Attentional Control Data Collection: A Resource for Efficient Data Reuse

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Abstract

Publicly available data are required 1. to assess the reproducibility of each individual finding in the literature, and 2. to promote the reuse of data for a more efficient use of participants' time and public resources. While cuurently used data repositories are well suited for the first goal, they do at this point not sufficiently address the latter goal. Here, we show how structured collections of open data can be very useful as they allow a larger community of researchers easy access to a large body of data from their own research area. We introduced the Attentional Control Data Collection, an SQL data base for attentional control experiments. We illustrate the structure of the data base, how it can be easily accessed using a shiny app and an R-package, and how researchers can contribute data from their studies to the data base. Finally, we conduct our own initial analysis of the large number of data sets in our data base, assessing the reliability of individual differences. The analysis highlights that reliability is generally low, and provides insights into planning future studies. For example researchers should consider to increase the number of trials per person and condition to at least 400.

Keywords: Open Data, Attentional Control, SQL

Word count: X

⁴⁰ Attentional Control Data Collection: A Resource for Efficient Data Reuse

⁴¹ Making data openly available has been a central demand by reformers since the start

⁴² of the reproducibility crisis in psychology (Nosek et al., 2015). Fortunately, this demand has

⁴³ lead to a considerable increase in data availability. While only about 25% of data were

⁴⁴ shared after request in 2006 (Wicherts, Borsboom, Kats, & Molenaar, 2006), publicly sharing

⁴⁵ data upon publication is now more and more the norm. Between 2014 and 2021, the

⁴⁶ percentage of open data badges awarded at the journal *Psychological Science* drastically

⁴⁷ increased from 16 to 78 percent (Bauer, 2022). This cultural shift is also increasingly

⁴⁸ institutionalized: Universities and funding agencies prioritize open data, and some journals

⁴⁹ even mandate the publication of data with every published article (Sloman, 2015). In

⁵⁰ addition, technology like the Open Science Framework (OSF) and other data sharing services

⁵¹ enable an easy process for researchers, further reducing barriers to share data.

⁵² Data sharing serves two goals: 1. To make the scientific process more transparent and

⁵³ enable error and fraud detection, and 2. to make the scientific process more efficient by

⁵⁴ allowing data reuse for different research projects. Current data sharing efforts, however,

⁵⁵ seemingly focus overwhelmingly on the first goal (Crüwell et al., 2023; Hardwicke et al., 2021;

⁵⁶ Obels, Lakens, Coles, Gottfried, & Green, 2020). We argue that, as a result, current data

⁵⁷ sharing procedures do not sufficiently meet the second goal. Whenever researchers complying

⁵⁸ with common data sharing procedures publish an article, they share the corresponding data

⁵⁹ on the OSF, ideally in a format that allows to redo the exact analyses reported in the article.

⁶⁰ The OSF repository is linked in the article, and readers may access the data through this

⁶¹ link and check whether analysis code and shared data correspond to the results section in

⁶² the article. From an ethical standpoint, this process seems reasonable: Data shared through

⁶³ this process are often aggregated and cleaned allowing reproduction of results without

⁶⁴ sharing unnecessary details of participants' behavior. However, one may also argue that this

⁶⁵ approach is unethical - not sharing raw, unaggregated data that is easy to find and reuse, is

⁶⁶ a mismanagement of public resources and participants' time.

⁶⁷   To enable data reuse, data sharing needs to be approached differently. Consider as an
⁶⁸ example a researcher (like the first author of the current paper) might me interested in the
⁶⁹ Stroop task (Stroop, 1935). The Stroop task is popular in cognitive psychology (MacLeod,
⁷⁰ 1991), so we may assume that many studies include this or similar tasks in their studies.
⁷¹ Instead of running yet another Stroop experiment, the researcher decides to use existing data
⁷² to explore their research question before designing a more targeted study. First, the
⁷³ researcher needs to be able to find open Stroop task data. Currently, they could either search
⁷⁴ for papers on the topic and check whether open data are provided, or search directly via
⁷⁵ OSF or other data sharing servers. However, neither of these options is very promising as the
⁷⁶ vast majority of articles in the literature does not provide raw data, and data sharing servers
⁷⁷ are not equipped with sufficient search options. Second, data sets need to be accessed easily
⁷⁸ and in a general, understandable format ready for reuse. There are data sharing formats that
⁷⁹ provide this structure (Wilkinson et al., 2016), but they are rarely used. Moreover, data are
⁸⁰ usually shared on the level necessary for the original analysis. In case of the Stroop task,
⁸¹ researchers might share the Stroop effect per participant, but for this new analysis the
⁸² researcher needs trial-level data. So again, there is yet another barrier for data reuse.

⁸³   We think it is necessary to provide a data sharing solution that solves the current
⁸⁴ problems and enables easy and efficient data reuse. Here, we propose to gather open data
⁸⁵ sets from a specific research area in an SQL data base. This process requires little to no
⁸⁶ work from the authors of the original papers in addition to current data sharing policies,
⁸⁷ some work from the lab(s) setting up the data base, and little to no work from the
⁸⁸ researchers who wish to reuse open data. We describe the process and structure we used to
⁸⁹ set up a data base of attentional control tasks called the Attentional Control Data Collection
⁹⁰ (ACDC). The data base currently includes 64 data sets from 12 publications from tasks like
⁹¹ the Stroop, Simon, and flanker tasks (see Appendix). Subsequently, we show how researchers

92 can contribute their own data to the data base, how the data can be explored using a Shiny

93 app and accessed for reuse using an R-package. In an example analysis, we assess the

94 reliability of the included tasks. This section highlights how an open data base like ACDC

95 can aid meta-analytic efforts as well as methodological innovation.

96   To provide a little history of the project, the Attentional Control Data Collection was

97 inspired by a collection of open data sets from attentional control tasks by the Perception

98 and Cognition Lab led by J. Rouder (url). Colleagues provided the first author and Rouder

99 with data sets for their statistical work (Haaf & Rouder, 2017; Rouder, Kumar, & Haaf,

100 2023). To ensure that data sets were accessible, we gathered them in a github repository.

101 However, there was little structure to the collection, and github repositories are neither

102 stable entities nor are they designed as data storage. Here, we describe how a structured

103 data collection can be achieved and which benefits it provides.

