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1 *Implementing Code Review in the Scientific Workflow: Insights from*
2 *Ecology and Evolutionary Biology*

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9
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11 open science, transparency.

12
13 ***Abstract***

14 Code review increases reliability and improves reproducibility of research. As such, code review
15 is an inevitable step in software development and is common in subjects such as computer
16 science. However, despite its importance, code review is noticeably lacking in ecology and
17 evolutionary biology. This is problematic as it facilitates the propagation of coding errors and a
18 reduction in reproducibility of published results. To address this, we provide a detailed
19 commentary on how to effectively review code, how to set up your project to enable this form of
20 review and detail its possible implementation at several stages throughout the research
21 process. This guide serves as a primer for code review, and adoption of the principles and
22 advice here will go a long way in promoting more open, reliable, and transparent ecology and
23 evolutionary biology.

25 ***Introduction***

26 Across scientific disciplines, researchers increasingly rely on code written in open-source
27 software, such as R and Python, to clean, manipulate, visualise, and analyse data (Lai et al.
28 2019; Peikert and Brandmaier 2021; Peikert et al. 2021). Such software allows for increased
29 transparency and reproducibility compared to software that operates through point-and-click
30 interfaces (“User Interface” or “UI-based”), such as Minitab and SPSS (Obels et al. 2020). One
31 of the key benefits of this code-based software is flexibility, because researchers can tailor
32 analyses to their specific research needs which would otherwise be unavailable. However, the
33 flexibility of code comes at a cost, as it means that it can be more error-prone (Budd et al.
34 1998). These errors may be conceptual (e.g., implementing the wrong function for a given task),
35 programmatic (e.g., indexing the wrong column of a data frame), or syntactic (e.g., the incorrect
36 spelling of a statement or function). Although UI-based software is also prone to conceptual
37 errors, programmatic and syntactic errors are more common in code-based software. These
38 errors can contribute to a lack of reproducibility or to the propagation of incorrect results (see
39 Obels et al. 2020 for a review of code and data in psychology). Indeed, several high-profile
40 retractions have centred on these types of mistakes (Miller 2006; Ma and Chang 2007; Bolnick
41 and Paull 2009; Huijgen et al. 2012; Williams and Bürkner 2020). One way to minimise potential
42 errors, besides carefully annotating code and following best coding practices, is to undergo a
43 process of code review. However, unlike in some disciplines (such as in computer science and
44 software development) where code review is routinely implemented (Nelson and Schumann
45 2004; Badampudi et al. 2019), it is noticeably absent from the research and publication
46 processes in other academic disciplines that rely on code to make inferences and predictions
47 (Indriasari et al., 2020), including ecology and evolutionary biology.

48

49 To address this, we advocate for a fundamental shift in research culture that brings code review
50 into all stages of the research process, as reviewing of code is necessary to facilitate error
51 correction and to confirm the reproducibility of reported results. This is particularly important as
52 analyses are becoming ever more complicated, especially in the fields of ecology and
53 evolutionary biology (Touchon and McCoy 2016). But how can we implement code review? By
54 whom, when, and how can it take place? In this paper, we provide some suggestions about how
55 to conduct a code review and how to produce code that facilitates this form of review. Finally,
56 we discuss the application of code review throughout the entire process of publication, from the
57 early stages of pre-publishing right through to after work is published. Although we focus mainly
58 on issues and techniques related to the R and Python coding languages due to their popularity
59 in the fields of ecology and evolutionary biology (Mislán et al. 2016; Lai et al. 2019), the
60 concepts and principles we discuss are widely applicable.

61

62 ***What should code review evaluate?***

63 Code review is the process of either formally (as part of the peer review process) or informally
64 (as coauthors or colleagues) checking and evaluating each other's code. It is critical to help
65 avoid conceptual, programmatic, and syntactic errors in code and can take place at any stage of
66 the research cycle; pre-submission, during formal peer review, or post-publication. Although the
67 manner and scope in which code review occurs may vary depending on the position in the
68 research cycle, the core priorities remain the same: to ensure code is as reported in methods, is
69 able to successfully run, is reliable, and is able to reproduce stated results.

