values (see Supplementary Table S5). This pattern was replicated when we used recomputed *p*-values (Supplementary Table S6) and reported *p*-values (Supplementary Table S7). Overall, these results indicate that the rate of *p*-values just below the 5% significance mark at the field level is unrelated to adopting or mentioning open science practices at the article level.

We also tested the possibility that a complementary pattern might emerge, where the

¹⁰ We used the 2013 as the reference year since the open science revolution was first introduced around 2012 and we anticipated it taking at least one year for open science topics to appear in published papers.

adoption of open science practices might normalize or require the reporting of non-significant p -values. Using pooled p -values, we observed the proportion of non-significant p -values was positively related to the open science dictionary [$B = 2.5977$, 95% CI [1.088; 3.778], Odds Ratio = 13.43; see Supplementary Table S8)]. Here, articles scoring the highest on open science dictionary ($max = 1.42$) are nearly forty times more likely to report non-significant p -values in their analyses ($exp[2.5977*1.42] = 39.99$). While this pattern was only replicated with reported p -values (Supplementary Table S10), we observed that the proportion of non-significant p -values was also positively related to the *preregistration* subcategory when using pooled p -values (see Supplementary Table S8), to *replication* using recomputed p -values (see Supplementary Table S9), and to *open science* and *preregistration* subcategories using reported p -values (see Supplementary Table S10). This provides a consistent picture of a positive relationship between open science and the increased reporting of non-significant p -values per paper.

Language and citation rate effects. We fit linear mixed effects regression models with year (continuous) and the number of authors per paper (continuous) as fixed effects, plus journal, first author, and last author for each paper as random intercepts.

Certainty. The rate of verbal certainty was significantly associated with the open science dictionary [$B = 0.37$, $SE = 0.15$], $t = 2.46$, $p = .014$, 95% CI [0.097, 0.645], $R^2c = 0.28$]. At the subcategory level, verbal certainty was significantly related to preregistration, [$B = 1.38$, $SE = 0.45$], $t = 3.06$, $p = .002$, 95% CI [0.716, 2.277], $R^2c = 0.28$], and marginally related to replication, [$B = 0.55$, $SE = 0.31$], $t = 1.76$, $p = .079$, 95% CI [-0.053, 1.070], $R^2c = 0.28$], but not open science via open data and materials ($p = .358$). H_1 was supported, with preregistration most strongly linked to certainty (see Supplementary Table S11 for all LIWC relationships).

An alternative explanation for this effect is that the positive relationship between

certainty and open science is semantic (e.g., they tend to naturally co-occur in the same sentence), not psychological as suggested by LIWC assumptions. To investigate this possibility, we identified sentences containing at least one certainty term from the LIWC dictionary in our collection of open science articles ($n = 536$ total articles). The average number of words per sentence for this collection was 32 words and therefore, we selected a window of 16 words to the left and right of all identified certainty words. If a high percentage of certainty words tend to naturally co-occur with words from our open science dictionary in this window, the relationship would reflect semantic co-occurrence. This procedure extracted 35,369 sentences containing a certainty term, which were then run through LIWC to count terms in our open science dictionary. The results suggest only 1% of sentences (384/35369) had co-occurring certainty and open science terms in the same window. Therefore, the relationship between certainty and open science is not merely semantic because the frequency of this co-occurrence is very low.

Citation rate. The number of citations per paper was not statistically related to the open science dictionary [$B = -1.370\text{e-}04$, $SE = 5.462\text{e-}03$], $t = -0.03$, $p = .980$, 95% CI [-0.009, 0.011], $R^2c = 0.28$], nor any of the subcategories ($ps > .316$). H_2 was not supported.

Discussion

Open science practices in the published communication literature have increased gradually over time, with non-flagship journals leading the charge in the adoption of open science. The current work informs to what extent the field of communication has experienced a cultural shift within the open science revolution and where communication can improve.