SQLight Database

105   One of the most standard ways in computer science for storing data is using a

106 Structured Query Language (SQL) data base. SQL allows to create, access and manipulate a

107 structured data storage. SQL data bases consist of data tables and relations between these

108 tables. There are many flavors of SQL data bases. Here, we decided to use an SQLight data

109 base, a lightweight solution that allows us to store the entire data base in a single file of

110 moderate size that can be downloaded by researchers for data reuse. In this section we

111 describe the structure of the data base and the data currently included. Researchers who

112 simply want to use ACDC may safely skip this section.

Database Structure

114   SQL databases are composed of several data tables consisting of rows and columns.

115 Each row in a data table has a primary key (essentially a row ID) which uniquely identifies

116 it. To connect one table to another table in the database, tables may contain foreign keys

which reference a unique row in another data table. In contrast to primary keys, these
foreign keys can have duplicate values in the data table, as long as they are unique in their
primary table. For instance, a study table may store information about all studies in a
database where each row corresponds to a single study. Here the primary key is the
study_id. We can ensure that our database links each study to the publication it was
published in by adding a foreign key called publication_id to the study table. This foreign
key references the unique identifier of the respective publication in a publication table.
Figure 1 illustrates the relationship between study table and publication table. While
publication_id links to a single row in the publication table, it can occur several times in the
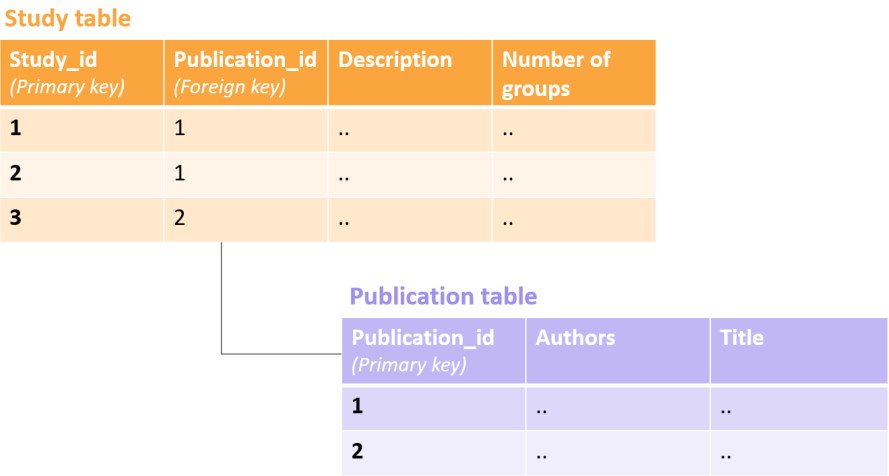study_table as there can be several studies per publication.

Study table

Study_id (Primary key)	Publication_id (Foreign key)	Description	Number of groups
1	1	..	..
2	1	..	..
3	2	..	..

Publication table

Publication_id (Primary key)	Authors	Title
1	..	..
2	..	..

Figure 1. Illustrative example of using foreign and primary keys in a SQL database.

ACDC is adapted to the logic of publications consisting of one or multiple studies
which in turn include one or more data sets. The whole structure of ACDC is shown in
Figure 2. A *publication table* and a *study table* contain specific information about each
publication and study, respectively. Each data set within a study contains trial-level data
from an attentional control task within a certain study. *(Re-reading my text I find this*   *Julia*
previous sentence quite confusing. Shall I just take it out or is it necessary for the reader's
understanding?) If a between-subject manipulation exists, our data base contains a separate

134 data set for each group and each task. For instance, a study in which two groups (younger

135 and older adults) completed a Simon and a Stroop task would consist of four data sets (i.e.,

136 younger-Stroop, younger-Simon, older-Stroop, older-Simon) in the ACDC data base.

137   A *data set table* stores information about each data set, such as sample size, the

138 number of within-participant manipulations, and whether a fixation cross was used. The

139 *observation table* holds the trial-level attentional control task data (including response time

140 and accuracy). The task type of each data set (i.e., Stroop, Simon, Flanker, negative

141 priming, or other) and a description of which stimuli were presented in the task are

142 documented in the *task table*.

143   Note that since the congruency of stimuli, i.e., whether response and stimulus

144 attributes are compatible or incompatible, is part of every attentional control task, it is not

145 considered a separate within-participant manipulation in this database but is per default

146 included in the observation table. Any additional within-participant manipulations are coded

147 in the within ID column of the observation table. Further information about each condition

148 of each data set (such as the percentage of congruent trials, mean response time, and mean

149 accuracy) are recorded in the *within table*.

Included Data

151   Up to the date of submission of the manuscript, 64 data sets from 12 publications are

152 included in the database. The full list of data sets and references is provided in the

153 Appendix. The current database includes data sets from studies with an experimental as well

154 as a correlational focus. The data contain 10^7 observations collected from 9978 participants.

155   We did not conduct a systematic search for data sets nor attempted to distribute a

156 wider call for open data. Instead, we included the data sets that were already made available

157 to the lab for previous projects, and added data sets from collaborators bit by bit. This

