

Transparency and Reproducibility in the Journal of Contextual Behavioral Science:

An Audit Study

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Abstract

Increasing openness, transparency, and reproducibility in contextual behavioral science (CBS) through incorporating CBS-consistent open science practices was identified as a key aim of the ACBS Research Task Force. However, little data exist on the prevalence of open science practices currently being used in CBS research. This study aimed to address this gap by auditing the prevalence of open science and reproducibility practices in studies published in the Journal of Contextual Behavioral Science across 1 year, prior to the journal's adoption of open science recommendations (July 2020 – July 2021). Aims of the study were twofold: first, to characterize current use of open science and reproducibility practices in JCBS to serve as a point for future comparison; second, to compare the rate of open science and reproducibility practices in JCBS, the flagship journal for contextual behavioral science, against two recently published audits of top clinical psychology journals. Domains audited were use of pre-registration, practices to ensure adequate power, data availability statements, use of standard reporting guidelines, preprints, conflict of interest statements, and resource and code sharing. Results indicated that studies published in JCBS had low rates of pre-registration, data availability statements, preprint posting, and resource and code sharing. Use of mandated standardized reporting guidelines and conflict of interest disclosures, both required by JCBS at the time of the audit, reflected relative strengths. Power for correlational studies was superior to power for experimental studies; the latter reflected a relative weakness compared to other clinical psychology journals. Rates of practices required by JCBS were significantly higher than those not required. JCBS may consider strongly encouraging or mandating other open science practices to incentivize researchers to use them.

Keywords: Open Science, Reproducibility, Power, Contextual Behavioral Science

Transparency and Reproducibility in the Journal of Contextual Behavioral Science: An Audit Study

Over the last decade, the replication crisis in psychology (Open Science Collaboration, 2015) and unsuccessful large-scale attempts at replication (Klein et al., 2022) have illuminated methodological and statistical practices that hinder the progress of science at a meta-level. These practices undermine the credibility and trust of results published in psychology and range from relatively accepted traditions, such as an over-reliance on null hypothesis significance testing (Greenwald, 1975) and small sample sizes (Arch et al., 2022), to practices widely acknowledged as harmful, such as reporting exploratory results as confirmatory or *p*-hacking to obtain statistically significant findings (Simmons et al., 2011).

These practices are documented within clinical psychology (Nutu et al., 2019; Reardon et al., 2019; Tackett & Miller, 2019) and are likely to apply within the context of contextual behavioral science (CBS) research, but currently there are no data to suggest how widespread these issues may be. Moreover, there has been relatively little public attention to these broader scientific findings related to the problems in replicability and transparency within CBS research until the publication of the ACBS Research Task Force Report (Hayes et al., 2021), which identified the advancement of efforts to increase replicability and transparency consistent with CBS research strategy as a central aim of the report.

Integrating open science into CBS research culture represents one important direction for transparent and replicable scientific practices. Open science refers to a research philosophy guided by principles of transparency, openness and reproducibility, and the use of applied practices to advance these principles (Nosek et al., 2015). Open science is not a checklist of rules, but rather an array of practices that enhance transparency across all stages of the research

process, allowing other researchers important context to evaluate a study's methodology, findings, and implications (Kathawalla et al., 2021).

Open science methods can be employed before, during, and after data collection, as well as during or after preparation of resulting manuscripts. Key practices before data collection are designed to help researchers formulate the study design and primary hypotheses ahead of initiating the project and include prospective registration and planning for sufficient statistical power (Nosek et al., 2015; Reardon et al., 2019). Practices that occur after data collection and through manuscript preparation aim to promote open sharing of study methods, resources and funding information, and detailed results, so readers can interpret the study with full context and have the information needed to attempt replication. These practices encompass data sharing, preprints, use of standardized reporting guidelines, disclosure of conflicts of interest, and resource and code sharing (Nutu et al., 2019). We next describe each of these practices in more detail.

Prospective registration entails the process of making important details about the study (e.g., the design, planned analyses) available in a publicly accessible repository before enrolling participants. The aim here is to have an openly visible record of the initial study design and hypotheses, as well as all changes made to the study in a "time frozen" manner to provide transparency in the decisions and alterations made by the research team over time. In doing so, preregistration helps to clearly identify *a priori* hypotheses so that researchers are less likely to engage in research practices that undermine reproducibility, such as hypothesizing after results are known (Kerr, 1998) or presenting post hoc or exploratory analyses as confirmatory (Nosek et al., 2018).

