A survey of experimental stimulus presentation code sharing in major areas of psychology

Amit Rawal[1] †, Vuong Truong[2,3,4] †, Yu-Hui Lo[5,6], Lin-Yuan Tseng[5,6], and Niall W. Duncan[5,6]

1. Ernst Strüngmann Institute for Neuroscience in Cooperation with Max Planck Society, Frankfurt, Germany

2. Vision and Cognition Lab, Centre for Integrative Neurosciences, Tübingen, Germany

3. Department of Psychology, University of Tübingen, Germany

4. Max-Planck Institute for Biological Cybernetics, Tübingen, Germany

5. Graduate Institute of Mind, Brain and Consciousness, Taipei Medical University, Taipei, Taiwan

6. Brain and Consciousness Research Centre, TMU-Shuang Ho Hosptial, New Taipei City, Taiwan

† These authors contributed equally

Computer code plays a vital role in modern science, from the conception and design of experiments through to final data analyses. Open sharing of code has been widely discussed as being advantageous to the scientific process, allowing experiments to be more easily replicated, helping with error detection, and reducing wasted effort and resources. In the case of psychology, the code used to present stimuli is a fundamental component of many experiments. It is not known, however, the degree to which researchers are sharing this type of code. To estimate this, we conducted a survey of 400 psychology papers published between 2016 and 2021, identifying those that openly share stimulus presentation code. For those that did, we established if it would run following download and also appraised the code's usability in terms of style and documentation. It was found that only 8.4% of papers shared stimulus code, compared to 17.9% sharing analysis code and 31.7% sharing data. Of shared code, 70% ran directly or after minor corrections. For code that did not run, the main error was missing dependencies (66.7%). The usability of the code was moderate, with low levels of code annotation and minimal documentation provided. These results suggest that stimulus presentation code sharing lags behind other forms of code and data sharing, potentially due to less emphasis on such code in open-science discussions and in journal policies. The results also highlight a need for improved documentation to maximise code utility.

experiment code | open science | reproducibility
Correspondence: ***niall.w.duncan@gmail.com***

Introduction

Computer code plays a vital role in modern science, from the conception and design of experiments through to final data analysis (10). This importance of code has recently come further into focus to the scientific community both through the lens of the response to the "replication crisis" (2, 37) and through the growth of the open science movement (3). This has lead to the active promotion of code sharing across a range of scientific disciplines (6, 32, 42, 49).

In the case of psychology, the code used to present stimuli is a fundamental component of many experiments. It is this code which determines what form stimuli take and the manner in which they are displayed, determining what the participants experience and the responses they can make. Viewed through the lens of code sharing, there are clear advantages to making this stimulus presentation code openly available. Such sharing increases the opportunity for the detection of errors (21, 56). This can help reduce potentially erroneous findings resulting from incorrectly specified stimulus presentation properties. Relatedly, having access to the original code is of use to those trying to replicate previous work as it removes the scope for flaws in the replication attempt that could arise from having to reverse-engineer a stimulus presentation paradigm (14, 34, 48). Finally, since psychology studies often involve the use of similar experimental paradigms, having the code to instantiate those paradigms already available for reuse and adaptation reduces wasted effort and resources (8, 22, 50). This is particularly true in the case of experiments that utilise complex stimuli or require integration of multiple modalities.

The described advantages of code sharing are diminished if other researchers are unable to understand or execute it. In terms of code comprehension, the computing community has developed guidelines and standards for how one writes and shares code in order to make it as readable as possible. For example, annotation of code is encouraged so that it is easy to understand what is being done by any given line or section. Similarly, informative variable names are encouraged so that their purpose is clear and they are easy to track through the program (16). Going along with these in-code steps is the need to provide detailed and accurate documentation. This allows other researchers to understand what has been done and, ideally, why it has been done (53). Although resources are available for researchers to become familiar with good coding principles (30, 44), the majority of people creating scientific coding are estimated to be self-taught (18, 43) and so there is potential for considerable variation in the interpretability, and thus utility, of what stimulus presentation code is shared (33, 59). Similarly, the utility of shared code is lessened if it cannot be run by other researchers without extensive user intervention.

Although there are clear potential advantages to sharing stimulus presentation code, it is not clear to what extent psychology researchers are currently making their code available in this way. Previous work identifying a low level of general research material sharing within the field suggests that the majority of researchers are not, but those studies did not look at stimulus presentation code specifically (15, 19). This leaves the question of participation levels open and so a more specific understanding of the current state of the field would be useful for motivating future improvements.

Based on the described issues, the first aim of the current work was to survey a selection of recent publications in psychology that involved some form of experimental stimulus being presented to participants to establish what proportion of studies provided the stimulus presentation code in an openly usable format. Having identified those that did provide code, we then established whether or not it could be executed without significant user modification. Finally, the code and related documentation was appraised for how readable and informative it was.

Methods

Literature search

A literature search was conducted in June of 2021 using Google Scholar. Google Scholar was chosen as it includes searching of article main texts whereas other scholarly search engines, such as PubMed, only include titles and abstracts (39). This functionality was important as details of stimulus presentation methods are generally only given in the main body of an article.

The search target had two components, namely programming language and psychology topic. Since Python and MATLAB are the two of the most commonly used programming languages for psychology research (5), we limited our search to the two primary open-source stimulus presentation libraries for those languages: Psychtoolbox for MATLAB (28) and PsychoPy for Python (38). E-prime is also widely used by psychologists but is not open-source and so was excluded (5). The psychology topics searched for were: attention; emotion; executive function; learning & decision making; masking; motor & action; visual perception; and working memory. These eight widely studied topics were selected to produce a representative snapshot of the overall psychology literature.. These components were combined to produce the search string: *("PsychoPy" OR "Psychophysics Toolbox" OR "Psychtoolbox") AND ("⟨name of topic⟩").*

The search period was limited to between 2016 and 2021. Experimental works published in peer-reviewed journals or hosted on preprint servers were included in the study. Review papers were excluded, as were meta-analyses and preprints where data or code were embargoed. The first fifty suitable papers for each topic were retrieved (400 across eight topics). This number was chosen as it was observed that search results became less topic-specific after around the fifth page of Scholar results. Having collected this set of papers, duplicates that appeared under multiple psychology topics were removed (n = 9). The resulting set of papers was then appraised in a two step process. The first step involved establishing basic information about each work, including whether or not open data and/or code was available, along with publication metrics (Table 1). Those that provided stimulus presentation code were then passed on to a detailed code appraisal. A visual overview of the search and appraisal procedure can be found in Supplementary Figure 1.

Code appraisal

Stimulus presentation code was appraised according to three sets of criteria: Execution, Programming environment, and Usability (see Table 2).

The first of these, 'Execution', is concerned with whether the code runs or not. Code was deemed to run if the shared version executed successfully directly as downloaded or with minor modifications. Modifications that were classed as minor included installing a missing package, commenting out a line, or making small changes to syntax (e.g., changing data folder path names or altering slashes to fit operating system (OS) requirements). Such tasks were judged to be easily undertaken by researchers with non-expert levels of programming knowledge. Where code did not run, the type of error that prevented execution was recorded.

The 'Programming environment' category includes information about the tools used to write the code, including the OS of the computer where the code was created, the programming language, the stimulus presentation toolbox used, and the respective versions of these software. Software version was noted as software generally evolves over time, introducing incompatibilities that can affect the reusability and replicability of the code. Information about the programming environment was taken from various sources, including: the research article; descriptions or documentation provided on the platform where code was shared; and in annotations present in the code itself. Since each code set was appraised twice (see *Appraisal Procedure*, below), both appraisers independently searched for this information and resolved any inconsistencies between themselves.