158 approach was chosen to make the project feasible, and to first set up a working data base
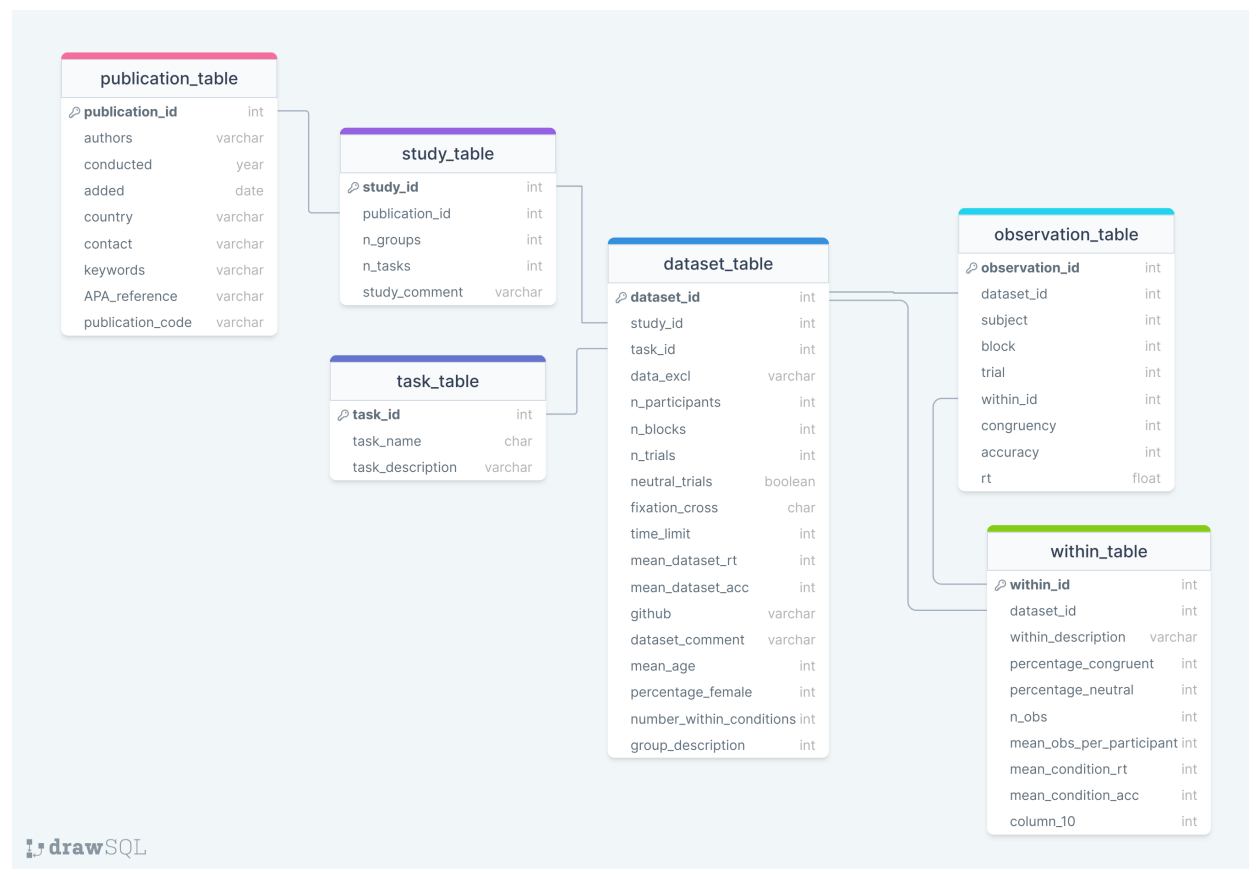
Figure 2. Structure of the ACDC database. Primary keys are indicated by the key symbol. References between data tables are illustrated through lines connecting columns across data tables. This overview includes the data type of each column: integers (int), numbers with decimal places (float), characters (varchar) and logical true/false values (booleans).

before large quantities of data are added.

Contribute

We are planning to continuously add attentional control task data to our data base. Researchers seeking to improve data accessibility and citation potential are invited to submit their data and related study meta-information via our online form.

To be eligible for the ACDC data base the data must have been collected for a published or pre-registered study using an attentional control task. *(Shall we define what we* *Julia* *mean by "attentional control" exactly?)* Researchers submitting the data must be allowed to publicly share them in anonymized format. Furthermore, the data files have to contain

168 trial-level information on anonymized subject IDs, reaction time, accuracy (i.e., correct/

169 incorrect), and a congruency variable, indicating whether distractor stimuli were congruent,

170 conflicting, or neutral. In case of between-subject manipulations and within-subject

171 manipulations (besides congruency), the files should contain a between and a within variable

172 indicating which condition a trial belonged to.

173   When submitting data to our online submission form, researchers will be asked to

174 provide meta-information about the publication and study, such as descriptions of the

175 attentional control task and the between and within manipulations. Data files can either be

176 uploaded in openly readable data formats or as a link to a repository, such as OSF or Github.

Julia 177   *(Shall we include the link to the website here? Or put it in the appendix?)*

Accessing the Database

179   One advantage of SQLite databases is that they are simply a file that can be

180 downloaded and locally accesses by anyone. Our database is provided in a github

181 repository.[1] To access the database, researchers can download the file `acdc.db`, and use the

182 SQLite tool of their choice. In addition, we build `R`-based tools to inspect, access, and select

183 data from ACDC. We introduce these tools, a shiny app and an `R` package, subsequently.

Shiny App

185   The easiest way to inspect the data is using our shiny app provided here. The app

186 allows to inspect all data sets or to select data sets with certain specification using the filter

187 box on the left. For example, if a researcher is interested in the flanker task, they may select

188 all flanker data sets for closer inspection. After selection, researchers can choose between an

189 overview of the included data sets, some descriptive statistics, and descriptive plots (see 3).

190 If they want to further analyze the data, they can download the data via the "get the data"

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[1] The newest version can be accessed via https://github.com/jstbcs/acdc-database/blob/main/acdc.db, the

Julia version at the time of submission can be found here. *(TODO: REPLACE WITH CURRENT COMMIT.)*

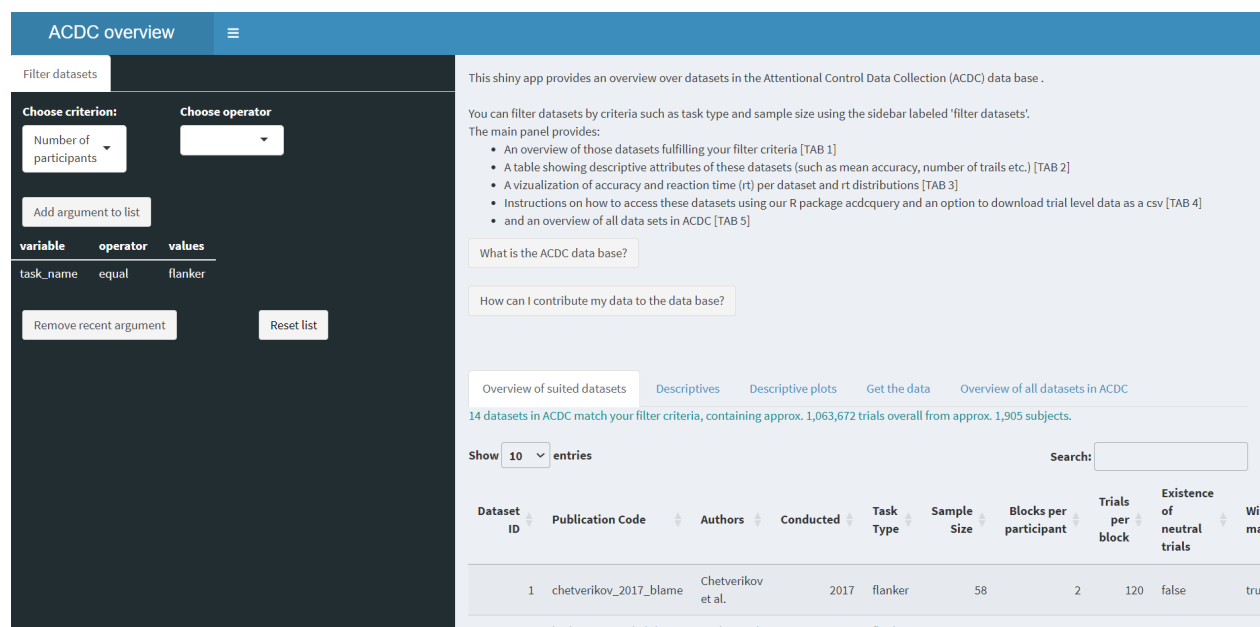191 tab, either directly as `csv` file or using the provided `R`-code.