Planning for sufficient statistical power is another key component of producing replicable findings. Power is defined as the likelihood that a study can detect a true effect if one exists

(Cohen, 1992), with adequate power usually reflecting at least an 80% chance to detect an effect of a given size. Underpowered studies are more likely to obtain biased results and inaccurate parameter estimates in the form of wider confidence intervals (Simmons et al., 2011). Combined with the tendency to only publish studies with statistically significant findings (i.e., the file drawer effect; Simonsohn et al., 2014), consistently underpowered studies lead to a published literature wherein effect sizes are overestimated. Though power is multiply determined (affected by sample size, chosen significance level, and the size of the effect in the population), sample size has been argued to be a good index of how likely an effect is to replicate (Brunner & Schimmack, 2016). Before collecting data, researchers are strongly recommended to conduct power analyses to plan for adequate sample size and to guide sample recruitment. Similarly, reporting the power analysis with the results of the study (as well as the effect size, significance level, and type of analyses used), as well any rules used in determining when to terminate recruitment, can also be used when reporting results to increase transparency about the desired sample size and reduce researcher degrees of freedom that may bias the design (Simmons et al., 2011).

Data sharing refers to the process of sharing de-identified participant data (not code for analysis or study materials) either openly, such as in an online repository or through online supplementary material, or upon request from other researchers (Naudet et al., 2018; Taichman et al., 2016). Similarly, resource and code sharing includes making analytic code, study protocol materials, or other elements of design methodology available in a public online repository or upon request from other researchers (Nosek et al., 2015).

Posting preprints of manuscripts submitted for publication allows for the immediate dissemination of scientific results online through dedicated repositories, without publication paywall and the often time-intensive peer-review process (Annesley et al., 2017). Use of

reporting guidelines, such as the Consolidated Standards of Reporting Trials (CONSORT) for clinical trials or the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) for systematic reviews and meta-analyses, describes reporting results in accordance with accepted guidelines for the type of project being conducted and aims to enhance consistency in reporting (Blanco et al., 2019). Conflict of interest (COI) disclosures are an established procedure in submitting articles for publication in healthcare professions (ICMJE, 2018). They describe situations when professional judgment regarding a primary interest may be influenced by a secondary interest, such as professional advancement or financial gain (Bero, 2017; Vasconcelos et al., 2013).

In the service of moving CBS research toward a culture of greater replicability grounded in open and transparent scientific practice, the *Journal of Contextual Behavioral Science* (JCBS) announced their adoption of open science recommendations in September 2021 for manuscripts submitted for publication (Association for Contextual Behavioral Science, 2021). At present, most JCBS publication guidelines are specified as recommendations rather than mandates. However, the journal has adopted procedures and standards for submission that necessitate several key open science practices for publication (see Table 1 for a complete set of required and recommended open science practices outlined in JCBS author guidelines at time of publication). These initiatives represent important steps toward creating an open science research culture within CBS. Yet, without a clear understanding of the prevalence of open science practices already used in published JCBS research, it is both difficult to determine the degree of need for scientific culture change and how to evaluate the effect of new editorial guidelines.

To address this gap, the current study aims to characterize the prevalence of transparency and replicability practices consistent with open science in recently published JCBS articles. In doing so, this study attempts to estimate to what degree researchers who recently published in

JCBS were engaging in open science practices immediately prior to JCBS' adopting open science guidelines to enable future comparison.

We also sought to better understand how the flagship journal for CBS compares to research published in other applied psychology journals with respect to open science practices. A central focus of this comparison was median sample size as a proxy for statistical power. The use of underpowered samples has been cited as an important vulnerability in treatment studies examining processes of change in Acceptance and Commitment Therapy (Arch et al., 2022), a significant subsection of CBS research, but it remains unclear how sample sizes in CBS studies compare to sample sizes in other closely adjacent disciplines. A recent audit study of two of the highest tier journals in clinical psychology, *Journal of Abnormal Psychology* (JAP) and *Journal of Consulting and Clinical Psychology* (JCCP) used median sample size (referred to as *N*-pact factor) as a proxy for examining statistical power in these journals over time (Reardon et al., 2019). The *N*-pact factor was selected because, although incomplete, sample size has been advanced as a good index of replicability (Brunner & Schimmack, 2016) and the median guards against bias in the parameter estimate from extremely low or high values. We chose to adopt the *N*-pact factor as our chosen metric of statistical power to be able to compare *JCBS* with other leading clinical psychology journals.

To accomplish these aims, we adapted methodology used in two prior audit studies (Nutu et al., 2019; Reardon et al., 2019) examining open science and reproducibility practices in clinical psychology journals and audited all articles published in JCBS one year prior to the publication of JCBS' open science recommendations. The results for JCBS were then compared to those in the two prior audit studies, with the caveat that the years of analyzed were not equivalent. We reviewed articles for seven domains identified as crucial to reproducibility and transparency: prospective registration, indices of statistical power (a priori power analysis and *N*-

pact factor (Reardon et al., 2019), data availability, resource and code sharing, preprints, use of reporting guidelines, and COI disclosures, (Nutu et al., 2019). As the primary aims of this study were descriptive, we did not specify a priori hypotheses.