Finally, the 'Usability' category recorded factors that are deemed good programming practice and which make code easier to understand and work with. Such factors included: the level of modularity in the code; whether variables were given meaningful names (e.g., stimulus_duration, visual_angle, etc.); the degree to which code was annotated; and the amount of documentation that was available for the code. In cases where experiment code was split over multiple files, the usability appraisal was conducted on the file that generated the stimuli.

Field	Description
Sharing	
Stimulus presentation code	Stimulus presentation code was shared [1] or not [0]
Data	Any form of data was shared [1] or not [0]
Analysis code	Code for statistical analysis or computational modelling was shared [1] or not [0]
Platform	Where code or data were shared [GitHub; OSF; Other]
Publication metrics	
Citations	Number of citations as shown in Google Scholar
Journal IF	Most recent journal impact factor listed on https://www.bioxbio.com/. For those not listed there, the first IF given by a search on Google was used

Table 1. Basic information recorded for each article identified through literature search. Relevant coding for each item is given in brackets.

Field	Description
Execution	
Code runs	Code runs in its original form/with minor corrections [1] or not [0]
Corrections	Corrections are required for code to run [1] or not [0]
Error type	Error(s) stopping code from running [syntax, hardware, missing dependency]
Programming environment	
Operating system	OS and version upon which code was run (e.g., Windows XP)
Language	Programming language used [MATLAB, Python] and its version (e.g., MATLAB 2016a)
Toolbox	Toolbox used for stimulus presentation [Psychtoolbox, PsychoPy] and its version (e.g., Psychtoolbox 3.0.12)
Usability	
Modularity	Stimulus presentation code comprised of one file with no helper functions [0]; one file with helper function(s) defined inside it [1]; or helper function(s) were in separate file(s) [2]
Variable naming	Meaningful [1] or arbitrary [0] variable names used in code
Annotation	Extent of comments in the code [minimal, moderate, comprehensive]
Documentation	Level of documentation available for code in the article, README file, website or within code. Mutually inclusive levels: [1] Specifies file that runs experiment [2] Provides information on code usage [3] Provides explanation of code implementation rationale and/or suggestions for adaptation of code for other uses

Table 2. Criteria used for code appraisal. Relevant coding for each item is given in brackets.

Appraisal procedure

Each set of stimulus presentation code was appraised independently by two researchers, assigned randomly amongst the four researchers undertaking appraisals. Each researcher would attempt to run the code on their own computer (see Table S1 for details about configuration) and then noted outcomes according to the different criteria outlined above, in *Code appraisal*.

Differences in objective criteria related to the code and metadata could occur for the following fields - *Programming language and version, OS and version, Stimulus presentation toolbox and version, and Modularity*. In these cases, discrepancies between the two appraisals could arise due to the same information being documented in different detail in different sources. For example, the Psychtoolbox version mentioned in an article and its corresponding GitHub README could have been 'PTB-3', while the OSF Wiki mentioned 'PTB-3.0.12'. Here, both appraisals would be matched to include the same amount of detail, as found in the most detailed source (OSF Wiki, in this example). Ratings of *Variable naming, Annotation*, and *Documentation* include a subjective element and so could vary between researchers. A single consensus rating between the two researchers was then arrived at through discussion between them. Each researcher ran code on different computers and so any cases where there were differences in *Code runs, Corrections*, and *Error types* were noted.

Description of data and statistical analyses

Variables of interest were presented as raw count of papers, along with percentage of total papers. To test whether data and code sharing were influenced by journal status (as taken to be reflected by the JIF), and whether sharing practice boosted the paper's popularity, we used Mann-Whitney U tests to compare JIF and citation counts for papers that shared stimulus presentation code, analysis code, or data, with papers that did not. P-values were adjusted for multiple comparisons according to the Benjamini-Hochberg procedure (4).

Results

Code and data sharing from 2016-2021

The search identified 391 unique articles (13 preprints). Amongst these, 30 (8.4%) shared their stimulus presentation code, 70 (17.9%) shared their analysis code, and 124 (31.7%) shared their data (Figure 1A). Throughout the five years sampled, there was an upward trend in the sharing of data, analysis code, and stimulus presentation code. In 2016, none of the articles shared stimulus presentation code, whereas in 2021 the number had increased to 10.20%. The same trend occurred for data sharing (19.64% to 44.90%) and analysis code sharing (1.79% to 26.53%) (Figure 1B). The relative proportions of code/data sharing held true across all of the research topics surveyed (Figure 1C). Regarding the choice of sharing platform, in the 131 (33.5%) articles that shared code and/or data, 66 (50.4%) were linked to OSF and 22 (16.8%) were linked to GitHub. Other options, including Dropbox, FigShare, OpenNeuro, Zenodo, Neurovault, and institution websites, accounted for the remaining 32.8%.

Looking at publication metrics, there was no difference in the number of citations to articles that shared stimulus presentation code and those that did not (U = 5,548.0, P_{FDR} = 0.29). There was also no difference in citations for articles that did or did not share analysis code (U = 10,001.0, P_{FDR} = 0.29) or data (U = 15,546.5, P_{FDR} = 0.29). In contrast, JIF was higher for articles that did share stimulus presentation code (U = 3649.0, $P_{FDR} < 0.001$). JIF was also higher for articles that shared analysis code (U = 6815.5, $P_{FDR} < 0.001$), and data (Mann-Whitney U = 11,245.5, $P_{FDR} < 0.001$). Data are shown in Supplementary figure 2.

Appraisal of 30 stimulus presentation code sets

Execution

In our sample of 30 code sets, 21 (70.0%) could be made to run in the first round of appraisal and 22 (73.3%) in the second (Figure 2A). The one code set that differed between rounds would run on Windows but not on Linux. Among these, corrections or modifications had to be made to 14 code sets (66.7%) in the first round of appraisal for them to run, and to 11 (50.0%) in the second. These corrections included actions such as commenting-out lines of code that required certain hardware (such as an eye-tracker), commenting-out code that attempted to load files not supplied with the source code, or adding additional lines of code to overcome an explicit error. For code sets where code could not be executed even after corrections, we categorized errors into three categories: syntax, hardware, and missing dependency. In the first round of appraisal, we encountered one syntax (11.1%; proportion within the total number of errors), two hardware (22.2%), and six missing dependency errors (66.7%), while in the second round, we encountered no syntax, two hardware (25%), and six (75%) missing dependency errors (Figure 2B).

Usability Eleven of the code sets (36.7%) included documentation (Figure 3A). Amongst these, ten (90.9%) explicitly specified which file (script/function) would execute the experiment code, eight (72.7%) provided information on the usage of the code, and eight (72.7%) provided explanations of their code implementation or suggestions on how to modify or adapt the code for other purposes.

Among the 30 code sets, six (20%) mentioned the OS of the computer where code was originally executed, five (16.7%) mentioned the OS and also its version, while the remaining 19 (63.3%) did not provide any details about the OS at all (Figure 3B). In terms of the programming language, 26 code sets (86.7%) were written in MATLAB (using Psychtoolbox) and the remaining four (13.3%) in Python (using PsychoPy). The version of the programming language was mentioned for five (16.7%) datasets. As for the toolbox (Psychtoolbox/Psychopy), 11 (36.7%) mentioned only the toolbox, while 19 (63.3%) mentioned toolbox and its version.