Figure 3. Interface of the ACDC shiny app. The side bar allows users to choose a criterion, operator, and value to filter data sets by. Chosen arguments are listed in the sidebar below and can be removed using the respective fields. The main panel shows general information about the app and the ACDC project, and provides detailed information about the filtered data sets and how to access the data.

192 Note that all descriptive statistics in the data base are aggregated across congruency

193 conditions. This was a deliberate choice when designing the shiny app. By withholding

194 information about the effect of interest, researches can inspect and select the data based on

195 varying characteristics of the data set (including distributional properties), but remain

196 unbiased as to the most relevant outcome variable. We hope that researchers can then

197 formulate (and perhaps preregister) hypotheses about their reanalysis without much

198 hindsight bias.

Response Time Distribuion for dataset_id: 6

Data is aggregated over all congruency conditions. Find more information about the within_id in the respective table.
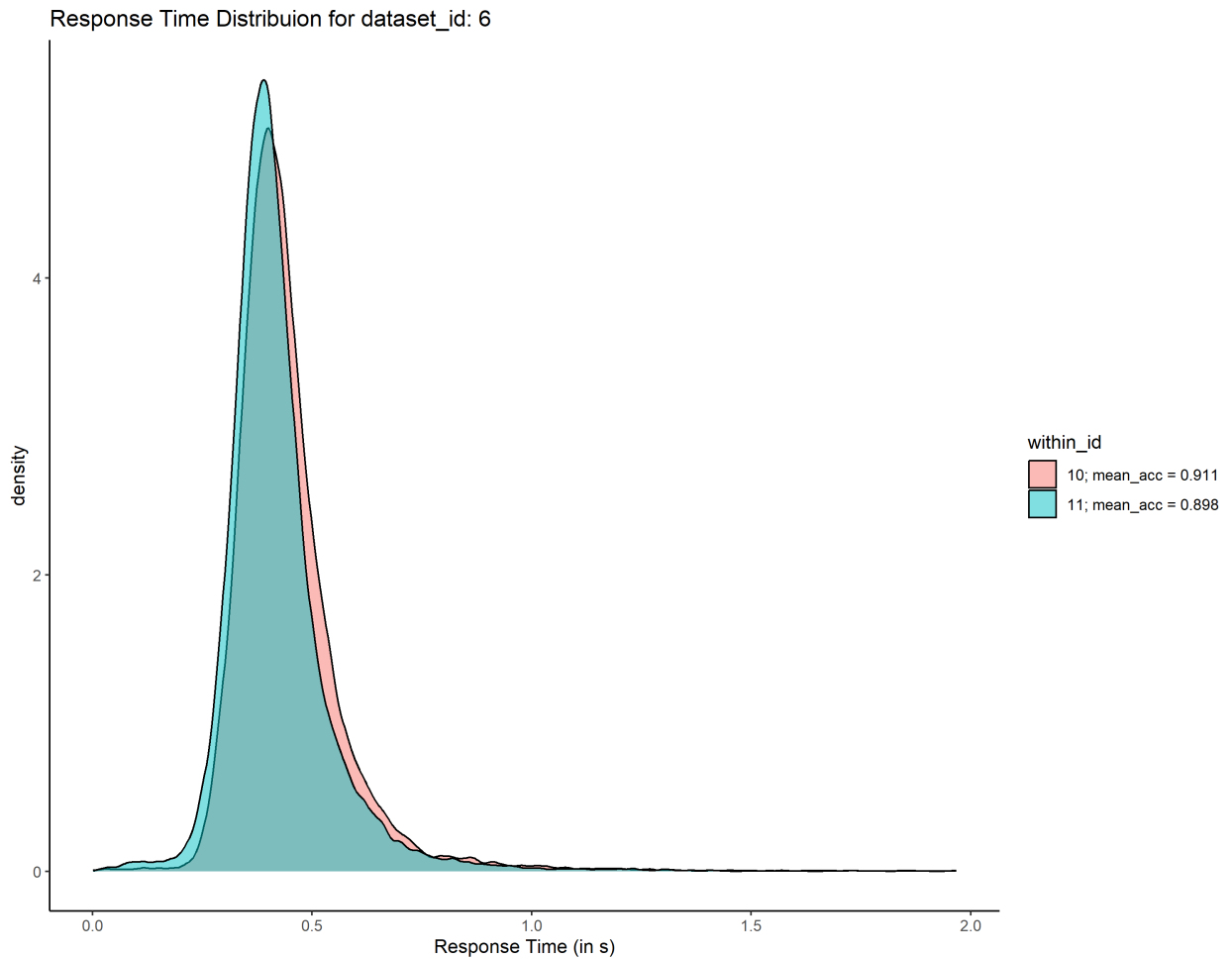
199

Julia (TODO: Enhance resolution of image?)