Method

The research protocol was prospectively registered on the Open Science Framework (osf.io/ye23f/).

Inclusion Criteria

Journal articles were selected from completed volumes of JCBS published one year prior to September 2021, the year that the JCBS open practice guidelines were published. This period included five complete issues from July 2020 – July 2021 (July 2020, October 2020, January 2021, April 2021, and July 2021). Eligible articles needed to include data, even if it was not statistically analyzed, such as in the case of systematic reviews or qualitative studies. At the time of this audit, JCBS required the inclusion of a COI statement and the use of PRISMA and CONSORT guidelines. All other practices were recommended but not required. Studies must have included group-level analyses to be included in the *N*-pact factor and statistical power calculations. As such, systematic reviews, single case designs, and exclusively qualitative studies were not included.

Primary Outcomes

For each article we rated the following. First, we coded the presence of a study registration (Yes/No; henceforth Y/N) and whether it was prospective (Y/N). The pre-registration was coded as prospective if it was posted prior to the date of the manuscript submission to JCBS.

Second, to examine data sharing, we coded whether the article included a data availability statement (Y/N). Data was coded as available if authors stated a means for accessing

their data (e.g., via email, online repository). If the article stated the data was not available, we coded whether they included a statement providing rationale for why the data was not available (Y/N).

Third, we rated whether articles used the standard reporting guidelines required by JCBS: PRISMA guidelines for systematic reviews/meta-analyses and CONSORT guidelines for randomized controlled trials. As such, we noted whether the study was a clinical trial or systematic review/meta-analysis, and whether PRISMA or CONSORT guidelines appeared to be used (Y/N/NA). We coded studies as clinical trials in a manner consistent with the National Institute of Health's definition: a research study in which one or more human subjects are prospectively assigned to one or more interventions to evaluate the effects of those interventions on health-related biomedical or behavioral outcome (*Adoption of Open Science Recommendations / Association for Contextual Behavioral Science*, 2021). In keeping with Nutu and colleagues (2019), we coded Y for the article if it appeared to employ reporting guidelines without explicitly reporting that it did (e.g., displaying crucial parts such as a CONSORT or PRISMA type diagram).

Fourth, we coded whether a preprint of the article was publicly available from the authors (Y/N). Preprints were identified by searching each article title and the last name of the first author on the first 3 pages of widely used preprint repositories (Open Science Framework, PsyArXiv, BioArXiv). We also searched each article title in Google Scholar and checked all listed versions, and also checked contextualscience.org.

Sixth, inclusion of a COI statement was examined (Y/N). If a conflict of interest was identified, we coded whether the authors then explained the nature of the competing interest (Y/N/NA).

Seventh, to examine resource and code sharing, we coded whether the authors included any supplementary materials in appendices, referenced as supplementary materials, or in a repository online (Y/N).¹

Finally, we coded two metrics related to statistical power. For articles that statistically analyzed data, we coded whether the article reported an a priori power analysis (Y/N/NA). Studies identified as systematic reviews or meta-analyses, single case, and qualitative or descriptive designs were excluded.

As our primary metric of power, we recorded the sample size of each unique study to calculate an *N*-pact factor for all samples reported on in JCBS during the relevant period. For articles with multiple studies, each sample size was recorded separately. For measurement development papers that included multiple samples as focal samples for primary analyses in the same study (e.g., measurement invariance), we included all unique samples. For non-typical studies, we followed decision rules reported in previous *N*-pact factor analyses (Fraley & Vazire, 2014; Reardon et al., 2019). Specifically, for longitudinal data we used the *N* of the largest wave (usually the initial wave) unless the focal analyses depended on participants having more than one wave of data, such as analysis of change scores. For clinical trial data, we recorded the sample size that reflected all participants for whom some data was collected (e.g., an initial screener was collected, but subsequently some participants were screened out or withdrew).

Data Extraction and Coding Method

¹ Our initial pre-registration stated we would not examine this criterion for cross-sectional designs. We thought initially this criterion would be most relevant for experimental studies and clinical trials that may have detailed protocols or manuals to share. As we coded studies, we realized that many researchers publishing cross-sectional studies were sharing a breadth of resources and feel it is important to capture those efforts. As such, we updated our coding protocol accordingly to capture resources shared in cross-sectional studies.

All articles were downloaded, and article titles were exported into excel. A coding guide (osf.io/ye23f/) was developed by the first author based on Nutu et al. (2019), Reardon et al (2019), and JCBS open science recommendations. One Bachelor's level researcher reviewed articles for eligibility, coded all article level outcomes, and marked any cases as unclear for a second reviewer. A postdoctoral level researcher verified all codes against the relevant articles and discrepant codes were resolved through discussion between the two raters and by referencing the coding guide developed by the first author. For cases where resolution could not be reached or both raters remained uncertain, the first author was consulted to reach consensus. Coding occurred over approximately 6 months (December 2021-June 2022).

