Furthering Open Science in Behavior Analysis: An Introduction and Tutorial for Using GitHub in Research

Article *in* Perspectives on Behavior Science · May 2019

DOI: 10.1007/s40614-019-00202-5

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Furthering Open Science in Behavior Analysis:
An Introduction and Tutorial for GitHub Repositories

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https://link.springer.com/article/10.1007%2Fs40614-019-00202-5

Number of text pages:	15
Number of tables:	1
Number of figures:	3

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Abstract

Open and transparent practices in scholarly research are increasingly encouraged by academic journals and funding agencies. Most aspects of Behavior Analytic practices have remained open and transparent because of established standards in single-case research, though strides towards incorporating statistical methods into Behavior Analytic research warrant a re-evaluation of research standards in light of these newer practices. This tutorial presents a review of the Open Science Foundation's guidelines for Transparent and Open Practices and provides instructions on how to use the free GitHub version control service to support transparent research. GitHub is a service that can be used to publicly archive various elements of scholarly research and is uniquely suited to research that involves statistical analysis and computer software. The GitHub service is reviewed, and the steps necessary to create a free account, initialize a repository, archive study files (i.e., syntax, data), and commit changes to local and remote repositories are provided. Implications of increased use of statistical methods are discussed, and archiving platforms such as GitHub are reviewed as one means of supporting open and transparent practices in research.

Introduction

Calls for greater research transparency in the social sciences have increased over the years (Grahe, 2018; Open Science Collaboration, 2015). Among the forces that have driven this trend towards more open research, the "replication crisis" has prompted a re-evaluation of various practices in scholarly research (Open Science Collaboration, 2012, 2015). The "replication crisis" refers to recent, unsuccessful attempts to replicate many of the statistically significant effects reported in hallmark psychological studies (Open Science Collaboration, 2015). Among the factors believed to contribute to these inconsistencies, various forms of questionable research and publication practices have been implicated (Branch, 2014; Gelman & Loken, 2013; John, Loewenstein, & Prelec, 2012; Nosek, Spies, & Motyl, 2012).

Concerning the field of Behavior Analysis, researchers that regularly use single-case research designs (SCRDs) have been less prone to issues regarding the replicability of their experiments (Branch, 2018). Among various reasons for this, SCRDs, by design, include some form of within- or between-subject replication (Horner et al., 2005; Smith, 2012). As a result, treatment results in recommended SCRDs are always reported alongside some evidence that the effect was replicable (Kazdin, 2011; Kratochwill et al., 2012). Aside from demonstrations of replicability, SCRDs are accompanied by thoroughly-documented parameters, such as populations, designs, and procedures (Smith, 2012; Wolery & Ezell, 1993). High levels of specificity in these areas are necessary to support direct replications at a later time (Kazdin, 2011). Additionally, the full data set in SCRDs is usually provided (visually) within the manuscript allowing others to perform visual analysis or for extraction at any later time (Wolery & Dunlap, 2001). Visual analysis functions in contrast to statistical analysis, as the full data set is always available in SCRDs so that the reader can determine effects visually (Horner & Swoboda, 2014). Statistical analyses and results are reported much differently, as authors usually describe findings observed following Null Hypothesis Statistical Testing (NHST). In this process, it is rare for both the full data set and analysis scripts to be immediately available for analytic replication (Houtkoop et al., 2018; Nuijten et al., 2017).

While SCRDs do not invite many of the issues associated with statistical inferences, such as misinterpretations of on *p* values (Branch, 2014; Nuijten, Hartgerink, van Assen, Epskamp, & Wicherts, 2016) and varying levels of statistical power (Kyonka, 2018), the advantages of SCRDs are not in simply avoiding all forms of statistical inference. Instead, many of the strengths of SCRDs and Behavior Analytic practices draw from the high levels of transparency in these types of research. For example, consider the level of detail included in peer-reviewed Behavior Analytic work. In the methods section, parameters of an experiment are thoroughly described and referenced, the dependent variables are explicitly defined with evidence of interrater agreement, and one of only several acceptable research designs is selected and referenced (Smith, 2012). In the results section, data collected through the course of an experiment is embedded directly into the publication (Wolery & Dunlap, 2001). As likely observed by readers familiar with the Open Science Framework's guidelines for Transparency and Openness Promotion (TOP; Nosek et al., 2015), the standards for transparency in SCRDs are higher than those associated with group designs and statistical comparisons.

While SCRDs will undoubtedly remain a defining feature of Behavior Analytic research and practice, statistical methods and practices have established a presence in Behavior Analytic research (Fisher & Lerman, 2014; Young, 2018). The exploration of novel methods and approaches offers new possibilities to Behavior Analysts but also presents new challenges (Shull, 1999). Whereas practices regarding SCRDs have traditionally been transparent, the conducting and reporting of statistical methods historically has not. For example, various aspects of large-scale studies may not contain the necessary information to replicate individual session conditions, assessments, or analyses. Further, study elements such as research materials (e.g., interview questions), analyses (e.g., syntax, source code), and data may not be available to support re-analysis or direct replication. As the field of Behavior Analysis ventures towards increased adoption of statistical practices and mainstream research designs, Behavior Analytic researchers must become aware of, and adapt to, the challenges associated with transparently conducting this type of research (Nosek et al., 2015; Open Science Collaboration, 2015).