Regarding the level of annotation present in the code, 21 code sets (73.3%) had moderate and six (20%) code sets had comprehensive levels of annotation. Only two code sets

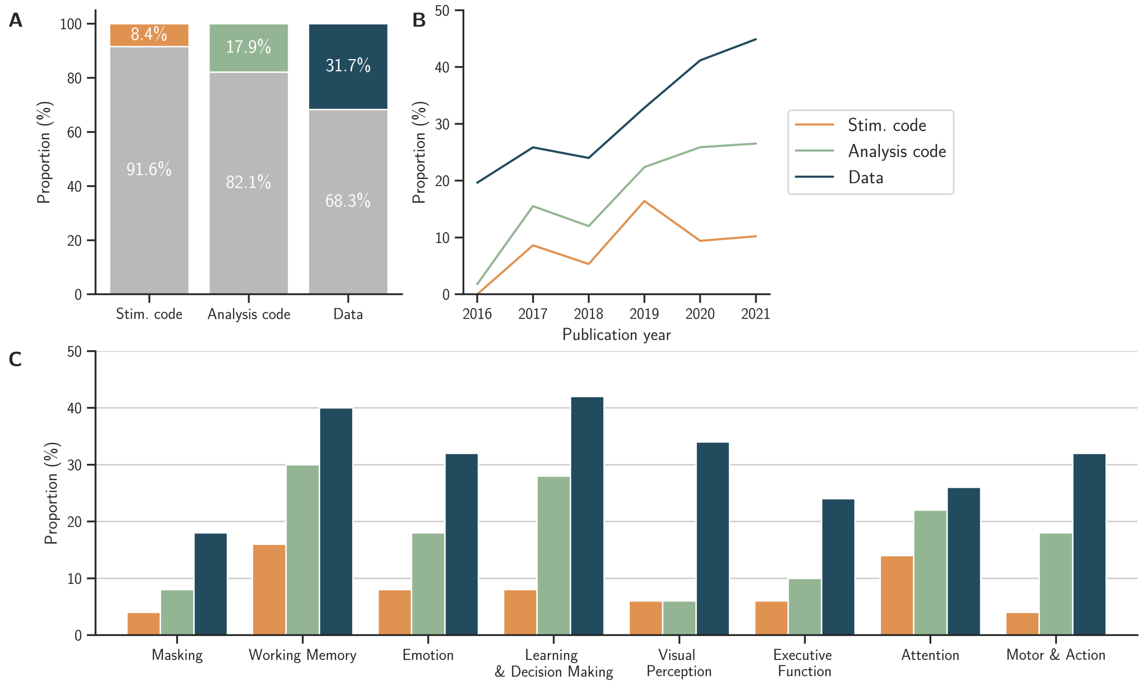

Figure 1. Descriptive statistics for the 391 unique articles identified. (A) Percentage proportion of articles that shared stimulus presentation code, analysis code, or data (coloured patches), and those that did not (denoted in grey). (B) Percentage proportion of articles each year that shared stimulus presentation code, analysis code, or data. (C) Percentage proportion of articles each that shared stimulus presentation code, analysis code, and data across eight major topics in psychology and cognitive science.

(6.7%) had minimal levels of annotation (Figure 3C). Looking at the modularity of the code sets, ten (33.3%) were assigned a modularity value of 0, meaning that the stimuli were presented from a single file that included all components and had no helper functions to modularize code functionality. Four code sets (13.3%) were assigned a modularity value of 1, where the single-file script included helper functions. The remaining 16 (53.3%) were assigned a modularity value of 2, where helper functions or meaningful components were separated into separate files. In all 30 code sets, for both rounds of appraisal, the appraisers found the majority of variable names to be meaningful, in that they reflected the values stored in those variables rather than having an arbitrary name.

Discussion

The results of this survey of recent literature reveal an apparent trend towards increased sharing of experimental materials and data for psychology research. Rates of stimulus presentation code, analysis code, and data sharing all increased over the period studied. This increase mirrors that seen in other research domains and would seem to indicate wider adoption of open science principles (15). The overall proportion of studies that are sharing materials remains low, however, particularly in the case of stimulus presentation code. Data was shared with almost one third of articles (31.7%) but only 8.4% shared stimulus code.

The difference in rates of sharing between data and code may reflect a greater emphasis on the former in journal policies (51). At the same time, researchers may have less confidence in sharing their code than they do data, feeling that their code is not written to a sufficient standard for other people to see. This lack of confidence in coding ability may arise in part from many research scientists having little or no formal training in how to write code (18, 43). Compounding this may be a lack of time and resources, which are cited by scientists as the primary reasons for them not sharing both code and data (1, 36, 54). Finally, a lack of enthusiasm for sharing code may be related to such behaviour not being rewarded by current academic incentive structures (1, 17, 20).

Addressing the aforementioned issues may help increase the sharing of stimulus presentation code. Firstly, journal policies that require code sharing in addition to data sharing would seem advantageous. Such policies need to be actively enforced though, as evidence suggests that current data sharing policies are often ignored by authors (13, 52). These active policies are preferable to more passive ones, such as the awarding of "badges", as evidence for the effectiveness of such measures is mixed (25, 46, 47). Secondly, learning how to code effectively could be encouraged as a fundamental skill for a modern research scientist (24). A wide range of educational resources are available online to assist with this (30, 44). It would be important that any move towards increased coding training not require it in addition to existing workloads though, given that a lack of time is already seen as

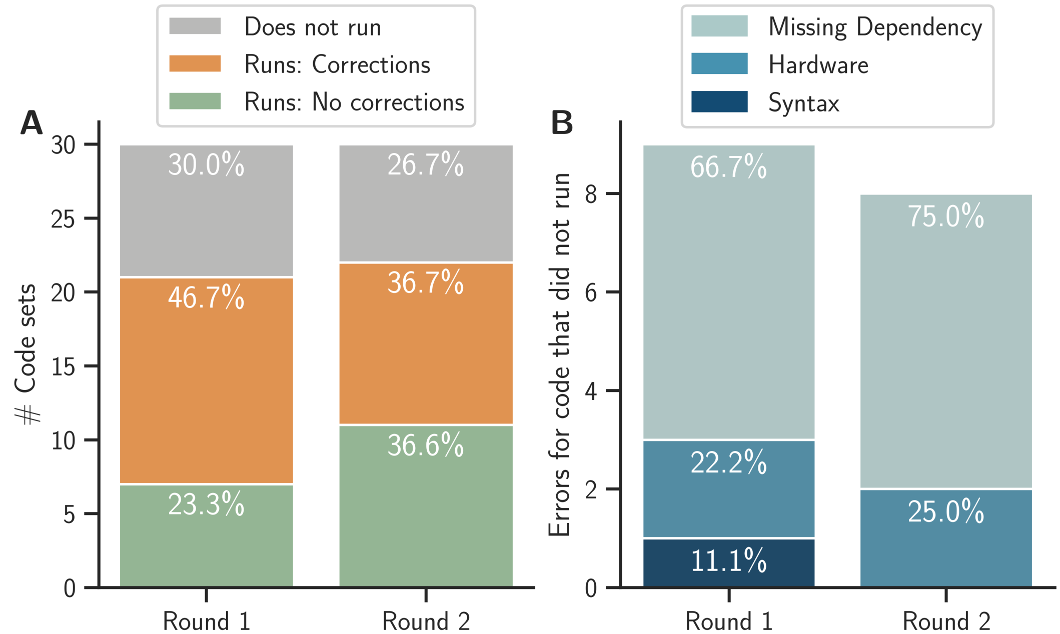

Figure 2. Execution: (A) Number and proportion of code sets that could be run without correction and after corrections for each round of appraisal. (B) Types of errors returned when the codes could not be run. Proportions of code sets in each category are shown as percentages in white.