70

71 Below we describe these key priorities as the four Rs of code review (Figs. 1 and 2):

72

73 *Is the code as Reported?*

74 Code is a key research output and a critical component of scientific methodology. As such, open
75 code accompanying written methods sections is becoming more common, following similar
76 pushes for Open and FAIR data (Lamprecht et al. 2020). Therefore, it is imperative that code is
77 checked for consistency when presented with the corresponding manuscript. These questions
78 help us avoid conceptual errors in code. Does the code match the description of what is
79 “Reported” within the methods section (Fig. 1)? Ensuring code matches the methods reported
80 is imperative to evaluate whether the code is doing what is stated in the manuscript and what it
81 is intended to do by the user. For instance, methods may state that an analysis uses a
82 generalised linear model with Poisson error, but the code instead fits a Gaussian error structure.
83 Reviewing for this mismatch must be part of code review. In addition, and equally important for
84 reproducibility is whether the relevant packages (with appropriate version numbers) are stated
85 somewhere in the manuscript? In general, it is good practice to, at the very least, list the
86 packages (with version numbers) that are integral to the analysis or to visualisation in the
87 manuscript. These can be obtained by using the “citation()” function in R or using the
88 “setuptools” package in Python. A full list of all packages used (and versions), for instance
89 those involved with cleaning and tidying of data, could be given elsewhere such as in an
90 associated .R or .py file.

91

92 *Does the code Run?*

93 Even if code matches the methodology reported in a paper, this does not mean the code is
94 executable (i.e. can “Run”). Programmatic and syntactic errors can make code fail to rerun. For
95 example, code will not be able to be run (Fig. 1) if the appropriate packages are not listed
96 (and thus not installed) or if there are spelling mistakes. Data sharing, where possible, should
97 accompany code sharing, so that code can be fully rerun with the original data. If data sharing is
98 not possible, some simulated data or a data snippet should be provided so that the code can be

99 rerun. In cases where it would take a long period of time to rerun code (for instance with some
100 forms of Bayesian modelling), the code should be accompanied with appropriate model outputs
101 (readily provided by the author, see below “Output reproducibility”).

102

103 *Is the code **R**eliable?*

104 Errors can still propagate through code that runs and produces an output, because code can
105 produce incorrect results in a reproducible manner (i.e., every time the code is run). For
106 example, if code selects or modifies the wrong column in a dataset, the code will still run, but
107 produce a reproducible yet inaccurate result (i.e., the code is not “Reliable”). This type of error
108 could easily be conceptual, arising from a misunderstanding of the dataset, or programmatic,
109 such as from indexing by number and mistaking the column order. Although some coding
110 techniques, such as explicitly indexing by column name, can help avoid many of these
111 mistakes, this type of error is common and also extremely difficult to pick up by anyone without
112 deep familiarity with the dataset and code. These errors are thought to scale with the number
113 and complexity of code (Lipow 1982). Although intrinsically linked to evaluating whether code
114 can be run (the second “R”), evaluating code reliability means not only ensuring that the code
115 runs to completion without error, but examining intermediate outputs of the code to ensure there
116 are no mistakes. The functions “identical()” in R and “numpy.array_equal()” in Python can be
117 useful at this stage of code review to compare object similarity between newly-generated and
118 previously-saved intermediate outputs.

119

120 *Are results **R**eproducible?*

121 The last “R” of code review builds on the previous code review stages, and is perhaps the most
122 fundamental: can the code produce the output, and thus support the conclusions, given in the
123 paper (Goodman et al. 2016)? As several recent papers have highlighted (Archmiller et al.

124 2020; Obels et al. 2020; Errington et al. 2021; Minocher et al. 2021; Tiwari et al. 2021),
125 reproducibility in research results is often very low. Therefore, the final step of code review is
126 ensuring that final outputs when code is rerun match those reported in analysis and results
127 sections. With that said, at times obtaining the *exact* same result is not possible. Some level of
128 tolerance must therefore be applied especially when dealing with stochastic methods in which
129 parameter estimates will change between subsequent runs. This can occur for example if the
130 “set.seed()” function in R or “random.seed” function in Python has not been used prior to
131 stochastic sampling. Providing model outputs can go some way in helping with this (see above),
132 however it does not allow for the code to be explicitly run to see if you can obtain similar results
133 as stated in the paper (regardless of potential time taken). In this case, newly generated results
134 should be assessed to see if they matched (and how closely) to the conclusion (the direction
135 and significance level) and the numbers (intervals matching within one significant figure) of the
136 stated results (Archmiller et al. 2020). A useful example of this is also given in the
137 supplementary material of Archmiller et al. (2020), in which a mean of 4.12 and interval of 3.45
138 to 4.91 reproduces the conclusion and numbers of a study with a mean of 4.00 and interval of
139 3.3 to 5.0. Similar conclusions would be drawn if these means (and CIs) were higher (e.g., 6.5,
140 6.0 to 7.0), but the numbers would not be considered quantitatively reproduced. On the other
141 hand, the conclusions and numbers would not be reproduced if the model instead produced a
142 mean of 4.1 with an interval of -1 to 8.4 (as the confidence interval here overlaps with 0). It is
143 worth noting and mentioning in your review how closely the numbers and conclusion matched
144 with the reported results.

