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Want to see more behavior? Consider institutional-level positive reinforcement

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ABSTRACT

In their review of 160 articles in the *Journal of Contextual Behavioral Science* (*JCBS*), Newsome, Newsome, Fuller & Meyer (2019) argued prior *JCBS* authors have disproportionately relied on self-report measures to the neglect of more overt measures of behavior. I agree that increasing the frequency of more overt behavioral measures of behavior could potentially improve the quality of the scholarship within *JCBS*. To encourage these changes, we might consider a fuller analysis of the factors maintaining the status quo, and further discuss the practical ways we might reinforce the behaviors we desire among our fellow scientists. In this commentary, I offer several steps the leadership within *JCBS* and the Association for Contextual Behavioral Science (ACBS) might take to encourage these changes. With skillfully-applied positive reinforcement, we might use our science to improve our science.

In their provocative article, Newsome, Newsome, Fuller & Meyer (NNFM; 2019) argued that behavioral measures, described as "the numbers reported are direct reflections of the values obtained through measurement of dimensional qualities of behavior" (p. 2), are underutilized within the *Journal of Contextual Behavioral Science* (*JCBS*), the flagship journal for the Association for Contextual Behavioral Science (ACBS). After expounding on their definition, NNFM reported that among the 160 articles they reviewed, 75% "did not include behavioral measures" (p. 4), whereas 91% of the reviewed measured behavior with self-report measures.

In their discussion, NNFM encouraged those interested in publishing in *JCBS* to diversify their measurement practices to include overtly behavioral measures, such as response times, rates, durations, and latencies. They also encouraged researchers to analyze self-report data from a more behavioral perspective. As a possible way to encourage these practices, they suggested future researchers might explicitly justify measurement practices: "We do suggest that papers in which the authors cannot fully justify their selection of reported measures warrant greater scrutiny by reviewers, editors, and readers" (p. 7).

I appreciate that NNFM offered a few suggestions to encourage more diverse and overtly-behavioral measurement practices. However, if NNFM and other likeminded parties would like to change the way future *JCBS* authors measure behavior, their cause would benefit from a greater focus on how researchers might learn about and skillfully adopt these practices (see King, Pullmann, Lyon, Dorsey, & Lewis, 2018). Before discussing change possible strategies, a little context might be of use. After all, "the scientist's behavior is itself an act in context" (Biglan & Hayes, 2016, p. 49; cf.; Long & Sanford, 2016).

1. What about context?

An important element missing from NNFM's report is a contextual analysis of why so few manuscripts in *JBCS* include "behavioral" versus self-report data. Toward that end, consider the membership of ACBS, the parent organization of *JBCS* (see Table 1). As of the time of this writing (April 22, 2019), only 10% (i.e., 838/8299) of the members listed in the ACBS registry endorsed "Applied Behavior Analyst" as their profession. In contrast, 65% of the membership (i.e., 5434/8299) identified as "Counselor/therapist/clinician."

To be sure, membership in ACBS is not identical to authorship in *JCBS*. Detailing the training backgrounds of the *JBCS* authorship would require a systematic review of its own. But the numbers from the ACBS registry give a clue as to why we might expect such a large percentage of self-report data within *JCBS*. Though they are deemphasized within behavior-analytic circles, self-report data are widely used within the social sciences, including many of the sub-disciplines within psychology. We should not be surprised upon finding patterns consistent with those norms within the pages of *JCBS*.

But why is this the norm? Self-report measures are abundant, accessible, and, as indicated by the target article, generally accepted by the peer-review process as adequate to investigate the research topics many social scientists find of interest. Self-report measures are often

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Table 1
(Applied) behavior analysts are a small minority among the ACBS membership.

Profession	*n*	%
Counselor/therapist/clinician	5434	65.5
Student	1546	18.6
Researcher	935	11.3
Applied Behavior Analyst	838	10.1
Consultant	749	9.0
Educator	748	9.0
Social Worker	748	9.0
University Faculty	719	8.7
Other	552	6.7
Coach	523	6.3
Administrator	241	2.9
Psychiatrist	171	2.1
Occupational Therapist	111	1.3
Nurse	109	1.3
Physician	103	1.2
Physiotherapist	39	0.5

Note. Answers are to the question: "Please select the category (or categories) that best describes your profession." The categories in the Profession column were those provided on the ACBS website and the categories are not mutually exclusive. For example, 126 members selected both "Applied Behavior Analyst" and "Researcher". In the interest of transparency, I am currently listed as "Counselor/therapist/clinician" and "Researcher".

easy to search for and download for little to no cost, and are relatively easy to administer in person, online, or by mail. Composite scores of their items, typically sums or averages, are generally deemed suitable for the kinds of rudimentary analyses one learns in upper-level undergraduate courses and introductory graduate courses. Easily-accessible video-sharing websites contain many free tutorial videos designed to help researchers analyze Likert-type data with a variety of contemporary statistical programs.

Perhaps we need training resources. Given common practices in social science research, coupled with concerns regarding the integrity of measurement, it seems reasonable and perhaps necessary to provide basic resources for those lacking a background in the measurement practices advocated for by NNFM. At present, such resources are scarcely available. For instance, within the "Assessment Measures" section of the main ACBS website, the only resource listed under "Behavioral Measures for Lab-Based Studies" is "Task Persistence Measures" (https://contextualscience.org/behavioral_measures_for_labbased_studies), the hyperlink for which was broken at the time of this writing. Among the "Assessment Measures," one may also find a link to "Computerized Measures" (https://contextualscience.org/computerized_measures). However, the resources for those measures are restricted to annual-fee-paying ACBS members. Given these resource limitations, it is a stretch to expect a movement towards multi-method behavioral assessment.