Analyses

Primary outcomes coded are presented as raw counts and rates expressed as percentages. The *N*-pact factor parameter was calculated as the median sample size for studies that used nomothetic statistical methods to analyze data. Samples used in single case design studies and qualitative analyses were excluded to avoid systematically biasing the estimate with necessarily small samples that use idiographic analysis.²

N-pact factors are reported for all studies and broken out by correlational studies and experimental studies. We chose to separately characterize correlational from experimental studies as experimental studies may involve small samples due to the increased cost and difficulty associated with carrying out experimental designs relative to correlational designs (Reardon et al., 2019). Finally, in line with previous *N*-pact factor analyses (Fraley & Vazire,

² We initially planned to include meta-analyses in the *N*-pact factor estimate, but upon reflection, we decided not to include them. We reasoned this metric would not actually reflect the construct of interest, the average power of recruited studies published in JCBS, as researchers have little control over the number of studies available to be included in a meta-analysis compared to when they recruit a sample for an empirical study. This decision represents a deviation from our pre-registration. Meta-analyses were included in coding for all practices other than those concerning statistical power.

2014; Reardon et al., 2019), we calculated the statistical power consistent with the observed *N*-pact factors across effect sizes. For consistency with prior studies (Fraley & Vazire, 2014; Reardon et al., 2019), we reported observed power based on population effect sizes for accepted benchmarks for small ($r = .1$; $d = .2$), medium ($r = .3$; $d = .5$), and large ($r = .5$; $d = .8$) effects (Cohen, 1992). Power calculations were conducted in G*Power (version 3.1.9.7) and used an alpha of .05. *N*-pact factors are outlined in Table 2 and assumed a two-tailed test and two independent groups³.

Results

Of the 117 available papers in the targeted JCBS issues, a total of 97 articles containing 100 unique studies and 105 unique samples met audit eligibility criteria and thus were audited. Studies were coded as cross-sectional correlational ($n = 55$), longitudinal/observational ($n = 12$), clinical trial ($n = 11$), experimental lab studies ($n = 8$), systematic review/meta-analyses ($n = 9$), single case designs ($n = 4$), and qualitative studies ($n = 2$). Registration was reported in six out of 97 articles (6.2%) of which five were prospective (83.3%). Six out of 97 articles (6.2%) included a statement explaining data availability, all of which stated their data was available. Four of these six articles posted their data online on the Open Science Framework repository. In terms of reporting guidelines, all nine systematic reviews/meta-analyses used or appeared to use PRISMA guidelines (100%) and six out of the eight clinical trials reporting primary results⁴ used or appeared to use CONSORT guidelines (75.0%). Twenty of the 97 total articles (20.62%) had preprints of their manuscripts available online. Ninety-four of the 97 articles (96.90%) included

³ Our intention was to provide a benchmark for the observed statistical power of these studies assuming analyses with low complexity. As such, power calculations did not account for other issues that may have affected observed statistical power, such as the number of analyses used. Thus, power estimates may reflect an overestimate of actual power achieved.

⁴ Clinical trials reporting secondary results were not evaluated for this criterion, as CONSORT guidelines are designed for reporting primary outcomes of clinical trials.

conflict of interest disclosures. Of the 14 articles that noted competing interests, 13 (92.86%) directly explained how the competing interest was resolved. In terms of resource and code sharing, 28 out of 97 articles (28.87%) included supplementary material either in attached appendices or online link. Materials included analytic plans, data analysis software, search terms & strategies, supplementary data, supplementary analyses, psychometrically validated self-report scales, intervention protocols, and a link to YouTube videos.

Regarding statistical power, 14 of the 86 articles identified as being appropriate to have a priori power analyses reported conducting one (16.27%, criteria described above). Twelve of these 14 included a sample size greater than or equal to the estimate specified in the power analysis (92.31%)

N-pact factor calculations are found in Table 2. The median sample size observed in coded studies was 200, with the median for correlational studies of 282.5 and for experimental studies of 56. For comparison purposes, Table 2 also includes median sample sizes for JAP and JCCP as summarized in Reardon et al. (2019).

Discussion

This study audited the flagship journal for contextual behavioral researchers, JCBS, to examine the rate at which seven widely accepted practices for increasing transparency and replicability have been used in recently published empirical articles. The aim of this analysis was to begin to characterize how much the JCBS research community had begun to adopt widely recognized open science and reproducibility practices by auditing research practices within studies published in the journal. Further, we aimed to establish a baseline for future evaluation of the success of the ACBS Open Science Recommendations and associated initiatives aimed at improving CBS research. We thus coded empirical articles for 2020-2021, the year prior to the publication of the ACBS Open Science Recommendations (Task Force on the Strategies and

Tactics of Contextual Behavioral Science Research, 2021) regarding whether they reported prospective registration, practices aimed at ensuring adequate statistical power, data availability, resource and code sharing, preprints, use of standardized reporting guidelines, and COI disclosures. At the time of the audit, only standardized reporting guidelines (CONSORT, PRISMA) and COI disclosures were mandatory practices for publication through JCBS.