This research contributes to ongoing discussions about the prevalence of open science subcategories in communication (e.g., replication). Although the frequency of replication in our database (0.97% of articles) is lower than prior estimates (Keating & Totzkay, 2019), we find a

consistent pattern, as mentions of conceptual replications ($n = 28$ unique papers only with conceptual replications) were more prevalent in communication than direct replications ($n = 10$ unique papers only with direct replications) in our sample. Across vastly different analytic approaches, we reach similar conclusions: replications are not mainstream in communication research, and conceptual replications are more common than direct replications.

We also observed that open science was positively related to verbal certainty, a pattern that suggests more open science adoption predicts more focus on certainty and confidence in the article itself. This effect is consistent with a long history of research that suggests word patterns reflect our attention and connect to psychological processes (Pennebaker, 2011). Scholars who use or mention open science tended to have more focus on certainty as revealed by their writing, a pattern that is not linked to semantics. Thus, these results suggest open science, particularly preregistration, may be helping to rebuild confidence in social science research that was questioned during the replication crisis (Nosek et al., 2018), although an alternative explanation is that authors with a more certain writing focus may also gravitate toward open science.

Several hypothesized relationships about the benefits of open science failed to emerge, however, such as the connection between open science adoption and citation rate. As a field, communication has been slow to respond to threats of QRPs and institute policies to curb their effects. Shortly after the open science revolution, psychology journals created policies and reward systems to make authors aware of and consider the benefits of open science research at the field level (Kidwell et al., 2016). Open science papers may not be cited more than non-open science papers because they are historically rare in flagship communication journals that are expected to “set the tone” for the field, and only recently have professional organizations endorsed more widespread adoption of open science (e.g., ICA2020’s theme was Open

Communication). Such low visibility makes open science the exception and not the rule in communication research. Scholars might question if such ideas are worthwhile when they do not see most papers executing, or organizations promoting, open science practices. Therefore, communication organizations and affiliated journals should develop an open science roll-out plan to encourage the adoption and uptake of such practices directed from leadership to authors. Indeed, a relatively high presence of articles adopting open science practices in some specialty journals as suggested by Figure 1 (*Journal of Media Psychology*, *Political Communication*, and *Communication Research Reports*) appear to be, at least in part, attributable to journal leadership calling for more open science (e.g., Bowman & Keene, 2018). This suggests the need for leadership and field-level policy efforts to increase the adoption and uptake of such practices.

Open science practices were also not statistically related to proportion of p -values between $.045 < p \leq .05$ in each paper, but non-significant p -values were positively associated with open science via replication (when using recomputed p -values), via preregistration (when using pooled p -values or reported p -values), and via open data and open materials (when using reported p -values). Why did these patterns emerge? We might have failed to detect a relationship between just significant p -values (e.g., $.045 < p \leq .05$) and open science practices because of the low rate of open science adoption over time and the number of papers in the p -value prevalence analyses dropped by nearly one-third compared to the full sample. Perhaps we did not have enough power to detect a small effect in a natural setting. We also cannot rule out the possibility that the decreasing proportion of p -values between $.045 < p \leq .05$ at the macro-level may also reflect true (yet unknown) changes in statistical significance—collectively—that are unrelated to how communication researchers engage with the QRPs. However, the positive relationship between $ps > .055$ and open science, particularly preregistration, is reasonable since open science

normalizes and expects transparent data reporting regardless of statistical significance.

Taken together, researchers and field decision-makers likely need to see and recognize the value of open science before research practices and associated significance reporting conventions change at a macro-level. Hence, visibility with open science or any new initiative is crucial. Even the most vigilant reader would rarely see an article that used or mentioned open science practices because they are scarce and tend to exist in journals with generally limited reach (compared to flagship journals). Until researchers see the benefits of open science at the author, journal, and the field, along with more institutional and organizational endorsement, one can expect that reporting conventions will remain consistent with “closed” science papers. Next, we discuss the limitations of these findings before highlighting their implications for the field of communication and beyond.