Transparency and Openness in Research

Recent trends towards “Open Science” have focused on increasing the transparency of scholarly work (Open Science Collaboration, 2012, 2015). Higher levels of openness in research have been suggested as one of several ways that the psychological community might curb various forms of undesirable research practices (Branch, 2014; John et al., 2012; Nosek et al., 2015; Open Science Collaboration, 2012). While various researchers have made similar calls for transparency (Branch, 2014; John et al., 2012), Nosek et al. (2015) highlighted a set of suggested standards and practices for peer-reviewed journals to follow. Given the variability in the expectations of journals regarding open and transparent research practices, these authors constructed guidelines to assist journals in assessing the degree to which their policies encourage transparent practices. These guidelines are hereafter referred to as the TOP guidelines, and eight dimensions of transparency are identified. Each guideline was designed to stand on its own and exists along a continuum, ranging from Levels 0 (i.e., not encouraging of the practice) to 3 (i.e., all elements must be publicly shared). Naturally, the levels of transparency required are accompanied by commensurate increases in the effort and resources needed on the part of the journal and authors. Resource-wise, Levels 1, 2, and 3 have been described as practices requiring minor, moderate, and substantial resources to sustain, respectively (Nosek et al., 2015). Each of the TOP guidelines is explained below.

Citation Standards. The first TOP guideline refers to the citation of individual study elements. More specifically, this reflects the degree to which journals actively *enforce* the citation of all study elements. For example, in Behavior Analytic research this would refer to practices such as citing the methods and procedures derived from earlier works (e.g., functional analysis, stimulus choice assessments). On the continuum outlined by Nosek et al. (2015), the most basic level of support (i.e., Level 1) could take the form of journals encouraging proper citation and providing examples of such. At the highest levels of support (i.e., Level 3), journals would require all citable elements of studies to be credited before potentially publishing the work. In this guideline, as well as those that follow, Level 0 represents no observable efforts to support openness or transparency (i.e., not addressing the standard).

Data Transparency. The second TOP guideline focuses on the data collected for the study. In research that is statistical, the availability of study data allows for statistical analyses to be revisited and potentially corrected in cases where earlier analyses may have been performed in error. Transparency here speaks to the analytical reproducibility of published work (Klein et al., 2018; Wasserstein & Lazar, 2016). At the most basic levels of support, articles published by a journal would have verbiage that indicates if study data are available. In contrast, the highest levels of support would consist of journals *requiring* authors to archive their study data in public repositories for the peer-review process as well as for the readers if the work is published. Many options for archiving study data are available, with most free of charge for students and researchers (Soderberg, 2018).

Analytic Methods (Code) Transparency. Whereas the second guideline represents data, the third is dedicated to the code that pertains to study analyses. For example, the syntax used to perform analyses is be expected to accompany archived data. Similarly, studies using custom software would naturally archive these as well. The most basic support for this guideline takes the form of journals providing descriptions in published articles if the source code is available. At the highest level of support, journals would require that authors publicly archive their syntax and source code both for the reviewers as well as for future replications.

Research materials transparency. Separate from data and code, the TOP guidelines also contain recommendations regarding the specific materials used in research (e.g., vignettes, survey and interview questions). In many cases, the exact language and presentation of items may be necessary to replicate a study at some later time (e.g., hidden zero effect). A basic level of support for this dimension of transparency would take the form of providing links to study materials if made available. In contrast, strong support for this guideline would take the form of journals requiring that authors publicly archive most, if not all, documents to support future replications.

Design and analysis transparency. The TOP guidelines also provide suggestions regarding the designs used in studies. This guideline speaks to transparency in expectations regarding acceptable study designs. Basic adherence to this guideline would take the form of journals suggesting some standard of study design. Alternatively, strong adherence to this guideline would mean that authors would have to conduct research that is consistent with a set of established design standards proposed by the journal.

Preregistration of studies. Beyond transparency in the reporting of research, the TOP guidelines suggest that journals encourage the preregistration of study protocols. Briefly, preregistration of protocols refers to an a priori specification of study designs and sample sizes before conducting research. Preregistration serves to better distinguish research that is confirmatory (i.e., hypothesis-testing) from research that is exploratory (i.e., hypothesis-generating) as well as provide greater transparency in research plans (Nosek et al., 2015). Basic adherence to this guideline would consist of journals encouraging preregistration and proving links to registered studies if available and strong adherence would consist of journals requiring all submissions to have been preregistered.

Preregistration of analysis plans. Similar to preregistering study plans, the TOP provides explicit guidelines regarding study analyses. The preregistration of analyses serves to document that analyses reported in published works correspond with those from the proposed plans. That is, preregistration of analyses attempts to avoid the issue of researchers selecting some analytic strategy (whether intentional or not) based on results that most conveniently support the desired hypothesis. Basic adherence to this guideline would consist of encouraging preregistration of analyses and linking to them if available. Alternatively, strong adherence would consist of journals requiring that all submissions have preregistered analysis plans.