R-Package

The R-package `acdcquery` allows a more customized, but still user-friendly interaction
with the database without ever writing any SQL code themselves (Lesche, Hoffstadt, & Haaf,
2023). Using three key functions, `connect_to_db()`, `add_argument()`, and `query_db()`,
the package enables connecting to the database, filtering the data based on any variable, and
load specified variables as a data frame into R. The `add_argument()` function allows easy
specification of filter arguments. Any variable present in any table in the database may be
used in the query. Users may also provide multiple arguments and control which of them
should be combined using *AND* and which will be combined using *OR* logic. Users can

210 additionally request any variable present in the database to be returned by the query *(Isn't   Julia*

211 *this sentence the same as the one above? "Any variable present in any table in the database*

212 *may be used in the query.").* The package constructs one SQL query combining all query

213 arguments and the requested variables. This SQL query will join multiple tables together if

214 the user requests variables from multiple tables or the query selection is based on variables

215 present in multiple tables. The query constructed by the package is optimized for speed by

216 automatically discarding unnecessary variables, choosing efficient ways to join tables, and

217 eliminating the need for temporary storage of query results. All arguments and requests are

218 combined simultaneously, allowing optimal use of SQL's base optimization.

219 **Queries and Output**

220   Below, we will illustrate several examples for using the database. Querying the

221 database consists of 5 steps. Connecting to the database, specifying the filter arguments,

222 specifying the relationship of filter arguments, specifying the target variables and finally

223 querying the database. For the first step, the package needs to be installed from CRAN and

224 loaded. Querying also requires that researchers download the database and establish a

225 connection using `connect_to_db()`.

```r
install.packages("acdcquery") # install package


library(acdcquery) # load package
db_filepath <- "path/to/database.db" # specify location of the db
conn <- connect_to_db(db_filepath) # establish a connection
```

226   The function `add_argument()` allows easy specification of the list containing query

227 arguments.

```r
argument_list <- list() # Initialize List


# Adding the first argument, n_participants > 100

argument_list <- add_argument(

  list = argument_list, # The list to which the new argument is added

  conn = conn, # The connection to the database

  variable = "n_participants", # The variable name from any table

  operator = "greater", # greater, less, equal, between

  value = 100

)


# Adding the second argument, task_name is either flanker or stroop

argument_list <- add_argument(

  list = argument_list,

  conn = conn,

  variable = "task_name",

  operator = "equal",

  value = c("stroop", "flanker")

)


# You can also specify your own SQL statement for more advanced control
# Adding a third argument manually, percentage_neutral > 0.1

argument_list <- add_argument(

  list = argument_list,

  conn = conn,

  statement = "SELECT within_id FROM within_table WHERE percentage_neutral > 0.1"

)
```

₂₂₈   This argument-list now contains three separate filter-arguments. In our case, we only

₂₂₉ want those cases for which all are true. The package also allows the user to specify which

₂₃₀ arguments should be combined using *AND* or using *OR*.

```r
all_true <- "AND" # All arguments combined using "AND"

one_true <- "OR" # All arguments combined using "OR"


# same numbers lead to combination via OR

# different numbers combination via AND

custom <- c(1, 1, 2) # (Argument 1 OR Argument 2) AND Argument 3
```

₂₃₁   The user can also specify which variables should be returned by the query. Here, any

₂₃₂ variable present in any table can be selected. To allow for fast queries in the case of limited

₂₃₃ involvement of multiple tables, the user can specify the table the query is centered on using

₂₃₄ the `target_table` argument of `query_db()`. In most cases, this is the observation-table

₂₃₅ containing trial data. If dataset-level data is of interest, it is wise to specify `target_table =`

₂₃₆ `dataset_table`. If all variables of the target table and some additional variables from other

₂₃₇ tables should be returned, simply add "default" to the vector specifying the target variables.

```r
# Trial data is of interest, also the task_name should be joined

mostly_trial_targets <- c("task_name", "dataset_id", "subject"

                          , "block", "trial", "rt", "accuracy")


# Mostly higher-level data is of interest

mostly_data_targets <- c("authors", "task_name"

                          , "n_participants", "mean_dataset_rt")


# All variables of the dataset_table + publication data

dataset_table_default <- c("default", "publication_id", "authors")
```

238   The argument-list, relationship of arguments, target variables and target table are then

239 supplied to the `query_db()` function.

```r
trial_results <- query_db(
  conn = conn,
  arguments = argument_list,
  target_vars = mostly_trial_targets,
  target_table = "observation_table",
  argument_relation = all_true
)


dataset_results <- query_db(
  conn = conn,
  arguments = argument_list,
  target_vars = dataset_table_default,
  target_table = "dataset_table",
  argument_relation = all_true # or any other valid specification
)
```

240   Additional info can be found on the package's GitHub page.

Reliability of ACDC Tasks

242   To illustrate how ACDC can be used for reanalysis, we provide an example data

243 analysis assessing the reliability of attentional control tasks.[2] Reliability of tasks like the

244 Stroop task has recently been the target of much debate (Draheim, Mashburn, Martin, &

245 Engle, 2019; e.g., Hedge, Powell, & Sumner, 2018; Rey-Mermet, Gade, & Oberauer, 2018;

246 Rouder & Haaf, 2019; Rouder et al., 2023). The current analysis can be understood as an

———

[2] For a full list of R-packages used for the analyses see Appendix.

247 extension of to the analysis of 24 data sets conducted by Rouder et al. (2023) (see their

248 Table 2).

249   Here, we rely on methodological development by Rouder and colleagues (Rouder &

250 Haaf, 2019; Rouder et al., 2023) to survey the reliability of data sets in ACDC. The authors

251 have made suggestions to update the analysis of reliability of individual differences in

252 cognitive tasks based on two simple observations. First, conventional measures of reliability

253 such as the split-half reliability or intra-class correlation are not well suited for cognitive

254 tasks as they are dependent on the number of trials. The reason for this dependency is that

255 observed between-subjects variability of a target effect is a combination of true individual

256 differences and sample noise. If sample noise is large, as is the case in these tasks, reliability

257 can be drastically reduced with a small number of trials compared to a large number of trials.

258 Second, unlike with psychometric tests, the number of trials of cognitive tasks is oftentimes

259 chosen arbitrarily, as a matter of preference by the lab conducting the experiment, making it

260 difficult to compare reliability across labs or across tasks (Rouder & Haaf, 2019).

261   The relationship between common reliability estimates and trial number is illustrated

262 in Figure 4B. The figure shows the split-half reliability coefficients for all ACDC data sets as

263 a function of the (log) number of trials per condition. The correlation between

264 split-half-reliability and log trial number is $r = 0.65$, 95% HDI $[0.50, 0.78]$, $\text{BF}_{10} = 2.62 \times 10^7$.