Limitations

One potential limitation of our automated word counting approach is that it cannot distinguish between authors using (e.g., conducting a *conceptual replication*) vs. mentioning open science practices (e.g., suggesting that future work should conduct a *conceptual replication*). We believe this is a noteworthy distinction, but a generally limited concern given our interests. If authors mentioned but did not use open science, this is valuable because such mentions increase the visibility of open science, which we suggest is lacking in communication.

As our human coding of the open science dictionary also revealed, there is some level of error associated with the automated text analysis approach because some terms would be missed if they did not follow our dictionary terms exactly (e.g., the term *conceptually replicate* would not be counted, but *conceptual replication* would be counted). However, dictionary-based automated text analyses try to develop a representative list of terms for a dictionary, not a

comprehensive list of terms for a dictionary (Boyd & Schwartz, 2021). By creating a dictionary for open science, this allowed us to examine the adoption of open science at the field level, with one trade-off being that we cannot identify and therefore count all terms that might exist related to open science phenomena. Furthermore, the open science dictionary is also more germane to quantitative versus qualitative research; thus, our description of the field reflects mostly quantitative communication research. Our approach was instrumental to survey open science and its dominant subcategories over time in a large number of papers, but future work should expand the dictionary to include other terms and subcategories (e.g., open access, open peer review).

Our relationships between the open science dictionary, p -value prevalence, and verbal certainty are not direct cause and effect. While some practices occur before paper writing (e.g., preregistration), others typically occur after paper writing (e.g., posting data). Similarly, our analysis does not eliminate the possibility that authors may selectively choose to publish based on a journals' openness to open science. Time-order effects for inference are important and worth considering in future work. Further, the effect sizes in this paper are small, but in a range that is consistent with prior work (Holtzman et al., 2019). Our ability to detect these effects benefited from the size of our dataset. The effect size estimate we provide for verbal certainty is per-word effect size; therefore, the cumulative effect may be more substantially meaningful than what appears. We presupposed that certainty in science is a positive heuristic, but other research suggests that uncertainty is perceived positively (Karmarkar & Tormala, 2010; Markowitz, 2021). Evaluating the boundaries of certainty in science writing is important future work.

In our p -value prevalence analyses, we could only retrieve p -values from a paper's main text and not those located in tables or appendices.¹¹ Further, our *statcheck* analyses partially

¹¹ In the online appendix, we provide an initial assessment of the likelihood our approach missed any p -values reported in tables and appendices. See “*Extraction Error Rate for P-Values*” section for details.

relied on recomputed *p*-values (7.2% of all tests had errors recomputed), meaning either the *p*-value was reported incorrectly, or the test statistic was reported incorrectly. Given concerns with statistical reporting errors and *p*-value reporting conventions (Nuijten et al., 2016; Vermeulen et al., 2015), the *reported p-values* (those extracted without test statistics) are also likely to be a less accurate representation of statistical effects than recomputed *p*-values. Still, we reached the same conclusion in our *p*-value analyses no matter how the statistical tests were counted.

Implications for Open Communication Research

Our analyses provide an important status update and perspective on future directions for the discipline regarding open science. In providing a survey of open science prevalence across communication research during a crucial period of empirical history, we argue communication research is inching toward but not readily adopting open science practices. For example, the rate of *power analysis* or *power analyses* in our study (appearing in 2.21% of papers) is only slightly elevated relative to other estimates (1.67%; Matthes et al., 2015). If power analysis and preregistration in general were more widely adopted, it would be reasonable to expect a greater increase over time. We conclude that the cultural shift to open communication science is beginning, and open science is not settled into our identity as a field. Other fields—such as psychology—that instituted changes in publishing and research practices in short order have seen a more striking increase in adoption since 2012 (Nosek, 2019). Communication research has largely been a bystander watching the open science parade go by. Our field has important work ahead to meet this paradigm-shifting scientific moment.