Replication. The final guideline refers to attempts to replicate earlier findings. Briefly, this guideline speaks to the willingness of a journal to review and accept replications of earlier studies. Basic adherence to this guideline would be journals encouraging the submission of direct replications. Alternatively, strong adherence to this guideline would be the use of Registered Reports. Journals supporting Registered Reports would review studies and determine the publishable merit based on the study design regardless of the outcome. In doing so, replications of existing studies may be published even in cases where the results are surprising and contrast the original works.

Archiving Information in Public Repositories

In reviewing each of the TOP guidelines, nearly all recommend archiving some element of research to a public repository (e.g., data, materials, analyses). Archiving resources online has historically required some level of technical proficiency on the part of the research team (i.e., hosting a personal web service) but a variety of user-friendly options are now available for free or at a low cost (Soderberg, 2018). For example, the Open Science Framework (OSF; www.osf.io) offers features such as preregistration and the archiving of study materials. Further, a range of newer options has also been developed to provide similar functionality with extended features (e.g., Code Ocean, Harvard Dataverse, Mendeley Data, DataNET, GitHub).

Each archiving system functions as a form of *version control*. Put simply; version control is a mechanism whereby iterations of information (e.g., data, source code) are stored and retained for future inspection (or comparison). Each iteration represents a change made by the researcher at some point in time (e.g., data is added, source code changed). For example, study materials or data archived in a repository might undergo various changes (e.g., removing incomplete sets) and these changes would be accompanied by documentation (i.e., the person who made the change, when, and why). For study elements, the full history of changes is retained and can be inspected by reviewers or readers at any future time. Even further, these materials may also be refined following publication (e.g., corrections, updates). The availability to document and timestamp these changes is desirable because it allows the reader to view the historical record of the research over time (e.g., materials at each stage, preregistration, final results).

Version control systems such as those provided by the Open Science Framework (www.osf.io) are robust and suited to archiving many types of research files (i.e., word processing, spreadsheets), and more specialized systems exist for larger and more complicated projects. For example, projects including complex statistical analyses and source code require a system that indicates how researchers individually contributed. In a Git-based approach to version control (e.g., GitHub, GitLab), collaborators "commit" their changes to repositories fundamentally timestamping contributions into the project's historical record. In this way, version control tracks who modifies files, when changes occur and document the reasons why changes were made. Aside from high levels of transparency, Git-based approaches to version control are particularly useful for projects that involve many contributors. For example, projects such as the Linux kernel (Torvalds, 2018) have involved over 15,000 contributors and over 200 companies (Corbet & Kroah-Hartman, 2017).

In contrast to archives that focus on binary files (e.g., spreadsheets), such as those OSF, Git-based archiving is particularly well-suited to documenting individual changes in plain-text files (e.g., comma-separated values). That is, these systems mark the specific areas and content that was changed. For example, this would include specific changes in statistical syntax (e.g., model structure) and where those changes were located, see Figure 1. This ease of access to changes is particularly desirable in the context of source code and statistical syntax, where even minor changes in the text can dramatically affect results and interpretations. As such, Git-based approaches to version control may be more appropriate for research questions that require novel statistical analyses (e.g., computer simulations). Given the recent trends encouraging the use of more advanced statistics (Young, 2018), Git-based approaches to version control may become an increasingly useful method for archiving this type of research. Even further, Git-based solutions may be increasingly relevant as Behavior Analysts continue to develop and release open source software (Bullock, Fisher, & Hagopian, 2017; Gilroy, Franck, & Hantula, 2017; Gilroy, Kaplan, Reed, Koffarnus, & Hantula, In Press; Kaplan, Gilroy, Reed, Koffarnus, & Hursh, In Press).

Using the GitHub Platform

While various services use the Git protocol for version control, this review focuses specifically on the GitHub platform (www.Github.com). GitHub is used extensively to archive and manage various projects, with over 33 million public repositories and over 28 million users at this time[1]. The GitHub service is particularly useful for Behavior Analysts because it provides options for those with varying levels of proficiency in computer programming. For example, users able to contribute to the Linux kernel would simply open a terminal (i.e., a command-line interface with the computer) and interact with the Git protocol directly (i.e., 'git clone https://github.com/torvalds/linux'). For those versed in computer programming, interactions with computers through the terminal is a frequent task. As an alternative to interfacing with the terminal, GitHub offers alternative interfaces for users who may not have the time to (or even wish to) learn to work directly with the command line. For example, GitHub provides a web-based interface where users may directly edit files (e.g., change text, add or remove the file) as well as a robust desktop computer program with greater flexibility. Both options offer a Graphical User Interface (GUI) for audiences that prefer to interact with Git visually rather than through the command line. To address readers with minimal experience with computer programming, this review focuses on using the GitHub desktop program and operating it using the GUI.