145

146

147

148

149

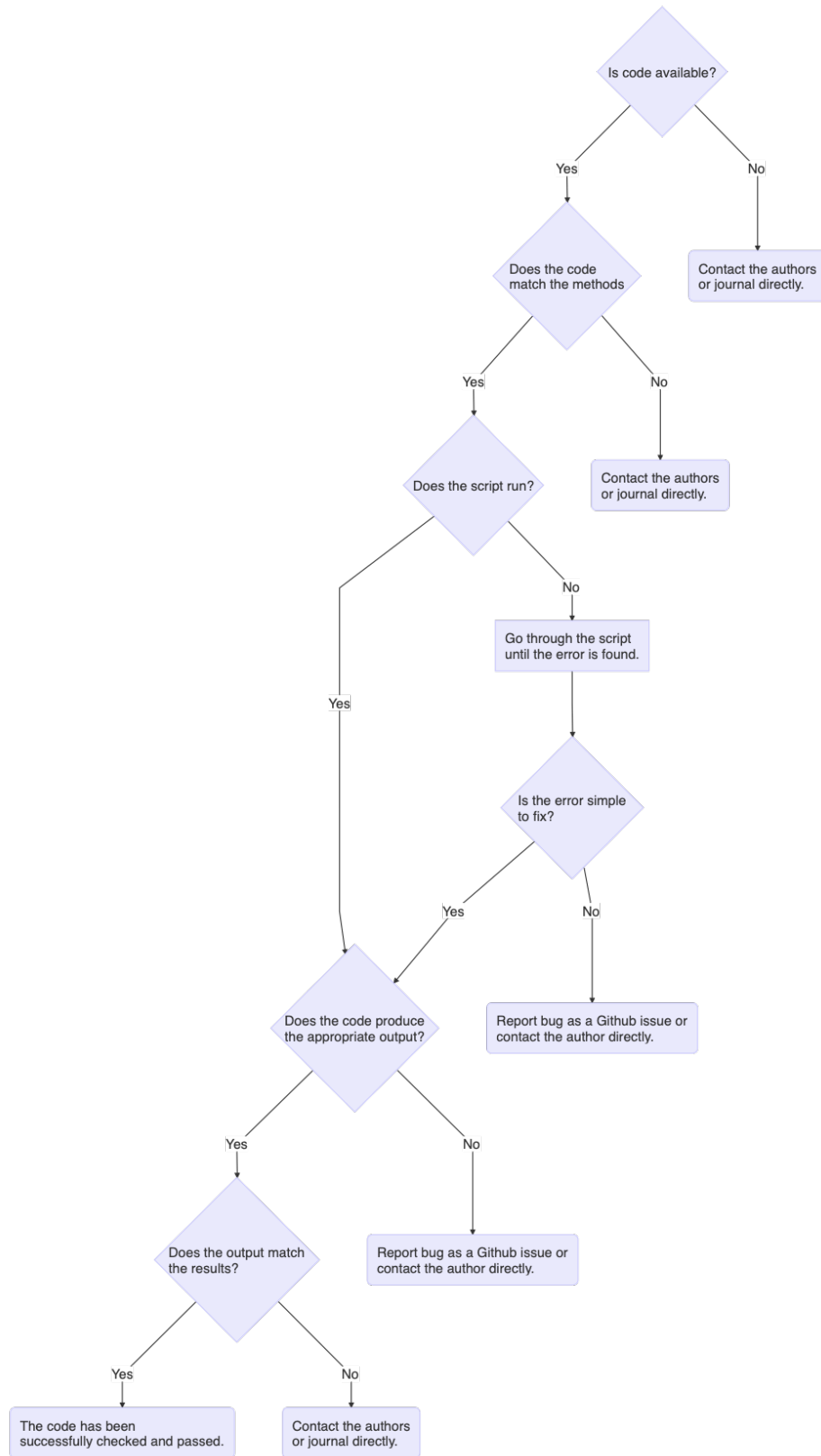
The 4Rs

- 1 Is the code as **R**eported?
Methods and code must match
- 2 Does the code **R**un?
Code must be executable
- 3 Is the code **R**eliable?
Code must be error-free
- 4 Are the results **R**e producible?
Results must be able to be reproduced

150

151 **Figure 1.** The four “Rs” of code review.

152



153

154 **Figure 2.** An example peer code review flowchart.

155 ***Setting up your code for effective code review***

156 Code review should evaluate if code matches reported methods, whether code runs and is
157 reliable, and lastly, if results can be reproduced. But in order for these questions to be
158 addressed, code must be written and shared in a way that it is possible for someone else to
159 rerun an analysis; both to allow for code to be reviewed and to be reused in the future when
160 properly maintained and contained (see Boettiger 2015). For this to happen, all necessary
161 scripts must be shared along with appropriate metadata indicating how the scripts interact with
162 one another, along with describing all other necessary software and appropriate versions. Often,
163 researchers lack formal training in coding, and learn to code in an *ad-hoc* fashion that excludes
164 training on general styling, appropriate use of workflows, and project organisation. As a result,
165 researchers may often not be aware of the steps necessary to set up code for a project in a
166 manner that reflects best coding practices. Therefore, below we list key principles (Fig. 3) that
167 will help make code reviewable at any stage of the research cycle.

168

169 *Project organisation*

170 Every project needs some form of directory organisation and folder structure. This is likely to be
171 largely driven by the function and form that your research takes, but an efficient and transparent
172 folder structure that keeps raw data separate from code and intermediate outputs should be
173 created. This helps to ensure that raw data is not accidentally modified or overwritten if any data