JCBS Audit Results: Relative Strengths and Areas for Growth

The audit indicated that most of the replicability and open science practices we assessed were infrequently used, or at least infrequently reported, in articles published in JCBS. Only 6% of empirical articles were pre-registered, showing that this has been an uncommon practice among CBS researchers, despite being recommended as a core practice among open science proponents (Nosek et al., 2015). This low rate is particularly notable as we used a liberal definition for pre-registration. Registrations that occurred prior to manuscript submission to JCBS were coded as pre-registered, allowing cases where researchers may have registered hypotheses and statistical plans prior to conducting analyses for previously collected data. While preregistration does not guarantee quality studies, several investigations suggest that preregistration improves study quality, enhances transparency, and has the potential to reduce bias (systematic or unintentional) in the reporting of results (Nosek et al., 2018). For example, preregistration has been associated with lower risk of bias in clinical trials (Tan et al., 2019) and improved study planning (Toth et al., 2021). Researchers, when surveyed, report that preregistration improves the hypotheses generation, research design, analysis planning, pilot study design, and project workflow (Sarafoglou et al., 2022). Lending support to why preregistration is valuable, a recent study comparing dissertations to published articles found that published articles had twice the ratio of supported to unsupported hypotheses compared to the dissertations and that this was the result of dropping nonsignificant analyses, adding statistically

significant hypotheses, reversing the predicted direction of hypotheses, and alterations to data (O'Boyle et al., 2017).

Our analyses also found that only 6% of articles (6 total) stated that they would be willing to share data and only 4 of these shared data online. Recent research showed that, among authors who stated their data were available in their publications, only 7% actually provided their data when contacted (Gabelica, Bojčićb, & Puljak, 2022). Based on that estimate, our findings suggest an extremely low rate at which data is being openly shared. Only 17% of eligible articles reported an a priori power analyses, suggesting that authors may often not be adequately attending to issues of statistical power when planning studies. Preprints were also relatively rare, with our search turning up preprints for 21% of articles. This practice seems particularly relevant for increasing the accessibility of JCBS articles given that it allows preprints, but restricts access to the final, published version. Preprints could be valuable for increasing the accessibility of study findings to consumers in lower income countries who may not otherwise have access to JCBS articles through membership as well as those who are not ACBS members.

A relative strength was that among the minority of studies reporting a priori power analyses, most (92%) met or exceeded their estimated sample needs. In addition, JCBS authors frequently used CONSORT (for clinical trials) and PRISMA guidelines (for systematic reviews) when relevant, with 88% (15 out of 17 articles) appearing to have used these guidelines to at least some extent. In addition, 97% of articles included a competing interest statement. These latter two were required practices at JCBS prior to the year of this audit. The current findings suggest that mandates have been successful in maintaining high rates of use for these open science practices. This is consistent with studies demonstrating associations between clinical trial registration mandates and subsequent increases in clinical trial registration (Phillips et al., 2017; Zou et al., 2018). In contrast, the practices that were used less frequently had not previously been

required or recommended at JCBS. A data sharing statement, but not data sharing requirement, became mandatory after the study window ended.

Comparison of JCBS to other Clinical Psychology Journals

Comparison with Nutu et al. (2019) facilitates making comparisons to the broader clinical psychology research literature. The Nutu study coded a randomly selected subset of articles ($N = 200$) from among 60 psychology journals published in 2017. They found similarly low rates of preregistration (3%) and data sharing (2%). Even though most journals at the time had mandatory disclosure statements they found that only half of articles actually included such a statement. They also found that preprints were found for less than 1% of articles. On the other hand, reporting guidelines were used in 76% of relevant articles. Overall, JCBS seems to have similarly low rates of preregistration and data sharing compared to other psychology journals. In contrast, JCBS had higher rates of disclosure statements, reporting guidelines, and preprints. However, the Nutu et al. (2019) study was conducted four years earlier than this JCBS audit, and thus it is possible (and likely) that other journals may have improved during this time period.

Sample Size and Power. As a proxy for statistical power, we assessed the median total sample size of the audited studies. In addition to power, larger sample size studies should result in more accurate parameter estimates (e.g., Fraley & Vazire, 2014; Greenland et al., 2016) and effects that are more likely to replicate. In keeping with the study by Reardon et al. (2019) summarizing the observed power at top applied clinical psychology journals in 2015, we focus our discussion on $r = .20$ (and where relevant, $d = .41$). We refer to this effect size as the “smallest practical effect” as it has been suggested to be a good threshold for clinically meaningful effects (Ferguson, 2009; See Table 1).