Installing the 'GitHub Desktop' Computer Program

The process of using GitHub Desktop begins by downloading the software from the GitHub website (https://desktop.Github.com). Installation files are provided for both the Windows™ and macOS™ operating systems, and the reader should download the necessary

[1] Numbers provided from https://github.com/search?q=is:public as of September 1, 2018.

files for their respective systems. If the reader has an existing account with GitHub, they should input their credentials into the GitHub Desktop computer program once it starts. If not, the GUI will assist the user in signing up an account. While the GitHub service allows users to create public repositories at no cost, the service also provides opportunities for researchers and labs to use a limited number of private repositories as well, at no cost. Once credentials are successfully inputted into the program, GitHub Desktop will note that there will be no 'local' repositories. At this point, the reader might either *create* a new repository, *add* a local repository, or *clone* a repository that already exists somewhere on the internet.

Creating a GitHub Repository

The process of creating a repository begins with selecting a directory (i.e., folder) on your local machine and instructing Git to place this location under version control[2]. This process requires both a location (e.g., Desktop) and a name for the repository (e.g., 'test repository'). While not mandatory, users are encouraged to initialize their repository with a README file. The README.md functions like a homepage for a repository, where the owner provides a description (e.g., introduction, overview) of the repository.

Similarly, authors should always include some documentation regarding how they want their work to be licensed. Discussions of specific licenses, and which to use, is beyond the scope of this tutorial and the reader is directed to the https://choosealicense.com website. The Choose A License website is hosted and curated by the GitHub development team. Regardless of the license type, the GitHub Desktop program assists the reader by including the LICENSE file that corresponds with their selection.

[2] We note here that a '.gitignore' file can be used to determine which files are tracked and which are ignored. Intermediate build objects and other binaries are traditionally not tracked because such objects are unlikely to be useful on other machines and are not tracked for this reason.

Committing Local Changes

Once selecting a license and clicking 'Create Repository,' the relevant directory will contain two files—the LICENSE and the README.md. Changes made to files in the repository are recorded, and changes can be *committed*, or written to record, with documentation summarizing the change(s). For example, should the reader open the README.md file with a text editor of choice (e.g., Notepad on Windows, TextEdit on macOS) and append "This is new text I've added" to the file, the GitHub Desktop program would indicate that there was a change in this file. A screenshot of this functionality is provided in Figure 2.

In the GitHub Desktop, the program displays information regarding which areas of files had content added to them (depicted in green) as well as areas where content was removed from them (depicted in red). In the simple change discussed (i.e., appending "This is new text I've added"), we can choose to *commit* this change to the repository we've created. In the program, we would do this by selecting the changes we would like to commit (denoted by check marks) and providing a summary of the change (i.e., "this is our first commit'). A more thorough explanation of the commit may also be entered in the "Description" area, but only a summary is required to make a commit to the repository. Notably, more than one change to one or more files can share the same commit (i.e., a single is not isolated to a single change). To commit all of this these changes to the repository, the reader would enter "this is our first commit" in the summary and click the "Commit to master" button to proceed.

Pushing Local Changes to Remote Repositories

Once a change is committed to a local repository (i.e., the directory on the reader's machine), the full sequence of changes may be viewed on the 'History' panel of the GitHub Desktop program. In this panel, the reader can view the full breadth of changes that have occurred within a repository, or individual files, since the repository was created. The changes for each respective commit are highlighted alongside information regarding who committed the change, when it was committed, and a description of why it was changed. A screenshot of this panel and its associated information is provided in Figure 3.

At this point, it warrants noting that commits exist on the user's *local* machine. If the reader was interested in pushing their *local* changes to a *remote* repository (i.e., on the internet, www.GitHub.com/USERNAME/NAME_OF_REPOSITORY), the program makes this process very simple requiring pressing the 'Push origin' button at the top of the program. Once this process begins, all the changes that have not yet been pushed to the *remote* repository on the internet will be uploaded. Once this is completed, users may view their repositories and all committed changes on GitHub (i.e., https://www.github.com/USERNAME).

Discussion

The purpose of this report was to review trends in open science and provide an overview of how GitHub can be used to support open and transparent research in Behavior Analysis. Recent reviews have found that many scholarly outlets (Nuijten et al., 2017) and funders (Houtkoop et al., 2018) are increasingly requiring research that is conducted more transparently. This report reviewed how to create a repository, commit changes, and push those changes so that archived materials can be accessed publicly. In keeping with the TOP guidelines, various elements of research can be made publicly accessible and linked to specific researchers or laboratories (i.e., analysis scripts, raw data, pre-prints).

While researchers maintain the option to provide study elements as supplemental materials, this approach is limited in comparison to GitHub for several reasons. First, platforms such as GitHub provide greater visibility to individual researchers. GitHub profiles can be designed to provide a researcher's background, their current labs, and various other aspects of their research (i.e., current and future projects). Second, individual study elements (i.e., syntax, source code) can be assigned individualized Digital Object Identifiers (DOIs), similar to peer-reviewed articles. For example, the Journal of Open Source Software provides DOIs for their peer-reviewed content (i.e., articles) and also uses Zenodo (https://www.zenodo.org) to archive corresponding software releases and mint individual DOIs. The free Zenodo service interacts with GitHub to provide DOIs and supplemental information regarding how frequently materials are viewed and downloaded. Third, using GitHub repositories to archive projects allows them to be refined following publication. For example, statistical methods developed in one paper may be updated and refined over time from publication to publication (Gilroy et al., 2017; Gilroy & Hantula, 2018). Simply including files as supplemental materials in a publication would omit information regarding who contributed to individual files, and when these changes were performed. Fourth, archiving study materials on GitHub provides a means for other researchers to contact the original researchers who gathered the data and wrote the code and other materials. In this way, other researchers would be able to consult more directly with those most familiar with these resources (Lo & Demets, 2016). Lastly, platforms such as GitHub provide opportunities for networking and collaboration. Open source collaborations typically occur regardless of geographical location or nationality, and this level of visibility opens new opportunities. Indeed, the GitHub platform has already facilitated international Behavior Analytic collaborations in the areas of Augmentative and Alternative Communication (Gilroy, 2016; Gilroy, McCleery, & Leader, 2018) as well as behavioral economics (Gilroy et al., 2017; Kaplan et al., In Press).