265 Figure 4D shows the relationship between split-half reliability coefficients and the (log)

266 number of participants. Theoretically, there should be no relationship. However, for purely

267 practical reasons, many studies with a large number of participants have in turn a low

268 number of trials. Therefore, empirically, we do find a negative relationship between the log

269 number of participants and split-half reliability, $r = -0.26$, 95% HDI $[-0.47, -0.03]$,

270 $\text{BF}_{10} = 3.41$.

271   To counter the lack of comparability of conventional reliability measures, Rouder et al.

272 (2023) proposed a measure of reliability that is derived from hierarchical modeling of the
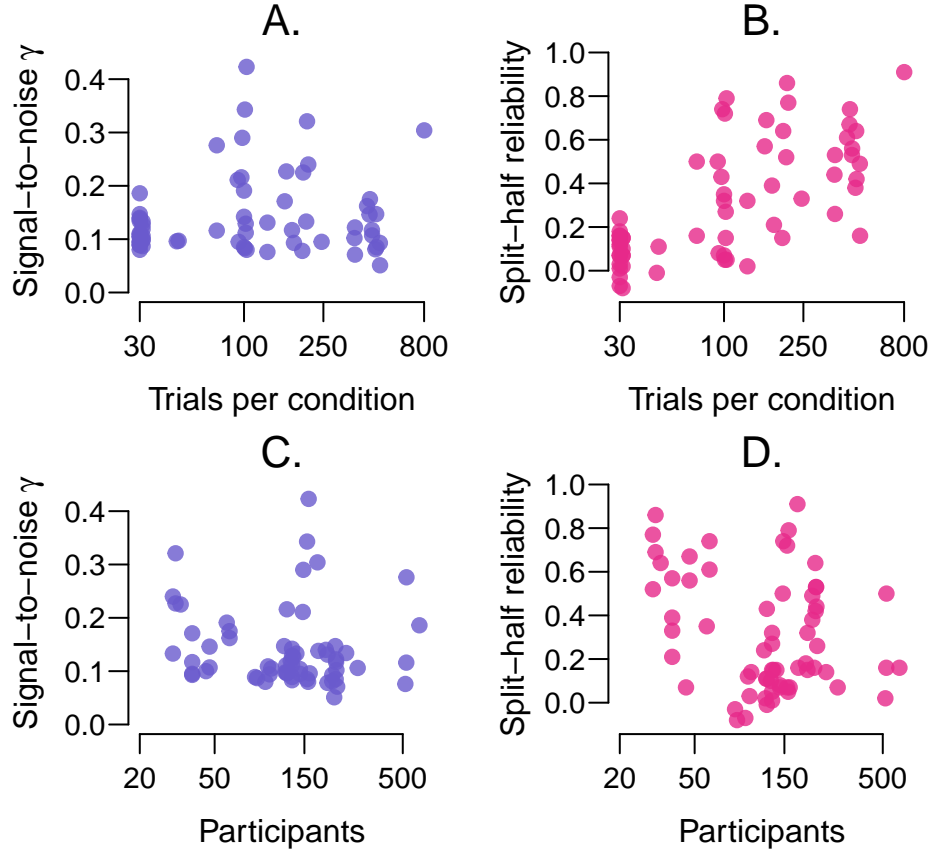
Figure 4. Reliability estimates as a function of number of trials and participants. A. The signal-to-noise ratio is independent of the (log) number of trials per condition but has a small positive correlation. B. The split-half reliability is highly correlated with the (log) number of trials per condition. C. The signal-to-noise ratio is independent of the (log) number of participants. D. The split-half reliability has a slight negative relationship with (log) number of participants due to the fact that large-participants studies commonly use a smaller number of trials per task.

trial-level data. This modeling approach allows to separately estimate true individual variability and sample noise. As a result, we may determine how much true variability there is relative to variability due to sample noise. This ratio, termed γ^2, can be expressed as

$$\gamma^2 = \frac{\sigma^2_{\text{true}}}{\sigma^2_{\text{noise}}},$$

where the numerator is the true variance of individuals' effects estimated by the model, and the denominator is the trial-by-trial within-person variability. For the purpose of

₂₇₈ individual differences research, σ^2_{true} represents the signal and σ^2_{noise} represents noise,

₂₇₉ therefore, Rouder and colleagues labeled γ^2 as the signal-to-noise ratio. Here, we use the

₂₈₀ square-root of γ^2, γ, representing a ratio of standard deviations as researchers tend to be

₂₈₁ more familiar with standard deviations rather than variances.
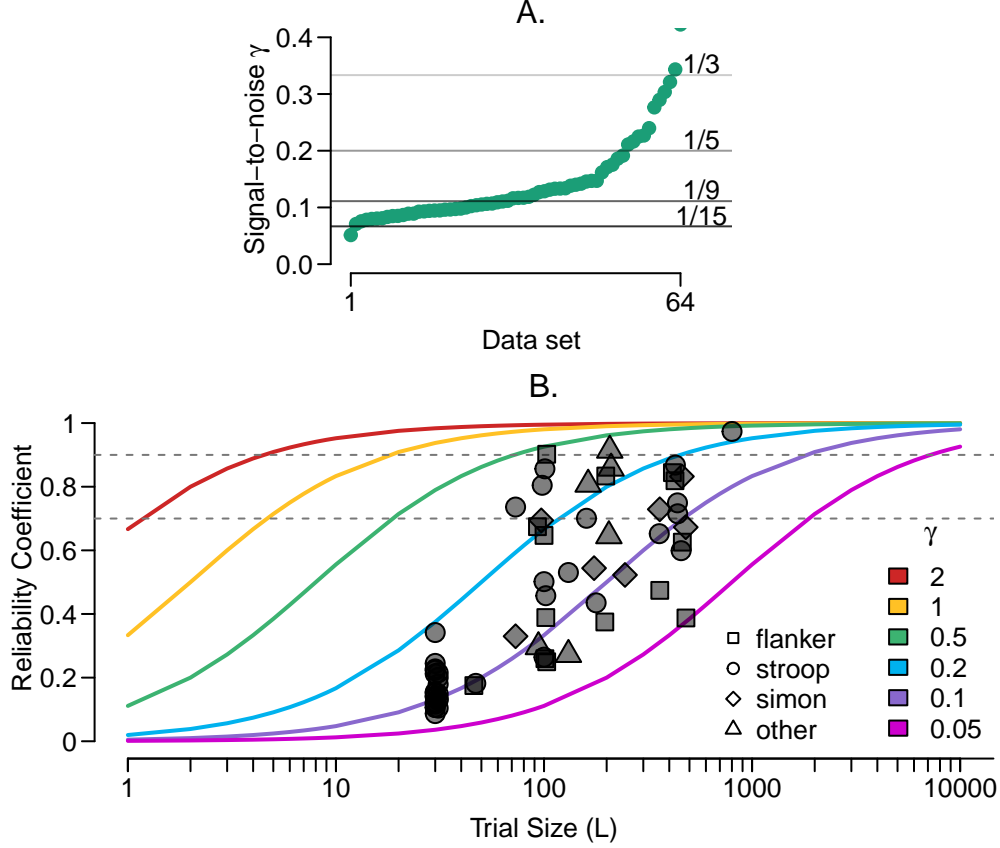
Figure 5. Signal-to-noise ratio and reliability. A. Signal-to-noise ratio γ for all data sets ordered from smallest to largest. B. Reliability as a function of number of trials for all data sets in ACDC. The lines represent different signal-to-noise ratios. For a fixed γ, the relationship between the number of trials per condition and the reliability is deterministic.