174 cleaning or wrangling techniques are applied. A simple folder and file structure such as this will
175 go a long way to help researchers from all coding skill levels understand the order and flow of
176 the data analysis. Particularly when the user creates sequentially labelled subfolders and scripts
177 where someone following the code knows which order things must be run (e.g., files beginning
178 with “01...”) in addition to dividing and naming folders to fit their purpose (e.g., data, scripts,

179 function). Several incredibly useful examples already exist (Cooper 2017; Alston and Rick 2021;
180 Chure 2023; see also <https://coderefinery.github.io/reproducible-research/> and
181 https://lakens.github.io/statistical_inferences/14-computationalreproducibility.html). Project code
182 should be stored and available on any data or code repository. Another option for organising a
183 project is to use pipeline tools (for instance see [https://github.com/pditommaso/awesome-](https://github.com/pditommaso/awesome-pipeline)
184 [pipeline](https://github.com/pditommaso/awesome-pipeline)), such as the targets R package (Landau 2021) or the Luigi package in Python (see
185 <https://www.martinalarcon.org/2018-12-31-a-reproducible-science/>). These tools allow users to
186 automate the process of data analysis, taking a raw dataset through the steps necessary to
187 produce data analysis and visualisation. The advantage to the user is that the code is
188 compartmentalised into logical steps (e.g., import raw data, data cleaning, data wrangling, data
189 analysis, data visualisation) and any changes to the code only affects the downstream steps.
190 For example, if we change the type of analysis we do, we do not need to re-import the data or
191 clean it again. This saves time in computation (especially important for complex long running
192 pipelines) but is also advantageous for reproducibility, and sharing and reuse of code.
193 Reviewers can effectively re-run the steps needed to produce a data analysis or figure without
194 having to re-run time consuming pre-processing steps.