Limitations

While the methods and approaches reviewed here are consistent with recommendations of greater transparency in research (Nosek et al., 2015), several concerns warrant noting. Primarily, many have expressed valid concerns that requiring transparent practices may be more taxing than those without (Tenopir et al., 2011). That is, requiring that journals and authors use these tools and abide by these guidelines would likely place even greater demands upon reviewers and editors already tasked with many responsibilities. Similarly, there have been concerns expressed by researchers that releasing their data before publication may expose them to a range of professional risks (Schmidt, Gemeinholzer, & Treloar, 2016). For example, releasing data before publication may result in publications being "scooped," potentially resulting in a loss of either credit or recognition for an original work (CITE?). As such, further support at the individual and organization levels is likely to be necessary to further support open and transparent practices.

References

Branch, M. N. (2014). Malignant side effects of null-hypothesis significance testing. *Theory & Psychology, 24*(2), 256-277. doi:10.1177/0959354314525282

Branch, M. N. (2018). The "Reproducibility Crisis:" Might the Methods Used Frequently in Behavior-Analysis Research Help? *Perspectives on Behavior Science*. doi:10.1007/s40614-018-0158-5

Bullock, C. E., Fisher, W. W., & Hagopian, L. P. (2017). Description and Validation of a Computerized Behavioral Data Program: "BDataPro". *The Behavior Analyst, 40*(1), 275-285. doi:10.1007/s40614-016-0079-0

Corbet, J., & Kroah-Hartman, G. (2017). *2017 Linux Kernel Development Report*. Retrieved from https://www.linuxfoundation.org/2017-linux-kernel-report-landing-page/

Fisher, W. W., & Lerman, D. C. (2014). It has been said that, "There are three degrees of falsehoods: lies, damn lies, and statistics". *J Sch Psychol, 52*(2), 243-248. doi:10.1016/j.jsp.2014.01.001

Gelman, A., & Loken, E. (2013). The garden of forking paths: Why multiple comparisons can be a problem, even when there is no "fishing expedition" or "p-hacking" and the research hypothesis was posited ahead of time. *Department of Statistics, Columbia University*.

Gilroy, S. P. (2016). FastTalker: Cross-platform AAC application. GitHub Repository. Retrieved from https://github.com/miyamot0/FastTalkerSkiaSharp

Gilroy, S. P., Franck, C. T., & Hantula, D. A. (2017). The discounting model selector: Statistical software for delay discounting applications. *J Exp Anal Behav, 107*(3), 388-401. doi:10.1002/jeab.257

Gilroy, S. P., & Hantula, D. A. (2018). Discounting model selection with area-based measures: A case for numerical integration. *J Exp Anal Behav, 109*(2), 433-449. doi:10.1002/jeab.318

Gilroy, S. P., Kaplan, B. A., Reed, D. D., Koffarnus, M. N., & Hantula, D. (In Press). The Demand Curve Analyzer: Behavioral economic software for applied researchers. *Journal of the Experimental Analysis of Behavior*.

Gilroy, S. P., McCleery, J. P., & Leader, G. (2018). A community-based randomized-controlled trial of Speech Generating Devices and the Picture Exchange Communication System for children diagnosed with autism spectrum disorder. *Autism Research*. doi:10.1002/aur.2025

Grahe, J. (2018). Another step towards scientific transparency: Requiring research materials for publication. *J Soc Psychol, 158*(1), 1-6. doi:10.1080/00224545.2018.1416272

Horner, R. H., Carr, E. G., Halle, J., McGee, G., Odom, S., & Wolery, M. (2005). The Use of Single-Subject Research to Identify Evidence-Based Practice in Special Education. *Exceptional Children, 71*(2), 165-179. doi:10.1177/001440290507100203

Horner, R. H., & Swoboda, C. M. (2014). Visual analysis of single-case intervention research: Conceptual and methodological issues. In T. R. Kratochwill & J. R. Levin (Eds.), *Single-case intervention research: Methodological and statistical advances.* (pp. 91-125). Washington, DC, US: American Psychological Association.

Houtkoop, B. L., Chambers, C., Macleod, M., Bishop, D. V. M., Nichols, T. E., & Wagenmakers, E.-J. (2018). Data Sharing in Psychology: A Survey on Barriers and Preconditions. *Advances in Methods and Practices in Psychological Science, 1*(1), 70-85. doi:10.1177/2515245917751886

John, L. K., Loewenstein, G., & Prelec, D. (2012). Measuring the prevalence of questionable research practices with incentives for truth telling. *Psychological Science, 23*(5), 524-

532.