₂₈₂ Figure 5A. shows the signal-to-noise ratio γ for all data sets ordered from smallest to

₂₈₃ largest. The median of γ is $Med = 0.12$ corresponding to a ratio of roughly 1 to 8. That is,

₂₈₄ for every unit of signal there are 8 units of noise. Using the ACDC data sets, we can also

₂₈₅ assess the independence of γ from the number of trials and participants. Figure 4A and C

₂₈₆ show these relationships. There is no correlation between the log number of participants and

₂₈₇ γ, $r = -0.12$, 95% HDI $[-0.32, 0.13]$, $\text{BF}_{10} = 0.44$, nor between the log number of trials and

288 γ, $r = 0.12$, 95% HDI $[-0.09, 0.36]$, $BF_{10} = 0.49$.

289   Overall, the assessment of reliability of the currently used attentional control tasks

290 shows mixed results. Signal-to-noise ratios of these tasks tend to be around 0.1-0.2,

291 highlighting overwhelming levels of trial-by-trial variability compared to true individual

292 variability of congruency effects. As shown in Figure 5B, here is no task type standing out

293 with consistently higher or lower reliability. That is, there is no argument based on reliability

294 that would make us prefer any task over another. However, the analysis can still help us plan

295 future studies better. Figure 5B shows the functional relationship between the reliability

296 coefficient and the number of trial through the signal-to-noise ratio. For tasks with a

297 signal-to-noise ratio around 0.2, around 100 trials per condition and person are needed for

298 acceptable levels of reliability. For tasks with a signal-to-noise ratio around 0.1, roughly 500

299 trials are needed. We also see that all studies with large numbers of trials have acceptable

300 levels of reliability. These insights match a recent finding by Lee et al. (2023). The authors

301 had participants go through almost 4000 trials per condition per task to assess how many

302 trials are needed for precise estimates of individual effects. They conclude that around 400

303 trials per person and condition (or 800 in total) are needed for stable estimates of individual

304 effects. From our current analysis using a larger number of studies and participants, we

305 arrive at the same conclusion.

Conclusion

307   Open data policies are required 1. to understand how many results in the literature are

308 reproducible, and 2. to promote the reuse of data for a more efficient use of participants'

309 time and public resources. While repositories like the Open Science Framework are well

310 suited for the first goal, they do at this point not sufficiently address the latter goal. We

311 argue that structured collections of open data are much more useful as they allow a larger

312 community of researchers an easy access to a large body of data. Here, we introduced the

313 Attentional Control Data Collection, an SQL data base for attentional control experiments.

314   The data base is easy to access using a shiny app and an R-package, and is built to grow

315   when researchers are willing to contribute their data in the future. We illustrate the

316   structure of the data base, how it can be accessed, and which type of analyses can be

317   conducted with such a large data collection.

318   The data base approach is related to meta-analysis, but different in two crucial aspects.

319   One major disadvantage of the data base approach is that it does not represent a systematic

320   overview, or even a representative sample of studies. To remedy this issue, researchers

321   planning to develop an open data collection could conduct a systematic review of the

322   literature including *all* studies with open data that meet their criteria in the data base.

323   However, as the field only recently started sharing data, older studies would still be

324   systematically excluded. One major advantage of the data base approach over meta-analysis

325   is that it opens the path to much more sophisticated research questions and analysis. As the

326   data base provides raw, unfiltered, trial-level data, we may use it for studying questions far

327   beyond congruency effects. Potential analyses target sequential effects, computational

328   modeling, or even methodological questions like the effect of online versus in-lab data

329   collection on data quality.

330   Finally, we hope researchers are willing to contribute data from their studies to ACDC

331   or other open data collections. If they already share their data on the OSF, we see no

332   disadvantage in also contributing to more structured data collection. In the best case, their

333   data will contribute to advancing the field without requiring unnecessary additional data

334   collection, leading to faster insights based on more data. This might also have benefits for

335   the researchers themselves as anyone using their data will also cite the original paper.

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Appendix A

All ACDC data sets

467 Table A1 contains all data sets that are part of the Attentional Control Data Collection at

468 the time of manuscript submission. The table is ordered by dataset ID and study, and

469 contains the number of trials per condition and participant, and the number of participants.

470 Additionally, three reliability estimates are included: The signal-to-noise ratio, γ, the

471 split-half reliability for 2000 random splits, ρ, and the corrected split-half reliability using

472 the Spearman-Brown formula, ρ^*.

Table A1
All datasets currently in ACDC.