195

196 *Project and input metadata*

197 Projects will instantly have better organisation and increased reproducibility when users know
198 *how* they should work through the various folders and subfolders. A README text file and
199 additional metadata gives users the signposts required to facilitate rerunning of code. This can
200 contain information on the packages used (e.g. the package name and version number), along
201 with a detailed description of the various data files, project aim, contact information of the
202 authors, and any relevant licences in place for code or for data (see
203 <https://choosealicense.com/licenses/> for more information). Furthermore, key information about
204 source data is critical for reproducing analysis code. If sharing data is inappropriate to your

205 study (for example when dealing with sensitive confidential data) then a user can provide a
206 sample of simulated data or a primer so that the code can be checked and read (Quintana
207 2020; Hennessy et al. 2022). However, if data is readily available, then providing detailed
208 information about what the data is (preferably in an associated README) and where the data is
209 (e.g., stored on a free data repository such as The Open Science Framework or OSF, Zenodo,
210 or Dryad) should be provided. Metadata should include information such as where the data
211 comes from, who the owners are, as well as what each column header entails, and any relevant
212 acronyms or shorthand notation (ideally following FAIR principles, so data is Findable,
213 Accessible, Interoperable, and Reusable; see Lamprecht et al. (2020). This is particularly useful
214 when controlled vocabulary is used throughout, and R packages such as codemeta (Boettiger
215 2017) and dataReporter (Petersen and Ekstrøm 2019) or Python packages such as
216 CodeMetaPy (Gompel 2023) and cookiecutter (Feldroy 2022) can help with this. Lastly, it is also
217 crucial to explain what possible data cleaning or curation occurred before the analysis code. For
218 instance, outlining what previous data manipulation or pre-processing steps have been taken to
219 obtain the data in its current state or when an intermediate data file was used.

220

221 Code Readability

222 Good readability of code is extremely important in enabling effective code review. Several quick
223 solutions exist to provide increased clarity: explicitly calling packages (via a package's
224 namespace, e.g. `package::function()` in R or `package.module.function` in Python), using relative
225 file paths (preferably with an associated R project file, if using R with RStudio or in a virtual
226 environment if using Python), removing redundant packages, and writing analysis code with
227 clear subheadings and easy-to-understand object names. Best practice coding tips, aided by R
228 packages such as `styler` (Müller and Walthert 2020) or `pycodestyle` in Python (Rocholl 2022) can
229 format code in a number of standardised styles (e.g., Google, tidyverse in R, or PeP8 in Python)
230 with a single line of code or a click of a button. Fortunately, several recent guides and primers

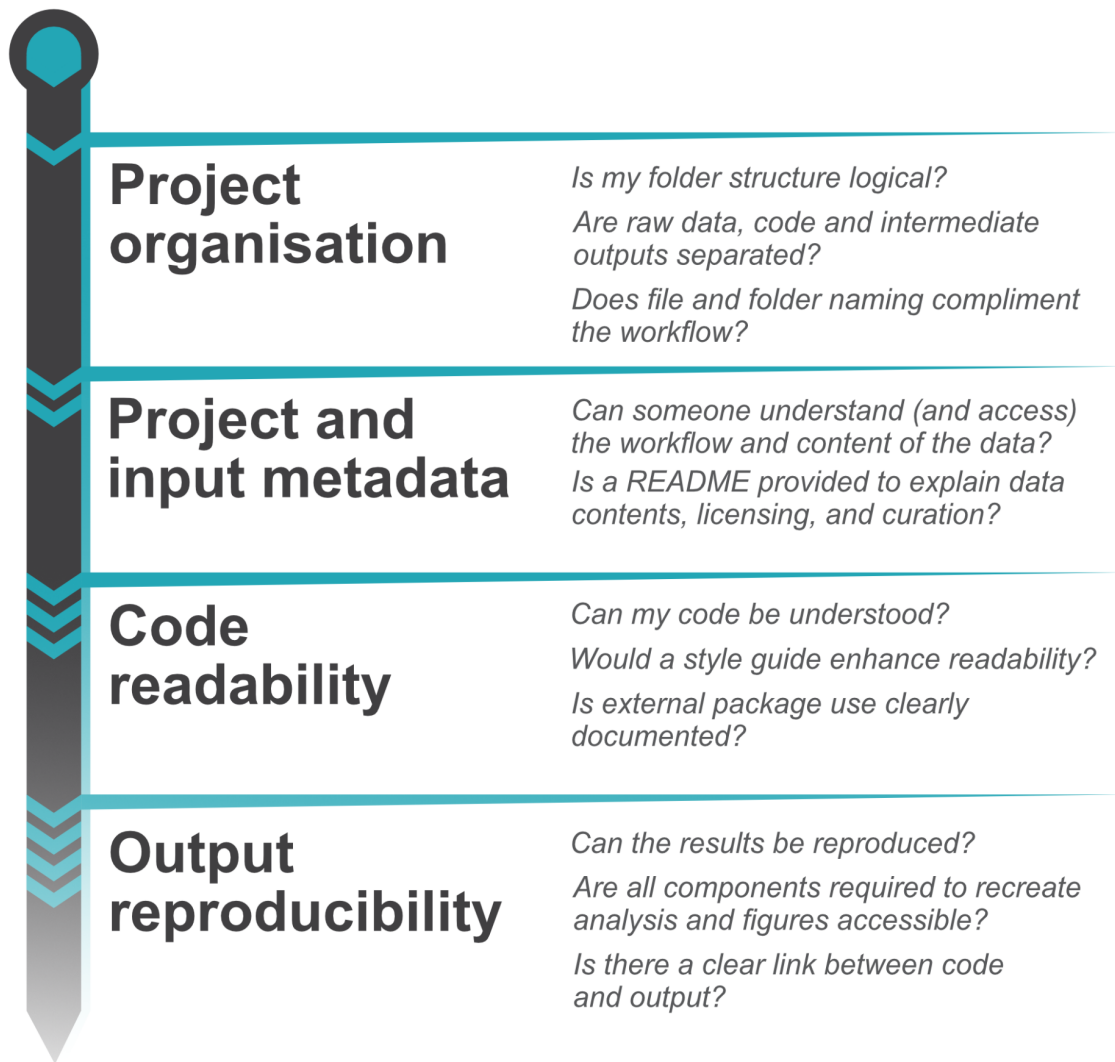
231 have been written that focus on increasing coding cleanliness (Sweigart 2020; Filazzola and
232 Lortie 2022; see Table 1 from Hunter-Zinck et al. 2021), so we urge the reader to consult these
233 guidelines for tips and advice on improving code readability.