Kaplan, B. A., Gilroy, S. P., Reed, D. D., Koffarnus, M. N., & Hursh, S. R. (In Press). The R package beezdemand: Behavioral Economic Easy Demand. *Perspectives on Behavior Science*.

Kazdin, A. E. (2011). *Single-case Research Designs: Methods for Clinical and Applied Settings*: Oxford University Press.

Klein, O., Hardwicke, T. E., Aust, F., Breuer, J., Danielsson, H., Hofelich Mohr, A., . . . Frank, M. C. (2018). A Practical Guide for Transparency in Psychological Science. *Collabra: Psychology, 4*(1). doi:10.1525/collabra.158

Kratochwill, T. R., Hitchcock, J. H., Horner, R. H., Levin, J. R., Odom, S. L., Rindskopf, D. M., & Shadish, W. R. (2012). Single-Case Intervention Research Design Standards. *Remedial and Special Education, 34*(1), 26-38. doi:10.1177/0741932512452794

Kyonka, E. G. E. (2018). Tutorial: Small-N Power Analysis. *Perspectives on Behavior Science*. doi:10.1007/s40614-018-0167-4

Lo, B., & Demets, D. L. (2016). Incentives for clinical trialists to share data. *New England Journal of Medicine, 375*(12), 1112-1115.

Nosek, B. A., Alter, G., Banks, G. C., Borsboom, D., Bowman, S. D., Breckler, S. J., . . . Yarkoni, T. (2015). Promoting an open research culture. *Science, 348*(6242), 1422-1425. doi:10.1126/science.aab2374

Nosek, B. A., Spies, J. R., & Motyl, M. (2012). Scientific Utopia: II. Restructuring Incentives and Practices to Promote Truth Over Publishability. *Perspect Psychol Sci, 7*(6), 615-631. doi:10.1177/1745691612459058

Nuijten, M. B., Borghuis, J., Veldkamp, C. L. S., Dominguez-Alvarez, L., Van Assen, M. A. L.

M., & Wicherts, J. M. (2017). Journal Data Sharing Policies and Statistical Reporting Inconsistencies in Psychology. *Collabra: Psychology, 3*(1). doi:10.1525/collabra.102

Nuijten, M. B., Hartgerink, C. H., van Assen, M. A., Epskamp, S., & Wicherts, J. M. (2016). The prevalence of statistical reporting errors in psychology (1985–2013). *Behavior research methods, 48*(4), 1205-1226.

Open Science Collaboration. (2012). An Open, Large-Scale, Collaborative Effort to Estimate the Reproducibility of Psychological Science. *Perspectives on Psychological Science, 7*(6), 657-660. doi:10.1177/1745691612462588

Open Science Collaboration. (2015). Estimating the reproducibility of psychological science. *Science, 349*(6251), aac4716. doi:10.1126/science.aac4716

Schmidt, B., Gemeinholzer, B., & Treloar, A. (2016). Open Data in Global Environmental Research: The Belmont Forum's Open Data Survey. *PLoS One, 11*(1), e0146695. doi:10.1371/journal.pone.0146695

Shull, R. L. (1999). Statistical inference in behavior analysis: Discussant's remarks. *The Behavior Analyst, 22*(2), 117-121. doi:10.1007/bf03391989

Smith, J. D. (2012). Single-Case Experimental Designs: A Systematic Review of Published Research and Current Standards. *Psychological methods, 17*(4), 10.1037/a0029312. doi:10.1037/a0029312

Soderberg, C. K. (2018). Using OSF to Share Data: A Step-by-Step Guide. *Advances in Methods and Practices in Psychological Science, 1*(1), 115-120. doi:10.1177/2515245918757689

Tenopir, C., Allard, S., Douglass, K., Aydinoglu, A. U., Wu, L., Read, E., . . . Frame, M. (2011). Data sharing by scientists: practices and perceptions. *PLoS One, 6*(6), e21101. doi:10.1371/journal.pone.0021101

Torvalds, L. (2018). Linux kernel source tree. Retrieved from https://github.com/torvalds/linux