ID	Task name	I	K	γ	ρ	ρ^*
Chetverikov et al. (2017)						
1	flanker	58	100	0.191	0.35	0.51
Enkavi et al. (2019)						
2	stroop	523	73	0.276	0.50	0.67
3	simon	522	73	0.116	0.16	0.28
4	other	516	131	0.076	0.02	0.04
Hedge et al. (2018)						
5	stroop	47	439	0.107	0.56	0.72
6	flanker	47	426	0.146	0.67	0.80
7	stroop	60	428	0.175	0.74	0.85
8	flanker	60	414	0.162	0.61	0.75
Kucina et al. (2023)						
9	other	31	163	0.227	0.69	0.82
10	other	30	205	0.133	0.52	0.68
11	other	31	207	0.321	0.86	0.92
12	flanker	33	198	0.225	0.64	0.77
13	other	30	210	0.240	0.77	0.87
Löffler, Frischkorn, Hagemann, Sadus, and Schubert (2022)						
14	stroop	148	98	0.290	0.74	0.85
15	flanker	147	93	0.211	0.50	0.67
16	negative priming	142	94	0.095	0.08	0.13
Ebersole et al. (2016)						
17	stroop	160	30	0.096	0.07	0.13
18	stroop	288	31	0.106	0.07	0.12
19	stroop	136	31	0.133	0.15	0.26
20	stroop	195	30	0.140	0.18	0.30
21	stroop	93	30	0.080	-0.07	-0.13

Table A1 continued

ID	Task name	I	K	γ	ρ	ρ^*
22	stroop	117	30	0.147	0.24	0.38
23	stroop	127	31	0.119	0.10	0.18
24	stroop	142	30	0.104	0.07	0.12
25	stroop	131	31	0.127	0.15	0.25
26	stroop	82	30	0.089	-0.03	-0.05
27	stroop	98	30	0.094	0.03	0.05
28	stroop	119	31	0.098	0.02	0.03
29	stroop	100	30	0.105	0.14	0.24
30	stroop	120	30	0.111	0.11	0.18
31	stroop	613	30	0.186	0.16	0.28
32	stroop	96	30	0.109	0.12	0.20
33	stroop	178	30	0.138	0.16	0.27
34	stroop	84	31	0.087	-0.08	-0.13
35	stroop	45	31	0.100	0.07	0.12
36	stroop	250	30	0.134	0.14	0.25
37	stroop	129	30	0.089	0.01	0.03
Pratte, Rouder, Morey, and Feng (2010)						
38	simon	38	245	0.095	0.33	0.48
39	stroop	38	160	0.171	0.57	0.72
40	simon	38	174	0.117	0.39	0.55
41	stroop	38	178	0.093	0.21	0.33
Rey-Mermet et al. (2018)						
42	stroop	129	102	0.129	0.27	0.42
43	stroop	129	100	0.142	0.32	0.48
44	flanker	129	102	0.112	0.15	0.25
45	flanker	129	101	0.083	0.05	0.09
46	stroop	155	101	0.343	0.72	0.83
47	stroop	155	100	0.085	0.07	0.13
48	flanker	158	103	0.423	0.79	0.88
49	flanker	157	103	0.080	0.05	0.10
Stahl et al. (2014)						
50	stroop	199	131	0.131	0.32	0.48
51	flanker	199	196	0.078	0.15	0.26
Tang, Bugg, Snijder, Conway, and Braver (2023)						
52	stroop	176	801	0.304	0.91	0.95
Von Bastian, Souza, and Gade (2016)						
53	stroop	121	47	0.097	0.11	0.18
54	simon	121	97	0.216	0.43	0.60
55	flanker	121	46	0.096	-0.01	-0.02
Whitehead, Brewer, and Blais (2019)						
56	stroop	221	438	0.117	0.53	0.69
57	simon	219	460	0.147	0.64	0.78
58	flanker	220	462	0.085	0.42	0.58
59	stroop	211	456	0.081	0.38	0.55

Table A1 continued

ID	Task name	I	K	γ	ρ	ρ^*
60	simon	211	480	0.093	0.49	0.65
61	flanker	216	481	0.051	0.16	0.26
62	stroop	222	358	0.102	0.44	0.61
63	simon	221	360	0.122	0.53	0.69
64	flanker	224	360	0.071	0.26	0.41

Note. γ = signal-to-noise ratio; I = number of participants; K = number of trials per condition; ρ = split-half reliability coefficient; ρ^* = Spearman-Brown corrected reliability coefficient.

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Appendix B

R-packages for analysis

⁴⁷⁴ All analyses were conducted using the following R packages: R (Version 4.2.2; R Core Team,

⁴⁷⁵ 2022) and the R-packages *acdcquery* (Version 1.0.1; Lesche et al., 2023), *BayesFactor*

⁴⁷⁶ (Version 0.9.12.4.5; Morey & Rouder, 2023), *coda* (Version 0.19.4; Plummer, Best, Cowles, &

⁴⁷⁷ Vines, 2006), *DBI* (Version 1.1.3; R Special Interest Group on Databases (R-SIG-DB),

⁴⁷⁸ Wickham, & Müller, 2022), *dplyr* (Version 1.1.3; Wickham, François, Henry, Müller, &

⁴⁷⁹ Vaughan, 2023), *DT* (Version 0.30; Xie, Cheng, & Tan, 2023), *forcats* (Version 1.0.0;

⁴⁸⁰ Wickham, 2023), *ggplot2* (Version 3.4.4; Wickham, 2016), *htmltools* (Version 0.5.6.1; Cheng

⁴⁸¹ et al., 2023), *knitr* (Version 1.45; Xie, 2015), *lubridate* (Version 1.9.3; Grolemund &

⁴⁸² Wickham, 2011), *MASS* (Version 7.3.58.2; Venables & Ripley, 2002), *Matrix* (Version 1.6.1.1;

⁴⁸³ Bates, Maechler, & Jagan, 2023), *MCMCpack* (Version 1.6.3; Martin, Quinn, & Park, 2011),

⁴⁸⁴ *papaja* (Version 0.1.2; Aust & Barth, 2022), *purrr* (Version 1.0.2; Wickham & Henry, 2023),

⁴⁸⁵ *readr* (Version 2.1.4; Wickham, Hester, & Bryan, 2023), *RSQLite* (Version 2.3.2; Müller,

⁴⁸⁶ Wickham, James, & Falcon, 2023), *shiny* (Version 1.7.5.1; Chang et al., 2023), *splithalf*

⁴⁸⁷ (Version 0.8.2; Parsons, 2021), *stringr* (Version 1.5.0; Wickham, 2022), *tibble* (Version 3.2.1;

⁴⁸⁸ Müller & Wickham, 2023), *tidyr* (Version 1.3.0; Wickham, Vaughan, & Girlich, 2023),

⁴⁸⁹ *tidyverse* (Version 2.0.0; Wickham et al., 2019), and *tinylabels* (Version 0.2.4; Barth, 2022).