Overall, results showed that the median study published in JCBS during the observational period (2020 – 2021) had 200 participants, which fell between median sample sizes reported in

JAP and JCCP in 2015 and demonstrated observed power that was adequate (.81) to detect the smallest practical effect. Similarly, power observed in correlational studies was a relative strength for JCBS. When examining only correlational studies, the median sample size was 282.50, resulting in strong power to detect the smallest practical effect (.86). However, it is worth noting that compared with recent data reported in Reardon et al. (2019), JCBS articles published in 2020-2021 had smaller correlational sample sizes. The median correlational study at JCBS was 24% smaller than in other leading journals five years previously. It is possible that the difference may be even greater today, as the combined median for correlational studies in JAP and JCCP for 2015 increased by almost 100 participants from 2010 and may have continued to increase since then (Reardon et al., 2019).

The median sample size of 56 for experimental studies published in JCBS was a relative weakness and resulted in inadequate power to detect the smallest practical effect (.33) and even medium effects (.45). Further, the median sample size of experimental studies in JCBS was approximately 37% the size of the median sample in leading clinical psychology journals in 2015 (Reardon et al., 2019). This relatively lower power has important implications for the CBS research as researchers are more likely to publish positive than negative findings (Franco et al., 2014, 2016). This risks greater rates of false positives and overestimates of effect sizes (Button et al., 2013; Nosek et al., 2022), which in turn risks misallocating resources, time, and effort in pursuing research programs based on chance findings (Reardon et al., 2019).

As a caveat to any comments about statistical power, it is important to consider that sample size is only one factor that needs to be interpreted in a larger context. The N-pact factor is not meant to be a comprehensive metric of power and is limited in that it cannot account for the complexity of research designs or the average effect size that journals tend to publish (Fraley & Vazire, 2014). Thus, it is possible that JCBS publishes research predominantly with large effect

sizes and therefore small studies are appropriately powered. Providing evidence against this conclusion, however, a recent meta-analysis of meta-analyses on Acceptance and Commitment Therapy found that most between-group comparisons were in the small-to-medium range (Gloster et al., 2020). This could be examined in a meta-analyses and related methods such as z-curve analyses (Sotola, 2022) looking at average effect sizes in JCBS.

A more thorough account of power would need to account for study design (number of conditions, within vs. between subjects, etc.), research topic, statistical methods and sample characteristics, among other factors. For example, experimental studies audited in this study represented a variety of study designs. These studies with multiple group comparisons wherein an experimental laboratory task was compared with a control condition ($n = 8$), randomized controlled trials ($n = 7$), and non-randomized clinical trials ($n = 4$). Due to the emphasis on between-group analyses in these designs, we chose to evaluate power estimates based on between-subjects tests and did not evaluate power estimates for within-subjects tests, which may have improved observed power in some cases. Notwithstanding, power estimates based on this audit are likely good-case scenarios, as we also did not account for factors that would further decrease power, such as analytic methods testing two conditions, tests containing unbalanced sample sizes, the number of statistical comparisons, or the use of a reduced alpha to level (e.g., 1%) to account for an increased family-wise error rate associated with multiple comparisons. Applying appropriate family-wise error corrections to mitigate the risk of false positives would require even larger sample sizes to preserve the observed power in this study.

Suggestions for Increasing Transparency and Replicability Practices in JCBS Studies

In the immediate term, we strongly recommend that JCBS require articles to explicitly report whether or not a broader defined list of important transparency and replicability practices were used or not used. For example, in recent years many authoritative scientific bodies have

recommended widespread archiving of primary research data and promulgated guidelines, including the idea that journals should include a mandatory data availability statement for all empirical articles (Cousijn et al., 2018). JCBS started requiring a data availability statement shortly after the audit period and we suggest JCBS extend this requirement to other important open science practices. If JCBS required all authors to state whether or not they followed a set of core transparency and replicability practices such as those reviewed in this article, this would at a minimum allow for an accurate assessment of how often these practices were utilized. It is possible that this could also signal to researchers that these practices are valued in the CBS community, which could increase their use over time, even if there are no explicit incentives from the journal for using them. JCBS could also support researchers in incorporating these practices by publishing or linking to clear “how to” documents explaining the core set of transparency and replicability practices the journal requires reporting on. This could also lower the barriers to compliance with open science practices, such as pre-registration, particularly for researchers in low and middle-income nations or at less research-focused institutions and support JCBS’ newer requirement of pre-registering clinical trials initiated after April of 2022.