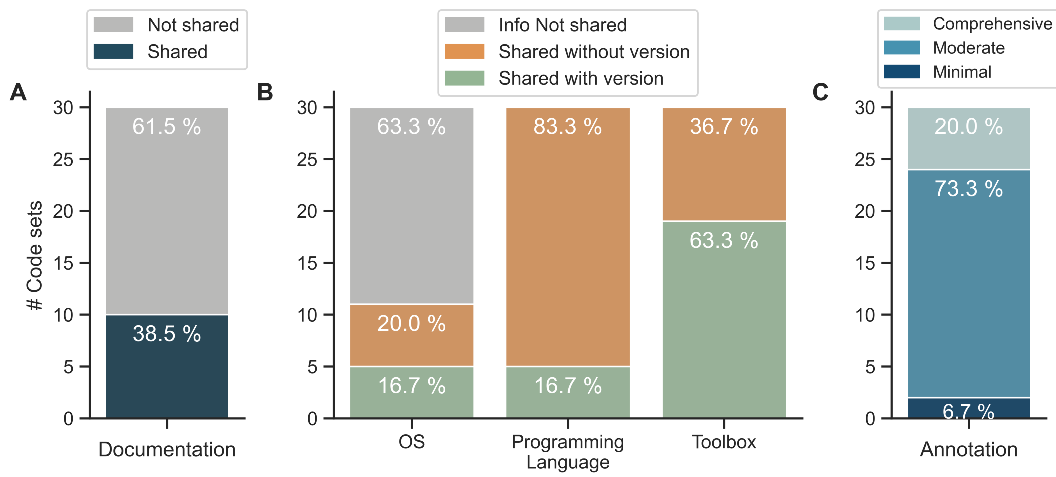

Figure 3. Usability: (A) Number and proportion of code sets that included documentation. (B) Number and proportion of code sets that shared information about the operating system (OS), programming language, and toolbox used, with or without relevant version numbers. (C) Ratings of the annotations provided within each code set. Proportions of code sets in each category are shown as percentages in white.

a barrier to code sharing (1, 54). In terms of incentives, sharing of data and other research materials is promoted through community guidelines such as FAIR (58) and TOP (34), as well as policies such as the European Union strategy for open science (7). How these schemes translate into changes in how hiring or promotion committees act, for example, or alter the academic prestige economy, will be key for changing stimulus presentation code sharing behaviour (11, 57).

Some prior work has suggested that data sharing can lead to the relevant work being cited more (9, 41, 60). No such effect was seen here in terms of increased citations for articles that shared stimulus presentation code. It may be that this contrast reflects field-specific citation behaviour, as prior work on data sharing and citations was not based on the psychology literature. Alternatively, the works included here may have been published too recently for an effect on citations to have become apparent. It also remains possible that citation behaviours differ depending on what type of materials are shared (e.g., data compared to stimulus presentation code), with direct investigation of this possibility perhaps justified in the future. Although no relationship was seen between stimulus presentation code sharing and citations, it was the case that sharing was associated with higher journal impact factors. This fits with prior observations that journals with higher impact factors are more likely to have stronger forms of data sharing policy (26, 45).

Although there was some variation in where experimental materials were shared, most was shared through either GitHub or OSF. These each have their advantages and disadvantages relevant to the utility of stimulus presentation code sharing. GitHub provides good functionality in terms of integrating with code creation pipelines and with ongoing collaborative code development. At the same time, GitHub repositories are not permanent and may be removed at any time by the author or, potentially, by GitHub itself. The utility of persistent links has been demonstrated in the context of data sharing and so is likely to also be salient for code sharing (12, 47). Services such as Zenodo that produce permanent objects and persistent DOI links may be useful in this context (23). OSF does allow for persistent storage and links and has additional advantages in terms of keeping all aspects of a research project together in one place (e.g., preregistration, experimental protocols, preprint, etc). Its current functionality is less developed from a code development and maintenance point of view than specialist services such as GitHub, which may act as a barrier to some researchers using it for stimulus presentation code sharing (29).

Of the stimulus presentation code that was shared, the majority of it ran with at most minor corrections. Approximately one third of code sets could not be run, primarily due to there being missing files or dependencies. A relatively high proportion of shared code that fails to run has been reported previously (55), often also highlighting missing files and dependencies as a major cause (52). This points to a need for improved code testing by authors upon upload to ensure that all files are present and that the code will run when ported to another system (35). Containerisation (e.g., *Docker*) and the use of environment build files (e.g., for Conda) may also aid in increasing the usability of code across different systems by packaging all required dependencies or providing machine instructions to install them automatically (40, 50).

A minority of stimulus presentation code that was shared included documentation. Of the documentation that was available, it most commonly provided only minimal information (e.g., specifying which file to run). Poor documentation like this is contrary to best practice and has been cited by researchers as a major barrier to reusing the code of others (1). As with code sharing more generally, community guidelines on software documentation have been produced (e.g., FAIR) but it remains to be seen what impact these have on community norms and what changes to incentive structures occur to support them (27, 31).

The level of annotation in the code was generally rated as moderate and variable names were mostly rated as being meaningful. Both of these factors are important for the reusability of the code. They are also important if the code is to be used as a resource for people to learn how to create and present experimental stimuli. As such, it is to be encouraged that the highest degree of annotation as is practical be included in shared code to help it become a resource for the community.

Conclusion

Stimulus presentation code has been increasingly shared over time. The level remains low, however. Such code is a potentially valuable resource for the psychology research community and so it may be worth taking steps to promote a culture in which sharing it is valued.

Acknowledgments

The authors thank Dr. Gabriele Bellucci for their constructive remarks on the manuscript. This work was supported by grants to NWD from the Taiwan Ministry of Science and Technology (108-2410-H-038-008-MY2; 110-2628-H-038-001-MY4). The preprint was created using a modified version of Ricardo Henriques' BioRxiv LaTex template (https://henriqueslab.github.io/resources/bioRxivTemplate/).

Contributions

AR: Conceptualization, Formal Analysis, Investigation, Methodology, Visualization, Writing – original draft;
VT: Conceptualization, Formal Analysis, Investigation, Methodology, Visualization, Writing - original draft;
YHL: Investigation, Methodology, Writing – review & editing;
LYT: Investigation, Methodology, Writing – review & editing;
NWD: Conceptualization, Formal Analysis, Methodology, Writing – original draft.

Data and code availability

The data and code used to conduct this analysis are available at https://osf.io/ka9ws/.