The rate of open science adoption identified by our paper offers a call-to-action for researchers, labs, and key decision makers in the discipline—including editors, reviewers, and communication organizations. Our results call upon communication researchers to learn about

and adhere to open research practices, preregister studies and analytic plans, and conduct direct replications. A first step towards this goal is to familiarize oneself with open science “How To” publications (e.g., Bowman & Spence, 2020; Lewis, 2020) and learn best practices. Our results also call upon communication journals, especially flagship journals, to adapt and reward the uptake of open science. Journals like *Political Communication* and *Communication Research Reports* place badges on papers using open data, open materials, and preregistration to indicate their adherence to open science, which can promote more open science adoption (Kidwell et al., 2016). Field-leading journals might consider creating special publication tracks for replications and registered reports to encourage robustness testing of our theories. Finally, our results call upon curriculum developers to make open science part of education and graduate training. Making open science practices normative for how communication scholars conduct research (e.g., transparent reporting and the normalizing of non-significant results) will encourage wider and more sustained adoption. Open science requires labor for researchers, and as our data suggest, the incentive structure of communication research should be reworked for open science practices to fully make their way to our field.

Open science practices are not a panacea for problems related to the credibility and validity of communication research, however, as they might introduce new problems for data anonymity, copyright, data privacy, and ownership. Further, there is no resolution for what open science exactly means for qualitative research (Haven & Van Grootel, 2019), which is a substantial portion of communication research. As a scientific community, we must determine what open *communication* research means. The shift toward open communication research requires researchers, journals, universities, and organizations to support and incentivize the growth of open communication research across research paradigms.

Drawing on prior concepts (see Acquisti et al., 2015), we suggest there are at least three types of open communication researchers: *fundamentalists* (e.g., those who believe open science must be practiced in all cases), *pragmatists* (e.g., those who value open science and support its adoption but recognize it might not be practical in all cases), and the *unconcerned* (e.g., those who believe “closed” science practices are adequate). While we recognize that it might be difficult to execute open science given the additional costs involved, this work and others highlight the value of open science. For the beginning stages of open science adoption, open communication fundamentalism, or creating a “call out” culture for those who do not follow all aspects of open science, might be uninviting for potential adopters. It will likely lead to field-level fractions instead of coalescence. The absence of open science does not guarantee bad science, nor its mere presence guarantee good science. We encourage the use of open science, when possible and practical for researchers, to encourage more credible communication research.

Implications Beyond Communication Research

Altogether, this research can impact the larger scientific community in several ways. First, the open science dictionary and our automated approach can be applied to other fields, testing a range of hypotheses related to open science adoption (see the OSF for the open science dictionary LIWC file). Second, other fields might use our approach to investigate cultural shifts, how open science developed over time, and how its adoption has impacted specific research communities and subfields. Third, our *p*-value prevalence analysis demonstrated the proportion of non-significant *p*-values was positively related to adopting open science. Open science practices may shift how people report their results, but more testing is needed. We hope this evidence suggests why open science adoption in communication and other sciences matters.

References

- Acquisti, A., Brandimarte, L., & Loewenstein, G. (2015). Privacy and human behavior in the age of information. *Science*, 347(6221), 509–514. <https://doi.org/10.1126/science.aaa1465>
- Bakker, B. N., Jaidka, K., Dörr, T., Fasching, N., & Lelkes, Y. (2021). Questionable and open research practices: Attitudes and perceptions among quantitative communication researchers. *PsyArXiv*. <https://doi.org/10.31234/OSF.IO/7UYN5>
- Bartoń, K. (2020). *MuMIn* (1.43.17). <https://cran.r-project.org/web/packages/MuMIn/index.html>
- Bowman, N. D., & Keene, J. R. (2018). A layered framework for considering open science practices. *Communication Research Reports*, 35(4), 363–372. <https://doi.org/10.1080/08824096.2018.1513273>
- Bowman, N. D., & Spence, P. R. (2020). Challenges and best practices associated with sharing research materials and research data for communication scholars. *Communication Studies*. <https://doi.org/10.1080/10510974.2020.1799488>
- Boyd, R. L., Blackburn, K. G., & Pennebaker, J. W. (2020). The narrative arc: Revealing core narrative structures through text analysis. *Science Advances*, 6(32), eaba2196. <https://doi.org/10.1126/sciadv.aba2196>
- Boyd, R. L., & Schwartz, H. A. (2021). Natural language analysis and the psychology of verbal behavior: The past, present, and future states of the field. *Journal of Language and Social Psychology*, 40(1), 21–41. <https://doi.org/10.1177/0261927X20967028>
- Chamberlain, S., Zhu, H., Jahn, N., Boettiger, C., & Ram, K. (2020). *rcrossref*: Client for various “CrossRef” “APIs.”
- Cheatham, L., & Tormala, Z. L. (2015). Attitude certainty and attitudinal advocacy: The unique roles of clarity and correctness. *Personality and Social Psychology Bulletin*, 41(11), 1537–