Given that our findings showed that JCBS required practices (i.e., conflict of interest disclosure and PRISMA/CONSORT guidelines) were much more regularly used than those not required, we recommend that JCBS consider mandating other transparency and replicability practices. For example, the Equator Network (EQUATOR Network, n.d.) lists other reporting guidelines that could be considered for inclusion on an either mandatory or recommended basis. JCBS could also strengthen their existing policy requiring a data availability statement by asking researchers to report on whether their data will be linked to an online repository with clear details for accessing the data (e.g., whether it is open access, how long the data will be available), as

research shows most researchers do not provide data when requested by email (Gabelica, Bojčićb, & Puljak, 2022).

Though open science mandates may be perceived by some as restrictive or overly punitive requirements that could stifle innovation, encouraging pre-registration and other practices that prioritize transparency can also create more space for innovation. For example, in 2022 JCBS started accepting Registered Reports whereby authors submit their methods and proposed analyses to JCBS for peer review prior to data collection. In this format, submissions found to be of high quality and scientific significance are published regardless of whether the results are significant. The aims here are to positively reinforce authors for conducting well-designed, innovative, high risk, high-reward studies and to mitigate the file drawer problem by promoting open discussion of all results found, statistically significant or not. One recent study suggests that registered reports decrease the file drawer problem, showing that only 44% of results were positive in registered reports compared to 96% of a random sample from the standard literature (Scheel et al., 2021). JCBS has taken important steps to build infrastructure to support open science by welcoming open access submissions and encouraging researchers to use to data repositories.

Beyond JCBS, the Association for Contextual Behavioral Science or the CBS research community could directly take steps to increase transparency and replicability over the longer term. For example, researchers could form multi-site collaborations to enable larger sample sizes or data sharing. If workgroups could write white papers and reach consensus on standards for high quality measures to use in studies, and if combined with open data sharing, this could allow for more statistically powerful meta-studies. Greater sharing of protocols and analytic syntax could also help with access and equity in settings or countries with fewer resources. In particular, CBS could encourage greater use of preregistration in all studies, as this practice appears to

encourage use of a priori power analyses and thereby better sample sizes, and improves study planning (Toth et al., 2021).

Open Science Practices as Expressions of CBS Values

We believe that commonly recommended transparency and replicability practices are fully consonant with CBS research principles (Task Force on the Strategies and Tactics of Contextual Behavioral Science Research, 2021) and the open science guidelines of JCBS. For example, the pragmatic truth criterion of CBS holds that goals of analysis must be stated before the analysis (Biglan & Hayes, 2015) and preregistration seems a strong fit for this aim, increasing the transparency of and accountability to the CBS and broader research community of which goals and analytic approaches were agreed to prior to the study (Ong, 2022). Similarly, open science practices such as sharing of data, code, and materials fits with stated CBS values (Hayes, 2013) around community, open and nonproprietary sharing of resources and the outputs of science, and fostering prosociality by increasing opportunities for researchers with fewer resources.

In order to not further perpetuate current inequities, the dialogue around open science needs to intentionally center equity, diversity, and justice (Fuentes et al., 2022). Thus, another potential benefit of the greater adoption of open science practices is that it could help to curb harmful and exclusionary research practices such as objectivism, knowledge hoarding, perfectionism, and an emphasis on quantity over quality that are linked to oppressive colonial systems (Abo-Zena et al., 2021; Quijano, 2007) and White supremacy (Fuentes et al., 2022; Okun, 2000). We are not implying that JCBS researchers are different from other researchers, but that the influence of these systems is endemic in most scientific research as currently situated (Sue et al., 2022). Centering collaborative research, data sharing, and transparency practices has the potential to help counter these tendencies.

Limitations

We offer this study as a way to encourage improvement in the JBCS publication standards and for reflection by the CBS research community on how they might promote the use of practices that advance openness and reproducibility. We encourage caution in generalizing these findings across the diverse CBS research community as it is impossible to know how representative this sample is of the larger CBS research community. However, the current findings are likely to be representative of recent articles published in JCBS.

In terms of limitations related to study methodology, coding was based on JCBS author report, which may not fully reflect what occurred behind the scenes. For example, it is possible that researchers conducted an a priori power analysis and not reported it. However, as our coding process conservatively counted a practice as being used even if the information about it was cursory or limited, it seems more likely that our estimates represent an upper bound on the use of these practices. Another potential weakness was that coding reliability was not formally evaluated. Despite the lack of a formal reliability metric, the coding process was thorough in that initial codes were conducted by the second author and verified by the third author for accuracy. During this process, the first author was brought in for consultation to resolve codes by consensus when information presented in studies was unclear, and also conducted a final review of the codes. Despite these multiple rounds, we cannot rule out the possibility that despite our best efforts, confirmation bias may have subtly influenced the coding process at some level. A handful of studies, particularly scale development articles, were difficult to code in terms of the type of study and may have affected N-pact estimates to a small degree.