References

1. Yasmin AlNoamany and John A. Borghi. Towards computational reproducibility: researcher perspectives on the use and sharing of software. *PeerJ Computer Science*, 4:e163, September 2018. Publisher: PeerJ Inc.
2. Monya Baker. 1,500 scientists lift the lid on reproducibility. *Nature*, 533(7604), May 2016.
3. George C. Banks, James G. Field, Frederick L. Oswald, Ernest H. O'Boyle, Ronald S. Landis, Deborah E. Rupp, and Steven G. Rogelberg. Answers to 18 Questions About Open Science Practices. *Journal of Business and Psychology*, 34(3):257–270, June 2019.
4. Yoav Benjamini and Yosef Hochberg. Controlling the false discovery rate: a practical and powerful approach to multiple testing. *Journal of the Royal statistical society: series B (Methodological)*, 57(1):289–300, 1995.
5. John A Borghi and Ana E Van Gulick. Data management and sharing: Practices and perceptions of psychology researchers. *PloS one*, 16(5):e0252047, 2021.
6. Jaqueline J Brito, Jun Li, Jason H Moore, Casey S Greene, Nicole A Nogoy, Lana X Garmire, and Serghei Mangul. Recommendations to enhance rigor and reproducibility in biomedical research. *GigaScience*, 9(6), June 2020.
7. Jean-Claude Burgelman, Corina Pascu, Katarzyna Szkuta, Rene Von Schomberg, Athanasios Karalopoulos, Konstantinos Repanas, and Michel Schouppe. Open Science, Open Data, and Open Scholarship: European Policies to Make Science Fit for the Twenty-First Century. *Frontiers in Big Data*, 2, 2019.
8. Iain Chalmers and Paul Glasziou. Avoidable waste in the production and reporting of research evidence. *The Lancet*, 374(9683):86–89, July 2009.
9. Garret Christensen, Allan Dafoe, Edward Miguel, Don A. Moore, and Andrew K. Rose. A study of the impact of data sharing on article citations using journal policies as a natural experiment. *PLOS ONE*, 14(12):e0225883, December 2019. Publisher: Public Library of Science.
10. Stephen Crouch, Neil Chue Hong, Simon Hettrick, Mike Jackson, Aleksandra Pawlik, Shoaib Sufi, Les Carr, David De Roure, Carole Goble, and Mark Parsons. The Software Sustainability Institute: Changing Research Software Attitudes and Practices. *Computing in Science Engineering*, 15(6):74–80, November 2013. Conference Name: Computing in Science Engineering.
11. Stephen J. Eglen, Ben Marwick, Yaroslav O. Halchenko, Michael Hanke, Shoaib Sufi, Padraig Gleeson, R. Angus Silver, Andrew P. Davison, Linda Lanyon, Mathew Abrams, Thomas Wachtler, David J. Willshaw, Christophe Pouzat, and Jean-Baptiste Poline. Toward standard practices for sharing computer code and programs in neuroscience. *Nature Neuroscience*, 20(6):770–773, June 2017. Number: 6 Publisher: Nature Publishing Group.
12. Lisa M. Federer. Long-term availability of data associated with articles in PLOS ONE. *PLOS ONE*, 17(8):e0272845, August 2022. Publisher: Public Library of Science.
13. Mirko Gabelica, Ružica Bojčić, and Livia Puljak. Many researchers were not compliant with their published data sharing statement: mixed-methods study. *Journal of Clinical Epidemiology*, 0(0), May 2022. Publisher: Elsevier.