1550. <https://doi.org/10.1177/0146167215601406>

- Colavizza, G., Hrynaszkiewicz, I., Staden, I., Whitaker, K., & McGillivray, B. (2020). The citation advantage of linking publications to research data. *PLOS ONE*, *15*(4), e0230416. <https://doi.org/10.1371/journal.pone.0230416>
- Cook, B. G., Lloyd, J. W., Mellor, D., Nosek, B. A., & Therrien, W. J. (2018). Promoting open science to increase the trustworthiness of evidence in special education. *Exceptional Children*, *85*(1), 104–118. <https://doi.org/10.1177/0014402918793138>
- Cottey, A. (2010). Openness, confidence and trust in science and society. *The International Journal of Science in Society*, *1*(4), 185–194. <https://doi.org/10.18848/1836-6236/cgp/v01i04/51492>
- Dienlin, T., Johannes, N., Bowman, N. D., Masur, P. K., Engesser, S., Kümpel, A. S., Lukito, J., Bier, L. M., Zhang, R., Johnson, B. K., Huskey, R., Schneider, F. M., Breuer, J., Parry, D. A., Vermeulen, I., Fisher, J. T., Banks, J., Weber, R., Ellis, D. A., ... de Vreese, C. (2021). An agenda for open science in communication. *Journal of Communication*, *71*(1), 1–26. <https://doi.org/10.1093/JOC/JQZ052>
- Epskamp, S., & Nuijten, M. B. (2018). *statcheck* (1.3.1).
- Haven, T. L., & Van Grootel, L. (2019). Preregistering qualitative research. *Accountability in Research*, *26*(3), 229–244. <https://doi.org/10.1080/08989621.2019.1580147>
- Head, M. L., Holman, L., Lanfear, R., Kahn, A. T., & Jennions, M. D. (2015). The extent and consequences of p-hacking in science. *PLOS Biology*, *13*(3), e1002106. <https://doi.org/10.1371/journal.pbio.1002106>
- Holtzman, N. S., Tackman, A. M., Carey, A. L., Brucks, M. S., Küfner, A. C. P., Deters, F. G., Back, M. D., Donnellan, M. B., Pennebaker, J. W., Sherman, R. A., & Mehl, M. R. (2019).

Linguistic markers of grandiose narcissism: A LIWC analysis of 15 samples. *Journal of Language and Social Psychology*, 38(5–6), 773–786.

<https://doi.org/10.1177/0261927X19871084>

Karmarkar, U. R., & Tormala, Z. L. (2010). Believe me, I have no idea what I'm talking about:

The effects of source certainty on consumer involvement and persuasion. *Journal of Consumer Research*, 36(6), 1033–1049. <https://doi.org/10.1086/648381>

Keating, D. M., & Totzkay, D. (2019). We do publish (conceptual) replications (sometimes):

Publication trends in communication science, 2007–2016. *Annals of the International Communication Association*, 43(3), 225–239.