234

235 Output reproducibility

236 One of the key principles and requirements of code is the ability to correctly reproduce
237 published graphs, statistics, and results. In order to do so, a user's code needs to provide a
238 clear link between each section of the code and the various reported graphs and outputs to
239 enable comparison of code to paper and to results. This should then facilitate checking that the
240 results produced by the code match the stated results in the publication. In some cases,
241 reproducing analysis from models can take considerable time to complete, for instance when re-
242 running complicated Bayesian models. In this case the "exact" reproducibility of results is not
243 always possible if code must simulate a stochastic process (e.g., Monte Carlo sampling
244 methods). In this case using set seed (see above) or saving simulation outputs still allows for
245 reproducible results (e.g., with the "saveRDS" function in R or the "pickle.dump" function in
246 Python) and can enable code reviewers to check the reproducibility of the reported results.

247



248

249 **Figure 3.** A basic workflow for reviewable code that can be adopted from the onset of a project.

250

251 ***Pre-Publication: Setting up a code review group***

252 Informal training coupled with insufficient time and incentives (Touchon and McCoy 2016),
 253 means that coding and subsequent analysis are often the responsibility of a single member of a
 254 team throughout a project's entire lifetime. This is in stark contrast to the research-team wide
 255 collaboration typical when developing methodology and experimental design. The individual

256 nature of writing research code is part of what makes pre-publication code review so unlikely,
257 but even more critical. Although code review has a place in the formal peer review process and
258 post-publication, one of the most important places for code review to take place is before
259 publication.

260 To achieve this, there must be a culture of peer code review among research teams. One of the
261 most effective methods by which researchers can establish a culture of peer code review in
262 research labs or among colleagues is by setting up a code review group. Here we draw on our
263 experience building a code review club (which we set up in collaboration with the Society for
264 Open, Reliable, and Transparent Ecology and Evolution, SORTEE) to present tips for
265 establishing this type of community. In particular, we focus on advice for removing the barriers
266 people have towards sharing their code and receiving feedback; be these due to a lack of time
267 and incentive, a lack of technical knowledge and unclear workflows, or due to social pressures
268 and the fear of being judged by peers (Gomes et al. 2022).