14. Sherona Garrett-Ruffin, Alexandra Cowden Hindash, Antonia N. Kaczkurkin, Ryan P. Mears, Santiago Morales, Katharina Paul, Yuri G. Pavlov, and Andreas Keil. Open science in psychophysiology: An overview of challenges and emerging solutions. *International Journal of Psychophysiology*, 162:69–78, April 2021.
15. David Giofrè, Geoff Cumming, Luca Fresc, Ingrid Boedker, and Patrizio Tressoldi. The influence of journal submission guidelines on authors' reporting of statistics and use of open research practices. *PLOS ONE*, 12(4):e0175583, April 2017. Publisher: Public Library of Science.
16. Björn A Grüning, Samuel Lampa, Marc Vaudel, and Daniel Blankenberg. Software engineering for scientific big data analysis. *GigaScience*, 8(5), May 2019.
17. Lou Hafer and Arthur E. Kirkpatrick. Assessing open source software as a scholarly contribution. *Communications of the ACM*, 52(12):126–129, December 2009.
18. Jo Erskine Hannay, Carolyn MacLeod, Janice Singer, Hans Petter Langtangen, Dietmar Pfahl, and Greg Wilson. How do scientists develop and use scientific software? In *2009 ICSE Workshop on Software Engineering for Computational Science and Engineering*, pages 1–8, May 2009.
19. Tom E. Hardwicke, Robert T. Thibault, Jessica E. Kosie, Joshua D. Wallach, Mallory C. Kidwell, and John P. A. Ioannidis. Estimating the Prevalence of Transparency and Reproducibility-Related Research Practices in Psychology (2014–2017). *Perspectives on Psychological Science*, page 1745691620979806, March 2021. Publisher: SAGE Publications Inc.
20. James Howison and James D. Herbsleb. Incentives and integration in scientific software production. In *Proceedings of the 2013 conference on Computer supported cooperative work*, CSCW '13, pages 459–470, New York, NY, USA, February 2013. Association for Computing Machinery.
21. John P. A. Ioannidis. Why Science Is Not Necessarily Self-Correcting. *Perspectives on Psychological Science*, 7(6):645–654, November 2012. Publisher: SAGE Publications Inc.
22. John P A Ioannidis, Sander Greenland, Mark A Hlatky, Muin J Khoury, Malcolm R Macleod, David Moher, Kenneth F Schulz, and Robert Tibshirani. Increasing value and reducing waste in research design, conduct, and analysis. *The Lancet*, 383(9912):166–175, January 2014.
23. Marco A. Janssen, Calvin Pritchard, and Allen Lee. On code sharing and model documentation of published individual and agent-based models. *Environmental Modelling Software*, 134:104873, 2020.
24. Ashley L. Juavinett. The next generation of neuroscientists needs to learn how to code, and we need new ways to teach them. *Neuron*, 110(4):576–578, February 2022.
25. Mallory C. Kidwell, Ljiljana B. Lazarević, Erica Baranski, Tom E. Hardwicke, Sarah Piechowski, Lina-Sophia Falkenberg, Curtis Kennett, Agnieszka Slowik, Carina Sonnleitner, Chelsey Hess-Holden, Timothy M. Errington, Susann Fiedler, and Brian A. Nosek. Badges to Acknowledge Open Practices: A Simple, Low-Cost, Effective Method for Increasing Transparency. *PLOS Biology*, 14(5):e1002456, May 2016. Publisher: Public Library of Science.
26. Jihyun Kim, Soon Kim, Hye-Min Cho, Jae Hwa Chang, and Soo Young Kim. Data sharing policies of journals in life, health, and physical sciences indexed in Journal Citation Reports. *PeerJ*, 8:e9924, October 2020. Publisher: PeerJ Inc.
27. Youngseek Kim and Melissa Adler. Social scientists' data sharing behaviors: Investigating the roles of individual motivations, institutional pressures, and data repositories. *International Journal of Information Management*, 35(4):408–418, 2015.
28. M Kleiner, D Brainard, D Pelli, A Ingling, R Murray, and C Broussard. What is new in psychtoolbox 3. *Perception*, 36(14):1–16, 2007.
29. Jonas Kubilius. I-review: sharing code. *i-Perception*, 5(1):75–78, 2014.
30. Romain F. Laine, Ignacio Arganda-Carreras, Ricardo Henriques, and Guillaume Jacquemet. Avoiding a replication crisis in deep-learning-based bioimage analysis. *Nature Methods*, 18(10):1136–1144, October 2021.
31. Anna-Lena Lamprecht, Leyla Garcia, Mateusz Kuzak, Carlos Martinez, Ricardo Arcila, Eva Martin Del Pico, Victoria Dominguez Del Angel, Stephanie van de Sandt, Jon Ison, Paula Andrea Martinez, Peter McQuilton, Alfonso Valencia, Jennifer Harrow, Fotis Psomopoulos, Josep Ll Gelpi, Neil Chue Hong, Carole Goble, and Salvador Capella-Gutierrez. Towards FAIR principles for research software. *Data Science*, 3(1):37–59, January 2020. Publisher: IOS Press.
32. Erin C McKiernan, Philip E Bourne, C Titus Brown, Stuart Buck, Amye Kenall, Jennifer Lin, Damon McDougall, Brian A Nosek, Karthik Ram, Courtney K Soderberg, Jeffrey R Spies, Kaitlin Thaney, Andrew Updegrove, Kara H Woo, and Tal Yarkoni. How open science helps researchers succeed. *eLife*, 5:e16800, July 2016. Publisher: eLife Sciences Publications, Ltd.
33. Zeeya Merali. Computational science: ...Error. *Nature*, 467(7317):775–777, October 2010.
34. B. A. Nosek, G. Alter, G. C. Banks, D. Borsboom, S. D. Bowman, S. J. Breckler, S. Buck, C. D. Chambers, G. Chin, G. Christensen, M. Contestabile, A. Dafoe, E. Eich, J. Freese, R. Glennerster, D. Goroff, D. P. Green, B. Hesse, M. Humphreys, J. Ishiyama, D. Karlan, A. Kraut, A. Lupia, P. Mabry, T. Madon, N. Malhotra, E. Mayo-Wilson, M. McNutt, E. Miguel, E. Levy Paluck, U. Simonsohn, C. Soderberg, B. A. Spellman, J. Turitto, G. VandenBos, S. Vazire, E. J. Wagenmakers, R. Wilson, and T. Yarkoni. Promoting an open research culture. *Science*, 348(6242):1422–1425, June 2015. Publisher: American Association for the Advancement of Science.
35. Pepijn Obels, Daniël Lakens, Nicholas A. Coles, Jaroslav Gottfried, and Seth A. Green. Analysis of Open Data and Computational Reproducibility in Registered Reports in Psychology. *Advances in Methods and Practices in Psychological Science*, 3(2):229–237, June 2020. Publisher: SAGE Publications Inc.
36. Christian Paret, Nike Unverhau, Franklin Feingold, Russell A. Poldrack, Madita Stirner, Christian Schmahl, and Maurizio Sicorello. Survey on Open Science Practices in Functional Neuroimaging, November 2021. Pages: 2021.11.26.470115 Section: New Results.
37. H. Pashler and E. Wagenmakers. Editors' Introduction to the Special Section on Replicability in Psychological Science. *Perspectives on psychological science : a journal of the Association for Psychological Science*, 2012.
38. Jonathan W Peirce. Psychopy—psychophysics software in python. *Journal of neuroscience methods*, 162(1-2):8–13, 2007.
39. Bas B. L. Penning de Vries, Maarten van Smeden, Frits R. Rosendaal, and Rolf H. H. Groenwold. Title, abstract, and keyword searching resulted in poor recovery of articles in systematic reviews of epidemiologic practice. *Journal of Clinical Epidemiology*, 121:55–61, May 2020.
40. W. Stephen Pittard and Shuzhao Li. The Essential Toolbox of Data Science: Python, R, Git, and Docker. In Shuzhao Li, editor, *Computational Methods and Data Analysis for Metabolomics*, Methods in Molecular Biology, pages 265–311. Springer US, New York, NY, 2020.
41. Heather A Piwowar, Roger S Day, and Douglas B Fridsma. Sharing detailed research data is associated with increased citation rate. *PloS one*, 2(3):e308, 2007.
42. Stephen M. Powers and Stephanie E. Hampton. Open science, reproducibility, and transparency in ecology. *Ecological Applications*, 29(1):e01822, 2019. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/eap.1822.
43. Prakash Prabhu, Hanjun Kim, Taewook Oh, Thomas B. Jablin, Nick P. Johnson, Matthew Zoufaly, Arun Raman, Feng Liu, David Walker, Yun Zhang, Soumyadeep Ghosh, David I. August, Jialu Huang, and Stephen Beard. A survey of the practice of computational science. In *SC '11: Proceedings of 2011 International Conference for High Performance Computing, Networking, Storage and Analysis*, pages 1–12, November 2011. ISSN: 2167-4337.
44. Andreas Prlić and James B. Procter. Ten Simple Rules for the Open Development of Scientific Software. *PLOS Computational Biology*, 8(12):e1002802, December 2012. Publisher: Public Library of Science.
45. David B. Resnik, Melissa Morales, Rachel Landrum, Min Shi, Jessica Minnier, Nicole A. Vasilevsky, and Robin E. Champieux. Effect of impact factor and discipline on journal data sharing policies. *Accountability in Research*, 26(3):139–156, April 2019.
46. Anisa Rowhani-Farid, Adrian Aldcroft, and Adrian G. Barnett. Did awarding badges increase data sharing in BMJ Open? A randomized controlled trial. *Royal Society Open Science*, 7(3):191818, March 2020.
47. Anisa Rowhani-Farid and Adrian G. Barnett. Badges for sharing data and code at *Biostatistics:* an observational study. Technical Report 7:90, F1000Research, March 2018. Type: article.
48. Sheeba Samuel and Birgitta König-Ries. Understanding experiments and research practices for reproducibility: an exploratory study. *PeerJ*, 9:e11140, April 2021. Publisher: PeerJ Inc.
49. Lior Shamir, John F. Wallin, Alice Allen, Bruce Berriman, Peter Teuben, Robert J. Nemiroff, Jessica Mink, Robert J. Hanisch, and Kimberly DuPrie. Practices in source code sharing in astrophysics. *Astronomy and Computing*, 1:54–58, February 2013.
50. Vanessa V. Sochat, Ian W. Eisenberg, A. Zeynep Enkavi, Jamie Li, Patrick G. Bissett, and Russell A. Poldrack. The Experiment Factory: Standardizing Behavioral Experiments. *Frontiers in Psychology*, 7, 2016.
51. Victoria Stodden, Peixuan Guo, and Zhaokun Ma. Toward Reproducible Computational Research: An Empirical Analysis of Data and Code Policy Adoption by Journals. *PLOS ONE*, 8(6):e67111, June 2013. Publisher: Public Library of Science.
52. Victoria Stodden, Jennifer Seiler, and Zhaokun Ma. An empirical analysis of journal policy effectiveness for computational reproducibility. *Proceedings of the National Academy of Sciences*, 115(11):2584–2589, March 2018. Publisher: Proceedings of the National Academy of Sciences.
53. Sara Stoudt, Váleri N. Vásquez, and Ciera C. Martinez. Principles for data analysis workflows. *PLOS Computational Biology*, 17(3):e1008770, March 2021. Publisher: Public Library of Science.
54. Carol Tenopir, Suzie Allard, Kimberly Douglass, Arsev Umur Aydinoglu, Lei Wu, Eleanor Read, Maribeth Manoff, and Mike Frame. Data Sharing by Scientists: Practices and Perceptions. *PLOS ONE*, 6(6):e21101, June 2011. Publisher: Public Library of Science.
55. Ana Trisovic, Matthew K. Lau, Thomas Pasquier, and Mercè Crosas. A large-scale study on research code quality and execution. *Scientific Data*, 9(1):60, February 2022. Number: 1 Publisher: Nature Publishing Group.
56. Anusha M Vable, Scott F Diehl, and M Maria Glymour. Code Review as a Simple Trick to Enhance Reproducibility, Accelerate Learning, and Improve the Quality of Your Team's Research. *American Journal of Epidemiology*, 190(10):2172–2177, October 2021.
57. Freda Wan, Wilhelmiina Toivo, Helena M. Paterson, Emily Nordmann, Phil McAleer, Kalliopi Mavromati, Rebecca J. Lai, Carolina E. Kuepper-Tetzel, Lisa M. DeBruine, James E. Bartlett, Dale J. Barr, and PsyTeachR Team. Open-source tutorials benefit the field. *Nature Reviews Psychology*, 1(6):312–313, June 2022. Number: 6 Publisher: Nature Publishing Group.
58. Mark D. Wilkinson, Susanna-Assunta Sansone, Erik Schultes, Peter Doorn, Luiz Olavo Bonino da Silva Santos, and Michel Dumontier. A design framework and exemplar metrics for FAIRness. *Scientific Data*, 5(1):180118, June 2018. Number: 1 Publisher: Nature Publishing Group.
59. Greg Wilson, D. A. Aruliah, C. Titus Brown, Neil P. Chue Hong, Matt Davis, Richard T. Guy, Steven H. D. Haddock, Kathryn D. Huff, Ian M. Mitchell, Mark D. Plumbley, Ben Waugh, Ethan P. White, and Paul Wilson. Best Practices for Scientific Computing. *PLOS Biology*, 12(1):e1001745, January 2014. Publisher: Public Library of Science.
60. Liwei Zhang and Liang Ma. Does open data boost journal impact: evidence from Chinese economics. *Scientometrics*, 126(4):3393–3419, April 2021.