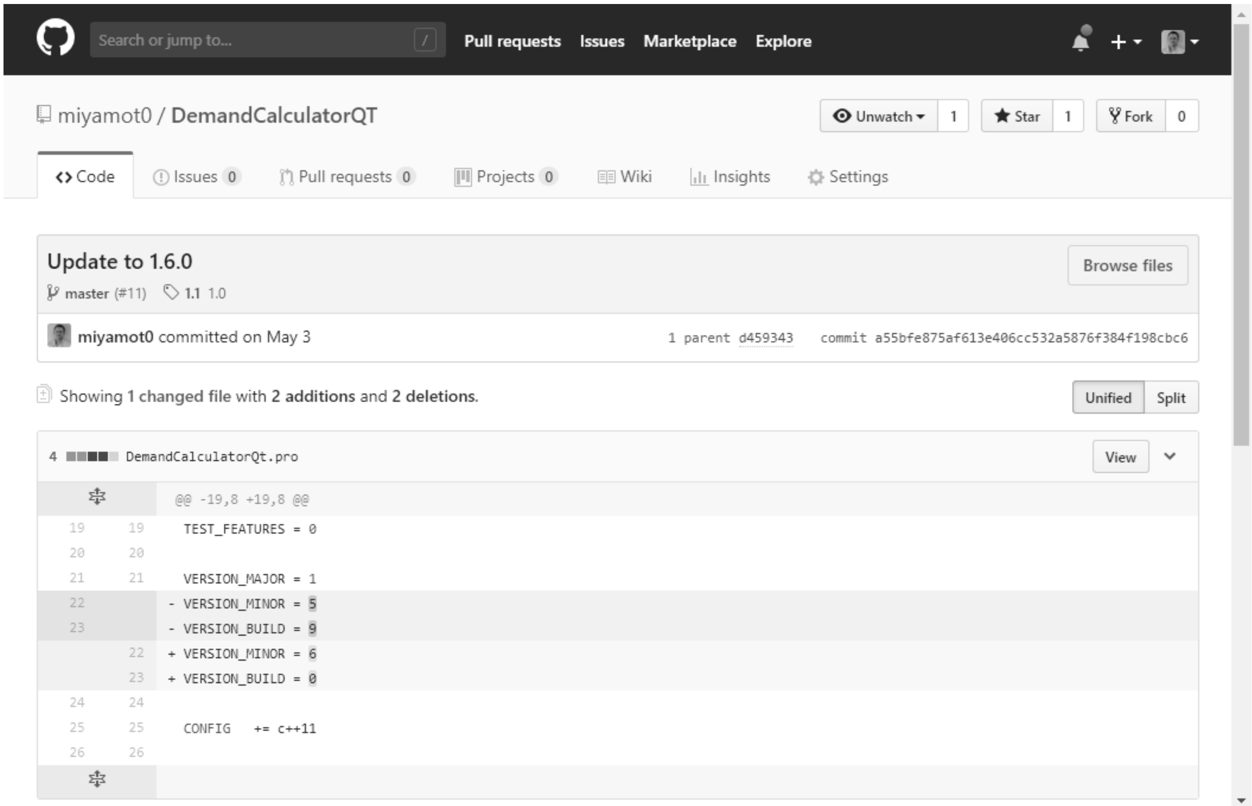
Wasserstein, R. L., & Lazar, N. A. (2016). The ASA's Statement on p-Values: Context, Process, and Purpose. *The American Statistician, 70*(2), 129-133. doi:10.1080/00031305.2016.1154108

Wolery, M., & Dunlap, G. (2001). Reporting on Studies Using Single-Subject Experimental Methods. *Journal of Early Intervention, 24*(2), 5.

Wolery, M., & Ezell, H. K. (1993). Subject descriptions and single-subject research. *J Learn Disabil*, *26*(10), 642-647. doi:10.1177/002221949302601001

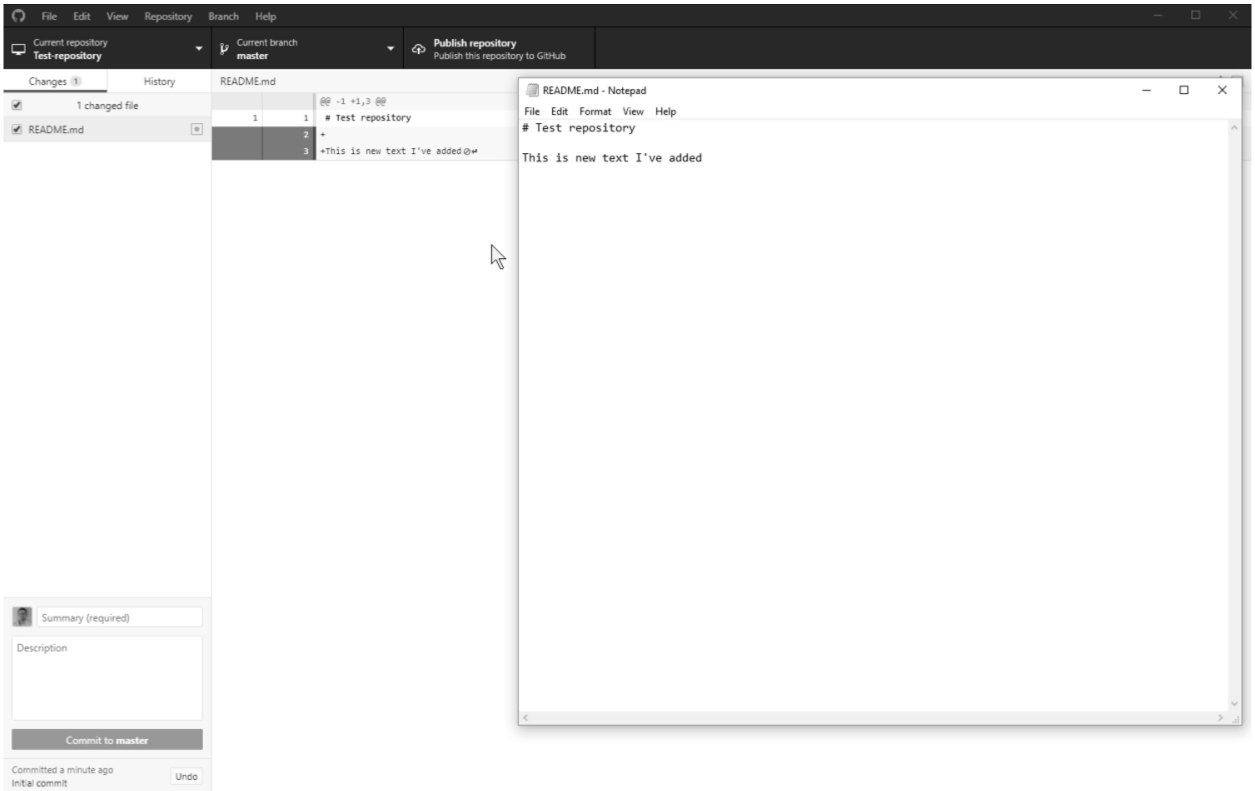
Young, M. E. (2018). A place for statistics in behavior analysis. *Behavior Analysis: Research and Practice, 18*(2), 193-202. doi:10.1037/bar0000099