269

270 Encourage collaboration from the start of a project

271 Code review can begin as early as the first initiation of a project and play a role beyond
272 publication; it is useful to keep continuous code collaboration at all stages of a manuscript.
273 Collaboration can be facilitated through various code-sharing platforms such as GitHub where
274 users can submit and comment on pull requests (see Braga et al. 2023). At SORTEE we
275 established a peer review group and used GitHub issues to summarise discussion of an
276 individual's code during an interactive zoom session (see [https://github.com/SORTEE/peer-
277 code-review/issues/8](https://github.com/SORTEE/peer-code-review/issues/8) for an example including a summary). However, it is important to find a
278 method of facilitating code review that works for your group.

279

280 Set clear goals for the review

281 Setting out what you want to achieve with each code review session is particularly important
282 when it comes to organising peer review meetings. Is the focus on general learning and
283 improving readability or is it to error-check and scrutinise the reproducibility of your code?
284 Having a clear structure and goal for each peer review session is important in order to focus
285 comments and advice to address the precise reason for review. Similarly, unless the aim of a
286 code review is to evaluate different analytical options, it would be better to leave methodological
287 questions aside to ensure code review is streamlined.

288

289 Normalize coding errors and establish a judgement-free environment

290 Code review volunteers often feel very anxious about showing code that may have errors. It is
291 therefore vital to normalise the existence of errors and highlight that perfection is never possible.
292 It is also useful to stress that there is no such thing as bad code (Barnes 2010) and there are
293 usually multiple ways to approach the same problem (Silberzahn et al. 2018; Botvinik-Nezer et
294 al. 2020). One of the most important statements for peer code review is that there is no single
295 way to code. It is important for code review not to get bogged down modifying or homogenising
296 style; as long as code is readable, then coding diversity should be encouraged. It is important to
297 create a relaxed environment where people can learn and correct mistakes without judgement
298 or fear of failure and everyone in the peer review group should have a chance to contribute and
299 speak.

300

301 Carefully consider group size

302 Usually, a smaller group is a friendly starting point for peer code review because it allows
303 people to feel more comfortable speaking up and participating. Small peer review groups
304 (potentially even one-to-one) can better facilitate peer-to-peer learning and more focused review
305 of code. However, there are also times when larger groups are more effective, such as having
306 wider discussions on general themes and tips. It is worth considering the aims in establishing

307 the group to help guide the ideal size. For instance, if your goal is to facilitate more general
308 discussions, then a big group size is more likely to enable this. However, if your goal is to
309 enable more focused review of code, then perhaps it is better to reduce the size of the peer
310 review group for this purpose.

311

312 Consider the incentives

313 Code review, outside of paper submission and the formal peer review process, can have a large
314 impact on an individual's project, from error-checking, to validation of appropriate statistical
315 analyses. This then poses the question: what incentives should reviewers of code get? If
316 deemed appropriate, the reviewer could be acknowledged using the MeRIT (Method Reporting
317 with Initials for Transparency) system (Nakagawa et al. 2023), "e.g., J.L.P. ran a linear mixed
318 model with a Gaussian error distribution. Code was checked by E.I.C.". In some circumstances,
319 it may even be appropriate for the reviewer to obtain co-authorship of the paper, if the review
320 fundamentally altered the project and subsequent paper. Incentives should be relative to the
321 impact of the reviewer on the project.

322

323 ***During Publication: Formal code review***

324 One of the most crucial aspects of code review can take place during the formal peer review
325 process. This is where reviewers are able to carefully follow and understand the logic of
326 analyses, much like the flow of writing from the introduction to the discussion of a paper
327 (Powers and Hampton 2019). In some journals, such as The Royal Society (see Data sharing
328 and mining | Royal Society 2023), Behavioural Ecology and Sociobiology (Bakker and Traniello
329 2020), and The American Naturalist (see Bolnick 2022) *both* code and data are available for
330 reviewers to assess right from the submission stage. In some cases, such as in Journal of Open
331 Source Software, the entire process of formal peer review, including that of code and

332 manuscript is hosted on GitHub and implemented via GitHub issues (see
333 <https://github.com/openjournals/joss-reviews/issues> for several useful examples). This, as
334 Fernández-Juricic (2021) points out, has several benefits. For authors, providing code during
335 peer review could lead to an increase in the quality of the manuscript, and for reviewers,
336 available code allows for a far deeper insight into the manuscript as there is a clearer link
337 between experimental methodology and statistical analysis (the First R; code as “Reported”).
338 These benefits are substantial and could ultimately contribute to the adoption of code review
339 during the publication process.