Supplementary materials

Papers included in the appraisal:

1. Kirsten CS Adam, Edward K Vogel, and Edward Awh. Clear evidence for item limits in visual working memory. *Cognitive psychology*, 97:79–97, 2017.
2. SP Ahmed, LH Somerville, and CL Sebastian. Using temporal distancing to regulate emotion in adolescence: modulation by reactive aggression. *Cognition and Emotion*, 32(4):812–826, 2018.

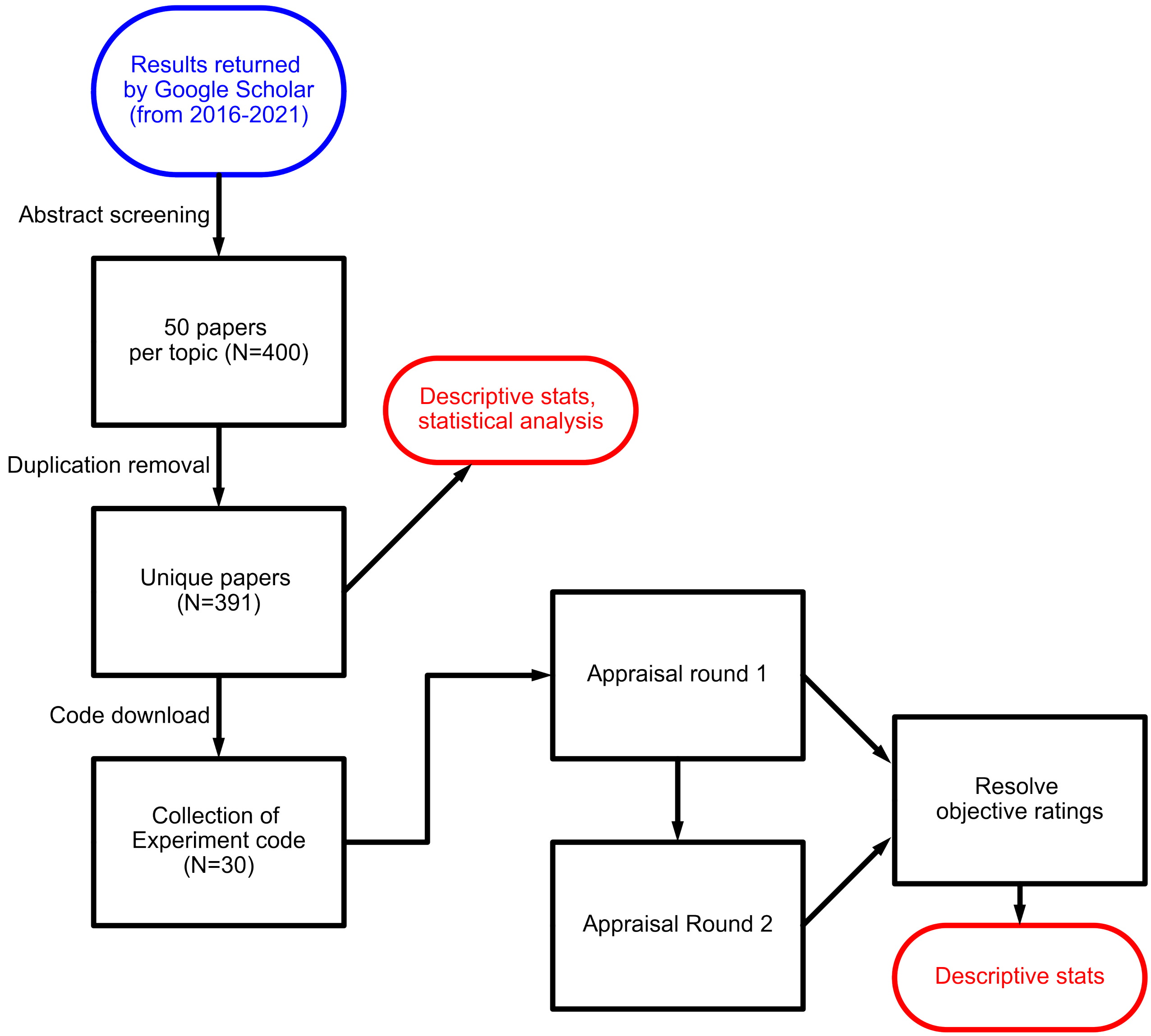

Figure S1. Flow diagram of the paper search and code appraisal procedures.

Appraiser	Computer configurations
AR	Windows-10, MATLAB-2021a, Psychtoolbox-3.0.17, Python-3.6.6, PsychoPy-3(v2021.1.4)
LYT	Ubuntu-18.04.5, MATLAB-2017a, Psychtoolbox-3.0.16 , Python-3.7.4, PsychoPy-v2020.2.5
YHL	Windows-10, MATLAB-2019b, Psychtoolbox-3.0.17, Python-3.6.6, PsychoPy-3(v2021.1.4)
VHT	Windows-10, MATLAB-2019a, Psychtoolbox-3.0.17, Python-3.6.6, PsychoPy-3 (v2021.1.4)

Table S1. Configuration information for appraisers' computers.

3. Ji Won Bang and Dobromir Rahnev. Stimulus expectation alters decision criterion but not sensory signal in perceptual decision making. *Scientific reports*, 7(1):1–12, 2017.
4. Phillip Cheng, Anina N Rich, and Mike E Le Pelley. Reward rapidly enhances visual perception. *Psychological Science*, 32(12):1994–2004, 2021.
5. Megan T DeBettencourt, Paul A Keene, Edward Awh, and Edward K Vogel. Real-time triggering reveals concurrent lapses of attention and working memory. *Nature human behaviour*, 3(8):808–816, 2019.
6. Juliet Dunstone, Mark Atkinson, Catherine Grainger, Elizabeth Renner, and Christine A Caldwell. Limited evidence for executive function load impairing selective copying in a win-stay lose-shift task. *PloS one*, 16(3):e0247183, 2021.
7. Cameron T Ellis, Lena J Skalaban, Tristan S Yates, and Nicholas B Turk-Browne. Attention recruits frontal cortex in human infants. *Proceedings of the National Academy of Sciences*, 118(12):e2021474118, 2021.
8. Jasper H Fabius, Alessio Fracasso, Tanja CW Nijboer, and Stefan Van der Stigchel. Time course of spatiotopic updating across saccades. *Proceedings of the National Academy of Sciences*, 116(6):2027–2032, 2019.
9. Jasper H Fabius, Tanja CW Nijboer, Alessio Fracasso, and Stefan Van der Stigchel. Intra-saccadic displacement sensitivity after a lesion to the posterior parietal cortex. *cortex*, 127:108–119, 2020.
10. Nathan Faivre, Laurène Vuillaume, Fosco Bernasconi, Roy Salomon, Olaf Blanke, and Axel Cleeremans. Sensorimotor conflicts alter metacognitive and action monitoring. *Cortex*, 124:224–234, 2020.