Figure 1. Committing changes in a Git-based project



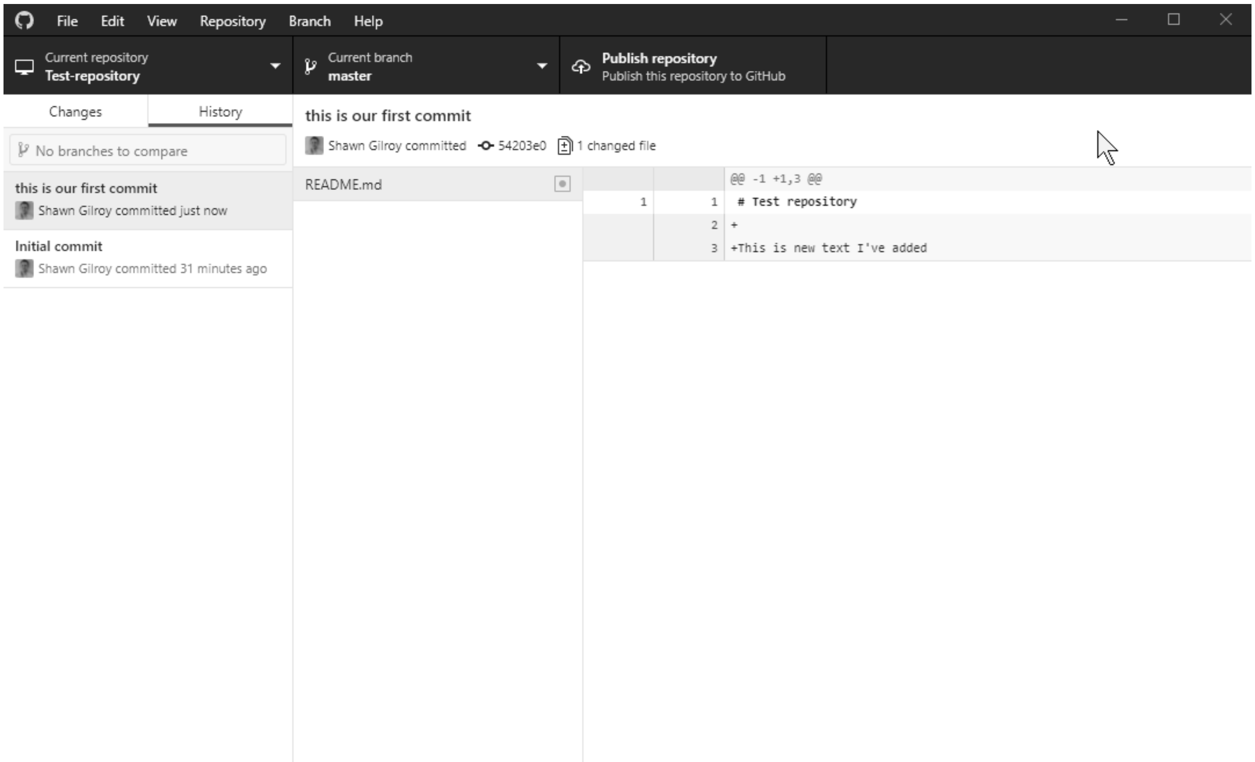
Note: The figure above shows a "diff" of a project file for a peer-reviewed software project. In this file, the author of the change is identified, the date of the change is noted, and the specific lines added and removed are displayed for each of the relevant files.

Figure 2. Tracking changes in files under version control



Note: This figure illustrates how GitHub Desktop detects instances when files are changed. In the example above, a blank line and the text "This is new text I've added" are appended to the file. This change is detected and described by the GitHub Desktop program, as denoted by the adding of a line (i.e., '+').

Figure 3. History of commits and changes in repositories



Note: The figure above depicts a history of commits to the local repository. In the 'Initial Commit,' the README.md and LICENSE files were added and in the 'this is our first commit' commit, the contents of README.md were modified.