340 However, beyond the availability of code during submission, there are numerous other hurdles
341 before effective and in-depth code review can be reasonably formalised as part of the peer
342 review process. One of the most pressing issues is finding suitable individuals to review code
343 given there is already a lack of willing reviewers in the current system. It is reasonable to expect
344 reviewers to check that code is as reported, but anything more in-depth could take up the time
345 of already overworked academics, who may not necessarily have the exact expertise needed to
346 check other people’s code. This needs to be fully considered and sufficiently addressed before
347 code review becomes a standard part of the peer review process.

348

349 ***Post-Publication: Reviewing code after publication***

350 Reviewing code post-publication is another facet of code review but one that has been much
351 less discussed. Although it does not prevent *publication* of incorrect results, it does enable
352 checking if code is indeed adhering to the R’s listed above. However, the initial question should
353 be, has all code used to produce the results been made available? This can either be a yes
354 (stored and available on any data or code repository) or a no. Fortunately, an increasing number

355 of journals are now *requesting* code be shared alongside scientific articles (Culina et al. 2020),
356 such as in supplemental materials or by linking to an online repository. This then allows for any
357 open and shared code to be checked and verified alongside methods section statements
358 (Stodden, 2011; Light *et al.*, 2014). However, unlike data, code is a lot less likely to be made
359 available regardless of these mandatory journal policies. As Figure 2 from Culina et al. (2020)
360 shows, although the number of journals that possesses a mandatory code rule is increasing
361 (from 15% to 79%; from 2015 to 2020) the number of articles that actually provide open code is
362 still around 27% (although this number varies considerably among journals). This suggests that
363 not many authors are adhering to this policy, which is an impediment to computational
364 reproducibility (Culina et al. 2020). However, there is hope to be found here. As Culina *et al.*
365 have shown, journals requiring code to be shared are increasing in number yearly and, as a
366 field, we already have improved substantially (Mislán et al. 2016; Culina et al. 2020; Jenkins et
367 al. 2023). In some cases, journals have implemented far stricter (and rightly so) data and code
368 requirements along with assigning corresponding data editors (see Bolnick 2022). However, the
369 first necessary step is for all journals to make it a requirement for *both* code and data to be
370 present from the very start of the submission stage (Powers and Hampton 2019; Fernández-
371 Juricic 2021). But what happens if the code is not available? In this case, the main option is to
372 reach out to the corresponding author (or perhaps the journal itself) and ask if the code could be
373 made available; similar to data being made available “upon reasonable request”.

374 The next part is relevant to the previous section above (“What should code review evaluate?). If
375 you find that the code associated with a manuscript does not adhere to any of the “R”s listed
376 above, then the first step is to contact the corresponding author (or if the paper uses the MeRIT
377 system, the person who actually conducted the analysis; Nakagawa et al. 2023). This could be
378 in the form of a GitHub issue if there is a repository for the code or an email (see Fig. 2). If there
379 is indeed an error in code, and it is not due to differences in software version (e.g., differences

380 in R and package versions) or due to inherent stochasticity (e.g., simulations or MCMC
381 sampling), then the authors should be given a chance to contact the journal themselves to
382 highlight and correct their mistakes. For instance, as per American Naturalist’s stance (see
383 Bolnick, 2022), authors who contact the journal to correct code or data errors will not be
384 penalised and corrections are encouraged (when warranted). However, in cases where updated
385 results would alter the narrative of a published paper, corrections may be more difficult to address
386 without newer methods of documenting changes. Publication versioning or “living” documents may
387 present a solid first step in such a scenario (Kane and Amin 2023). By encouraging post-
388 publication code review, we can both decrease the proliferation of coding errors and also
389 increase the reliability of published science.

390

391 ***Concluding remarks***

392 In this brief overview, we have provided a basic set of guidelines for peer code review,
393 recommendations for producing reviewable code, and considerations for how it should be
394 adopted at every level of research throughout the publication process. The principles and advice
395 listed here should form a baseline for code review that should be improved upon. We hope that
396 this encourages coders at all levels to try and promote more reproducible, transparent, and
397 open coding practices. In addition, we hope that this provides a primer to start a code reviewing
398 club of your own!

399

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