Finally, comparing the use of JCBS studies from 2020-21 to JCCP and JAP studies from five years earlier has two limitations. First, the latter journals report higher impact factors than JCBS during the periods studied. Thus, their superior study sample sizes and open science

practices could in part reflect their lower acceptance rates – that is, studies submitted to JCCP or JAP with smaller sample sizes or fewer open science practices were simply rejected. This suggests that the journals’ rejection/acceptance levels and requirements, rather than the broader research community, was responsible for the stronger sample size and open science practices evident at JCCP and JAP. Second, the time periods for comparing the two sets of journals were not matched, thereby adding a layer of speculation regarding how JCBS would compare to JCCP and JAP articles in the same time period.

Conclusion

This audit revealed that studies published recently in JCBS have significant room to grow in incorporating practices aimed to increase transparency and reproducibility in the planning, conducting, and reporting of research. Overall, studies recently published in JCBS are infrequently using many of the most commonly recommended practices for increasing the replicability and transparency of science, with notably low rates for core practices like preregistration, data sharing, reporting on statistical power, and data and resource sharing. The relatively low rate of practices not required in JCBS underscores the timeliness and importance of the open science recommendations released by JCBS.

Relative strengths of JCBS articles include high rates of practices required by JCBS during the audit period, such as conflict-of-interest statements and use of CONSORT and PRISMA guidelines when relevant. Considering this pattern of results, our data suggest that mandates work. When mandated, researchers tend to comply (Phillips et al., 2017; Zou et al., 2018). Conversely, when practices are not mandated (or even recommended), researchers don’t use these practices at high rates. Thus, if JCBS were to mandate the use of transparency and replicability practices, or at a minimum require a report on their use or omission, there is a strong possibility of increasing the quality of research in JCBS over time. We hope this paper will

advance consideration of how JCBS can continue to shape their journal submission policies to incentivize researchers to use open science practices. Similarly, we hope that CBS researchers will carefully consider our findings and work to incorporate some of these methods in their research in the service of openness, replicability, prosociality, and accessibility.

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Table 1. Open Science Practices Required and Recommended for JCBS Submissions.

Required practices	Use of PRISMA for systematic reviews, CONSORT for clinical trials Competing interest disclosures Data availability statement Pre-registration of RCTs that began data collection after April 2022 and all RCTs submitted for publication after April 2025
Recommended practices	Submission of Registered Reports for high risk/high reward empirical studies Use of open data and including direct link to data repository Pre-registration of all study types Deviations from pre-registrations should be outlined in manuscript Inclusion of openly available and accessible appendices to facilitate replication Inclusion of methods with more history and context of research studies to facilitate replication Sharing of preprints

Note: RCTs = randomized controlled trials. JCBS = Journal of Contextual Behavioral Science. This table includes all practices that are currently required or recommended as of February 2023. Required practices in bold were in place during the period in which audit took place (July 2020 – July 2021). Table compiled from JCBS author guidelines (<https://www.elsevier.com/journals/journal-of-contextual-behavioral-science/2212-1447/guide-for-authors>) and Open Science Recommendations put forth by ACBS board (https://contextualscience.org/news/adoption_of_open_science_recommendations).

Table 2. *Power to detect effect sizes in JCBS compared with top applied psychology journals*

Journal	Period	Number of Studies	Median Sample Size (NF)	Retrospective Power			
				Small ES	Medium ES	Large ES	Smallest practical ES (r = .2, d = .41)
All Studies							
JCBS	2020-2021	91 ¹	200	.29	.99	.99	.82
JAP*	2015	89	276	.38	.99	.99	.92
JCCP*	2015	101	184	.27	.99	.99	.79
Correlational Studies Only							
JCBS	2020-2021	72	227	.39	.99	.99	.86
JCCP & JAP Combined*	2015	108	297	.40	.99	.99	.94
Experimental Studies Only							
JCBS	2020-2021	19	56	.11	.45	.84	.33
JCCP & JAP Combined*	2015	80	151	.23	.86	.99	.71

Note: ¹105 unique samples were considered for inclusion and 9 meta-analyses & systematic reviews, 2 qualitative studies, 3 single case designs were excluded; *denotes NF reported in Reardon et al. (2019). For JCBS NFs, power calculations for overall and correlational NFs used effect size r and power for experimental NF used effect size d . Power was calculated using a two-tailed test at $\alpha = .05$ and assumed two independent groups. Benchmarks for small ($r = .1$, $d = .2$), medium ($r = .3$, $d = .5$), and large effects ($r = .5$, $d = .8$) were based on Cohen, 1992. Smallest practical effect refers to an effect size consistent with $r = .2$ as this has been suggested as a meaningful guideline for clinically relevant effects (Ferguson, 2009). JCBS = Journal of Contextual Behavioral Science; JAP = Journal of Abnormal Psychology; JCCP = Journal of Consulting and Clinical Psychology; N = the number of studies included in NF calculation; NF = N-pact Factor; ES = Effect size.