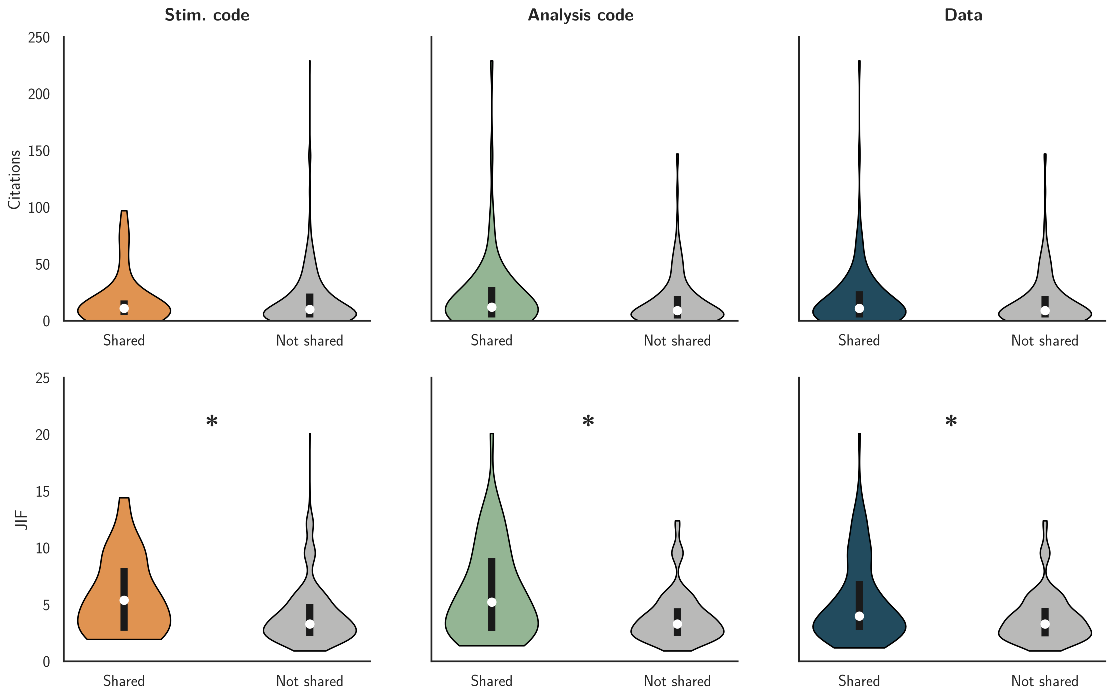

Figure S2. Factors related to publication metrics. Comparisons of citation counts for articles that did or did not share different objects (stimulus presentation code, analysis code, data) are shown in the upper row. Comparisons of journal impact factors (JIF) are shown in the lower row. * indicates a significant difference (P_{FDR} < 0.001).

11. Antonio Fernández and Marisa Carrasco. Extinguishing exogenous attention via transcranial magnetic stimulation. *Current Biology*, 30(20):4078–4084, 2020.
12. Hannah L Filmer, Ashleigh Griffin, and Paul E Dux. For a minute there, i lost myself... dosage dependent increases in mind wandering via prefrontal tdcs. *Neuropsychologia*, 129:379–384, 2019.
13. Joshua J Foster, Emma M Bsales, Russell J Jaffe, and Edward Awh. Alpha-band activity reveals spontaneous representations of spatial position in visual working memory. *Current Biology*, 27(20):3216–3223, 2017.
14. Katja Herrmann, Andreas Sprenger, Leoni Baumung, Daniel Alvarez-Fischer, Alexander Münchau, and Valerie Brandt. Help or hurt? how attention modulates tics under different conditions. *Cortex*, 120:471–482, 2019.
15. Maija Honig, Wei Ji Ma, and Daryl Fougnie. Humans incorporate trial-to-trial working memory uncertainty into rewarded decisions. *Proceedings of the National Academy of Sciences*, 117(15):8391–8397, 2020.
16. Chuan-Peng Hu, Yuxuan Lan, C Neil Macrae, and Jie Sui. Good me bad me: Prioritization of the good-self during perceptual decision-making. *Collabra: Psychology*, 6(1), 2020.
17. Julian Koenig, Peter Parzer, Niklas Haigis, Jasmin Liebemann, Tamara Jung, Franz Resch, and Michael Kaess. Effects of acute transcutaneous vagus nerve stimulation on emotion recognition in adolescent depression. *Psychological medicine*, 51(3):511–520, 2021.
18. Vanessa M Loaiza, Charlotte Doherty, and Paul Howlett. The long-term consequences of retrieval demands during working memory. *Memory & cognition*, 49(1):112–126, 2021.
19. Vanessa M Loaiza and Alessandra S Souza. An age-related deficit in preserving the benefits of attention in working memory. *Psychology and Aging*, 34(2):282, 2019.
20. Elizabeth C Nath, Peter R Cannon, and Michael C Philipp. Facial electromyography and subjective liking data from 70 new zealand participants in response to food images and chocolate samples. *Data in brief*, 29:105124, 2020.
21. Michael D Nunez, Aishwarya Gosai, Joachim Vandekerckhove, and Ramesh Srinivasan. The latency of a visual evoked potential tracks the onset of decision making. *Neuroimage*, 197:93–108, 2019.
22. Michael D Nunez, Joachim Vandekerckhove, and Ramesh Srinivasan. How attention influences perceptual decision making: Single-trial eeg correlates of drift-diffusion model parameters. *Journal of mathematical psychology*, 76:117–130, 2017.
23. Sonia Poltoratski, Alexander Maier, Allen T Newton, and Frank Tong. Figure-ground modulation in the human lateral geniculate nucleus is distinguishable from top-down attention. *Current Biology*, 29(12):2051–2057, 2019.
24. Anne-Raphaëlle Richoz, Junpeng Lao, Olivier Pascalis, and Roberto Caldara. Tracking the recognition of static and dynamic facial expressions of emotion across the life span. *Journal of vision*, 18(9):5–5, 2018.
25. Amanda K Robinson, Tijl Grootswagers, and Thomas A Carlson. The influence of image masking on object representations during rapid serial visual presentation. *NeuroImage*, 197:224–231, 2019.
26. Cooper A Smout, Marta I Garrido, and Jason B Mattingley. Global effects of feature-based attention depend on surprise. *NeuroImage*, 215:116785, 2020.
27. Cooper A Smout, Matthew F Tang, Marta I Garrido, and Jason B Mattingley. Attention promotes the neural encoding of prediction errors. *PLoS biology*, 17(2):e2006812, 2019.
28. Matilde M Vaghi, Fabrice Luyckx, Akeem Sule, Naomi A Fineberg, Trevor W Robbins, and Benedetto De Martino. Compulsivity reveals a novel dissociation between action and confidence. *Neuron*, 96(2):348–354, 2017.
29. Poppy Watson, Daniel Pearson, Michelle Chow, Jan Theeuwes, Reinout W Wiers, Steven B Most, and Mike E Le Pelley. Capture and control: Working memory modulates attentional capture by reward-related stimuli. *Psychological science*, 30(8):1174–1185, 2019.
30. Z Xu, KCS Adam, X Fang, and EK Vogel. The reliability and stability of visual working memory capacity. *Behavior Research Methods*, 50(2):576–588, 2018.