<https://doi.org/10.1080/23808985.2019.1632218>

Kern, M. L., Eichstaedt, J. C., Schwartz, H. A., Dziurzynski, L., Ungar, L. H., Stillwell, D. J.,

Kosinski, M., Ramones, S. M., & Seligman, M. E. P. (2014). The online social self: An open vocabulary approach to personality. *Assessment*, 21(2), 158–169.

<https://doi.org/10.1177/1073191113514104>

Kidwell, M. C., Lazarević, L. B., Baranski, E., Hardwicke, T. E., Piechowski, S., Falkenberg, L.-

S., Kennett, C., Slowik, A., Sonnleitner, C., Hess-Holden, C., Errington, T. M., Fiedler, S.,

& Nosek, B. A. (2016). Badges to acknowledge open practices: A simple, low-cost, effective method for increasing transparency. *PLOS Biology*, 14(5), e1002456.

<https://doi.org/10.1371/journal.pbio.1002456>

Levelt, W. J. M., Drenth, P. J. D., & Noort, E. (2012). *Flawed science: The fraudulent research practices of social psychologist Diederik Stapel*.

https://pure.mpg.de/pubman/faces/ViewItemFullPage.jsp?itemId=item_1569964

Lewis, N. A. (2020). Open communication science: A primer on why and some

recommendations for how. *Communication Methods and Measures*, 14(2), 71–82.

<https://doi.org/10.1080/19312458.2019.1685660>

Makel, M. C., Plucker, J. A., & Hegarty, B. (2012). Replications in psychology research: How often do they really occur? *Perspectives on Psychological Science : A Journal of the Association for Psychological Science*, 7(6), 537–542.

<https://doi.org/10.1177/1745691612460688>

Markowitz, D. M. (2019). What words are worth: National Science Foundation grant abstracts indicate award funding. *Journal of Language and Social Psychology*, 38(3), 264–282.

<https://doi.org/10.1177/0261927X18824859>

Markowitz, D. M. (2021). Words to submit by: Language patterns indicate conference acceptance for the International Communication Association. *Journal of Language and Social Psychology*, 40(3), 412–423. <https://doi.org/10.1177/0261927X20988765>

Matthes, J., Marquart, F., Naderer, B., Arendt, F., Schmuck, D., & Adam, K. (2015). Questionable research practices in experimental communication research: A systematic analysis from 1980 to 2013. *Communication Methods and Measures*, 9(4), 193–207.

<https://doi.org/10.1080/19312458.2015.1096334>

McEwan, B., Carpenter, C. J., & Westerman, D. (2018). On replication in communication science. *Communication Studies*, 69(3), 235–241.

<https://doi.org/10.1080/10510974.2018.1464938>

Nelson, L. D., Simmons, J., & Simonsohn, U. (2018). Psychology's renaissance. *Annual Review of Psychology*, 69(1), 511–534. <https://doi.org/10.1146/annurev-psych-122216-011836>

Nosek, B. A. (2019). *The rise of open science in psychology, a preliminary report*.