As mentioned by NNFM, the Implicit Relational Assessment Procedure (IRAP; Barnes-Holmes, Barnes-Holmes, Stewart, & Boles, 2010) is a prominent behavioral computerized tasks with the ACBS community. Happily, the ACBS website (https://contextualscience.org/implicit_relational_assessment_procedure_irap_website) does contain a working link to an open-source version of the IRAP (https://osf.io/kg2q8/; Hussey, 2018). However, unlike with conventional statistics for Likert-type data, there is only one freely-available video tutorial on the IRAP on the web (https://www.youtube.com/watch?v=yhWCBmzODxc). Accessibility is further limited in that the tutorial is not in English, the language used in the pages of *JCBS*.

If the *JCBS* editorial team, the leadership within ACBS, or other concerned parties such as NNFM value alternatives to self-report measures, the ACBS resource infrastructure requires expansion. However, video tutorials require no small effort to make. The same goes for generous free software, such as Hussey's open-source IRAP.

One way to reinforce efforts along these lines might be institutional recognition. During the annual ACBS world conference, we could confer a community service award for excellence in open-source software, tutorial material, or other similar efforts. This would make for a handsome line in the awards section of an academic résumé. Further, the *JCBS* editorial team might consider publishing a recurring section for technical tutorials covering topics such as study design, data collection, and data analysis. For exemplars, see the Teacher's Corner articles in *Structural Equation Modeling* (e.g., Fox, 2006).

2. Why not use signals?

It's well known that children will work for stickers. Some evidence suggests adult scientists will work for stickers, too, but in the form of research badges (Kidwell et al., 2016). At the beginning of 2014, *Psychological Science* started awarding badges for manuscripts with any combination of open data, open materials, and preregistration. Kidwell et al. showed the percentage of articles adopting those practices increased substantially over the 18 months following the badge policy adopted by *Psychological Science*.

If the editorial team of *JCBS* values "behavioral" data or manuscripts with multiple methods, they might consider a similar approach for those who adopt those practices. Doing so may require a taskforce to develop guidelines, which could be listed prominently on the *JCBS* website and in the instructions for submissions. The scientific community surrounding *JCBS* could go even further and offer badges for multi-method studies in the poster and symposium presentations at annual ACBS conferences. This way conference attendees could make more informed decisions on which presentations to spend their time on and vote with their feet.

3. Opportunities were missed

Before closing, I have a small issue to raise with NNFM. Throughout their article, NNFM used a narrow definition of "behavior," classifying all categories falling outside of their chosen definition as "non-behavioral." The dichotomy set them to open their Discussion section with:

In returning to our first question, *how do contextual behavioral scientists measure and report about behavior?* the answers are, 1) mostly non-behaviorally, 75% did not include behavioral measures, and 2) primarily by self-report scores (91%). (p. 4, emphasis in the original).

Though clever, their wording has the potential to offend the authors of 75% of the manuscripts they reviewed. It appears NNFM anticipated some pushback to their language, as they hedged on it twice in the paper: "The label of 'non-behavioral measure' should not be taken to mean that what is reported is without any basis in observations of behavior or its products" (p. 2), and, "In our coding strategy, self-report scores, third party reports, and transcription analysis were situated as sub-types of non-behavioral measures. However, that classification should not be taken as a statement about the limits of those sources of information" (p. 7). I agree with NNFM that their wording is potentially off-putting and fear it may thwart their efforts to differentially reinforce the kinds of behavioral measurement practices they advocated for.

To exemplify the limitation of their wording, by referring to self-report measures as "non-behavioral," NNFM weakened their ability to effectively highlight alternative ways to analyze those data. At one level of analysis, self-report data are obviously behavioral. Humans filled in bubbles by hand, used devices to click radial buttons on screens, and so on. As NNFM rightly pointed out, "the rates, counts, inter-response times, and latencies of survey-taking and self-reporting behaviors can be readily collected from those sources" (p. 7).

This topic could have been emphasized throughout the paper and might have served as a bridge between the seeming divide between "behavioral" and "non-behavioral" research strategies. For ideas how to make use of the "rates, counts, inter-response times …" of self-report data, self-report researchers might start by reading Meade and Craig (2012) and Maniaci and Rogge (2014). Those authors discuss survey validity issues using measures like response times, straightlining, and counts of failed attention checks. This would also make an excellent topic for a *JCBS* tutorial paper or a research workshop in an upcoming ACBS world conference.

4. Conclusion

In their target article, NNFM pointed out an undesirable pattern of behavior among the authors of recent *JCBS* articles. One of my goals for this commentary article was to sketch out how those behaviors are nested within an institutional context. Before moving to possible remedies, I pointed out multiple areas for improvement within the *JCBS*/ACBS infrastructure, some of which were small (e.g., a broken hyperlink) or idealistic (e.g., calling for more free resources).

To be fair to the *JCBS*/ACBS leadership, the institutions they serve operate within the context of the research and academic training norms of the greater social science community. Had the graduate and postgraduate training programs within our sciences placed a greater emphasis on the behavioral methods NNFM advocated for, we might have seen them represented with greater frequency in the pages of *JCBS*. Yet before we attempt to influence the behaviors among social scientists and educators across sub-disciplines, I recommend we focus first on the practices within *JCBS* and ACBS, even if that means holding them to unusually high standards. Hopefully some of the ideas expressed herein may be of use toward those aims. By following the principles of behavioral change developed by decades of careful behavioral science, I believe our institutional stakeholders can occasion and positively reinforce the rigorous research methods they seek from future authors. We can make our science better together.

Disclosure statement

The views expressed in this article are those of the authors and do not reflect the official policy or position of the Department of Veterans Affairs.

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