<https://www.cos.io/blog/rise-open-science-psychology-preliminary-report>

- Nosek, B. A., Ebersole, C. R., DeHaven, A. C., & Mellor, D. T. (2018). The preregistration revolution. *Proceedings of the National Academy of Sciences of the United States of America*, 115(11), 2600–2606. <https://doi.org/10.1073/pnas.1708274114>
- Nosek, B. A., & Errington, T. M. (2020). What is replication? *PLOS Biology*, 18(3), e3000691. <https://doi.org/10.1371/journal.pbio.3000691>
- Nuijten, M. B., Hartgerink, C. H. J., van Assen, M. A. L. M., Epskamp, S., & Wicherts, J. M. (2016). The prevalence of statistical reporting errors in psychology (1985–2013). *Behavior Research Methods*, 48(4), 1205–1226. <https://doi.org/10.3758/s13428-015-0664-2>
- Nuijten, M. B., van Assen, M., Hartgerink, C. H. J., Epskamp, S., & Wicherts, J. (2017). The validity of the tool “statcheck” in discovering statistical reporting inconsistencies. *PsyArXiv*. <https://doi.org/10.31234/osf.io/tcxaj>
- Open Science Collaboration. (2015). Estimating the reproducibility of psychological science. *Science*, 349(6251). <https://doi.org/10.1126/science.aac4716>
- Pennebaker, J. W. (2011). *The secret life of pronouns: What our words say about us*. Bloomsbury Press.
- Pennebaker, J. W., Booth, R. J., Boyd, R. L., & Francis, M. E. (2015). *Linguistic Inquiry and Word Count: LIWC2015*. Pennebaker Conglomerates.
- Price, P. C., & Stone, E. R. (2004). Intuitive evaluation of likelihood judgment producers: evidence for a confidence heuristic. *Journal of Behavioral Decision Making*, 17(1), 39–57. <https://doi.org/doi:10.1002/bdm.460>
- Simmons, J. P., Nelson, L. D., & Simonsohn, U. (2011). False-positive psychology: Undisclosed flexibility in data collection and analysis allows presenting anything as significant. *Psychological Science*, 22(11), 1359–1366. <https://doi.org/10.1177/0956797611417632>

- Simonsohn, U. (2013). Just post it: The lesson from two cases of fabricated data detected by statistics alone. *Psychological Science*, 24(10), 1875–1888.
<https://doi.org/10.1177/0956797613480366>
- Simonsohn, U., Nelson, L. D., & Simmons, J. P. (2014). p-Curve and effect size: Correcting for publication bias using only significant results. *Perspectives on Psychological Science : A Journal of the Association for Psychological Science*, 9(6), 666–681.
<https://doi.org/10.1177/1745691614553988>
- Song, H., Eberl, J.-M., & Eisele, O. (2020). Less fragmented than we thought? Toward clarification of a subdisciplinary linkage in communication science, 2010–2019. *Journal of Communication*, 70(3), 310–334. <https://doi.org/10.1093/JOC/JQAA009>
- Vermeulen, I., Beukeboom, C. J., Batenburg, A., Avramiea, A., Stoyanov, D., van de Velde, B., & Oegema, D. (2015). Blinded by the light: How a focus on statistical “significance” may cause p-value misreporting and an excess of p-values just below .05 in communication science. *Communication Methods and Measures*, 9(4), 253–279.
<https://doi.org/10.1080/19312458.2015.1096333>
- Wang, X., Liu, C., Mao, W., & Fang, Z. (2015). The open access advantage considering citation, article usage and social media attention. *Scientometrics*, 103(2), 555–564.
<https://doi.org/10.1007/s11192-015-1547-0>
- Washburn, A. N., Hanson, B. E., Motyl, M., Skitka, L. J., Yantis, C., Wong, K. M., Sun, J., Prims, J. P., Mueller, A. B., Melton, Z. J., & Carsel, T. S. (2018). Why do some psychology researchers resist adopting proposed reforms to research practices? A description of researchers’ rationales. *Advances in Methods and Practices in Psychological Science*, 1(2), 166–173. <https://doi.org/10.1177/2515245918757427>

Table 1

Journals in the Focal Dataset

Journal	<i>n</i>	Rationale for Selection	<i>M</i>_{Word Count}	<i>SD</i>_{Word Count}	<i>n_p</i>-values recomputed	<i>n_p</i>-values reported	<i>n_p</i>-values <i>pooled</i>
Annals of the International Communication Association	40	ICA	8,427.18	1,478.16	4	5	8
Communication Education	169	NCA	6,057.82	1,635.23	82	98	105
Communication Monographs	270	NCA, Song et al. (2020)	8,036.46	1,382.83	116	141	159
Communication Research	478	Song et al. (2020)	8,200.18	1,387.52	320	443	446
Communication Research Reports	398	Dienlin et al. (2021)	2,651.81	708.45	287	353	361
Communication Studies	351	Dienlin et al. (2021)	6,303.93	1,508.17	151	190	193
Communication Theory	215	ICA, Song et al. (2020)	7,075.43	1,261.80	5	18	19
Cyberpsychology, Behavior, and Social Networking	1,079	Song et al. (2020)	3,657.61	953.14	471	850	926
Human Communication Research	240	ICA, Song et al. (2020)	7,439.46	1,594.01	130	205	213
Information, Communication & Society	1,010	Song et al. (2020)	6,315.92	1,148.70	56	236	257
International Journal of Advertising	279	Song et al. (2020)	7,355.51	1,768.97	151	223	227
International Journal of Press/Politics	227	Song et al. (2020)	7,310.49	1,082.66	27	95	96
Journal of Advertising	194	Song et al. (2020)	7,289.72	1,976.76	127	155	161
Journal of Applied Communication Research	268	NCA	6,789.01	1,207.58	60	94	105
Journal of Communication	410	ICA, Song et al. (2020)	6,890.78	1,448.30	127	228	245
Journal of Computer-Mediated Communication	299	ICA, Song et al. (2020)	6,452.40	1,113.90	98	173	185
Journal of Health Communication	1,139	Song et al. (2020)	4,633.90	1,023.33	343	680	783
Journal of Media Psychology	194	Dienlin et al. (2021)	6,043.89	1,509.87	144	182	183
Management Communication Quarterly	214	Song et al. (2020)	7,062.44	2,675.56	44	68	68
Media Psychology	255	Song et al. (2020)	7,625.71	1,268.95	197	228	238
New Media & Society	1,098	Song et al. (2020)	6,090.61	912.70	132	298	330
Political Communication	280	Song et al. (2020)	7,250.56	1,445.04	40	161	161
Public Opinion Quarterly	398	Song et al. (2020)	5,133.37	1,829.20	52	239	244
Public Understanding of Science	538	Song et al. (2020)	6,261.73	1,524.53	65	200	212
Review of Communication	191	NCA	5,972.05	1,844.34	--	8	8
Science Communication	283	Song et al. (2020)	6,637.63	2,085.94	74	136	139

Note. Journals are arranged in alphabetical order. ICA = International Communication Association journal, NCA = National Communication Association journal. *n_p*-values recomputed = the number of papers per journal that contained strictly recomputed APA-formatted *p*-values. *n_p*-values reported = the number of papers per journal that contained reported *p*-values (independent of formatting). *n_p*-values pooled = the number of papers per journal with recomputed APA, augmented with remaining reported *p*-values. All values are number of papers retained in the models after listwise deletion.

Table 2

Terms in the Validated Open Science Dictionary

Subcategory	Term
<i>Open science</i>	dataverse
	github
	open data
	open materials
	open science
	osf
<i>Preregistration</i>	aspredicted
	power analyses
	power analysis
	pre-registered
	preregistered
	preregistration*
	registered report*
<i>Replication</i>	conceptual replication*
	direct replication*
	literal replication*
	replication studies
	replication study

Note. Terms with asterisks will retrieve any word that contains at least the prior characters (e.g., *direct replication* and *direct replications* will be counted). Since LIWC removes punctuation (replacing them with white space) during its word counting process and converts all terms to lowercase, URLs for open science repositories (e.g., *osf.io*, *github.com*, *aspredicted.org*) will still be counted because the domain name of each URL (e.g., *osf*, *github*, *aspredicted*) is retained. Therefore, terms such as *osf* will count acronyms and URLs.

Figure 1. The top panel represents articles containing at least one open science dictionary term. The bottom panel represents Pearson correlations between year and the open science dictionary. Error bars are bootstrapped 95% Confidence Intervals ($N = 5,000$ percentile replicates).

Figure 2. Trends in p -value prevalence for just significant values ($.045 < p \leq .05$) and non-significant p -values ($p > .055$). The shaded period in each figure (2012-2013) represents when the first articles would most likely appear after the open science revolution.