Reproducible Science

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Replicability School

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About me 👋

- Post-doctoral researcher in **Cognitive Psychology**, University of Padova.
- Research: Computational modeling of **cognitive** and **learning processes**, **Bayesian** hypothesis testing.
- PhD in Psychological Science, completed **March 6, 2025**.
- Passionate about reproducible science after struggling with disorganized datasets in my early research!

Our job is hard 🔥

- Running experiments
- Analyzing data
- Managing trainees
- Writing papers
- Responding to reviewers

Reproducibility helps!

- **Organizes** your workflow.
- **Saves time** by documenting steps.
- **Builds trust** in your findings.
- Enables others to **reproduce** and **extend** your work.

What is reproducible science?

At its core, reproducible science means that someone else, or even you, in the future, can **reproduce** your **results** from your **materials**: your data, your code, your documentation.

It means your workflow is **transparent**.

Keys to reproducible science 🔐

- **Data**: organize, document, and share your datasets in ways that are usable by others and understandable by you (even years later).
- **Code**: write analysis scripts that are clean, transparent, and reusable..
- **Literate programming**: combine code and text in the same document, so your reports are dynamic and replicable.
- **Version Control and Sharing**: track changes, collaborate, and make your work openly available using tools like GitHub and OSF.

So... Is reproducible science even harder?

At first, yes - but then…🧯🔥

- Helps you stay **organized**.
- Makes it **easier to remember** what you did.
- Allows others to **understand**, **reproduce**, and **build on** your work.

> *Learning the tools takes effort but once you do, your workflow becomes smoother, clearer, and more reliable.*

Outline

Data

Code

R projects

Literate Programming

Version Control

Data

Data types in research

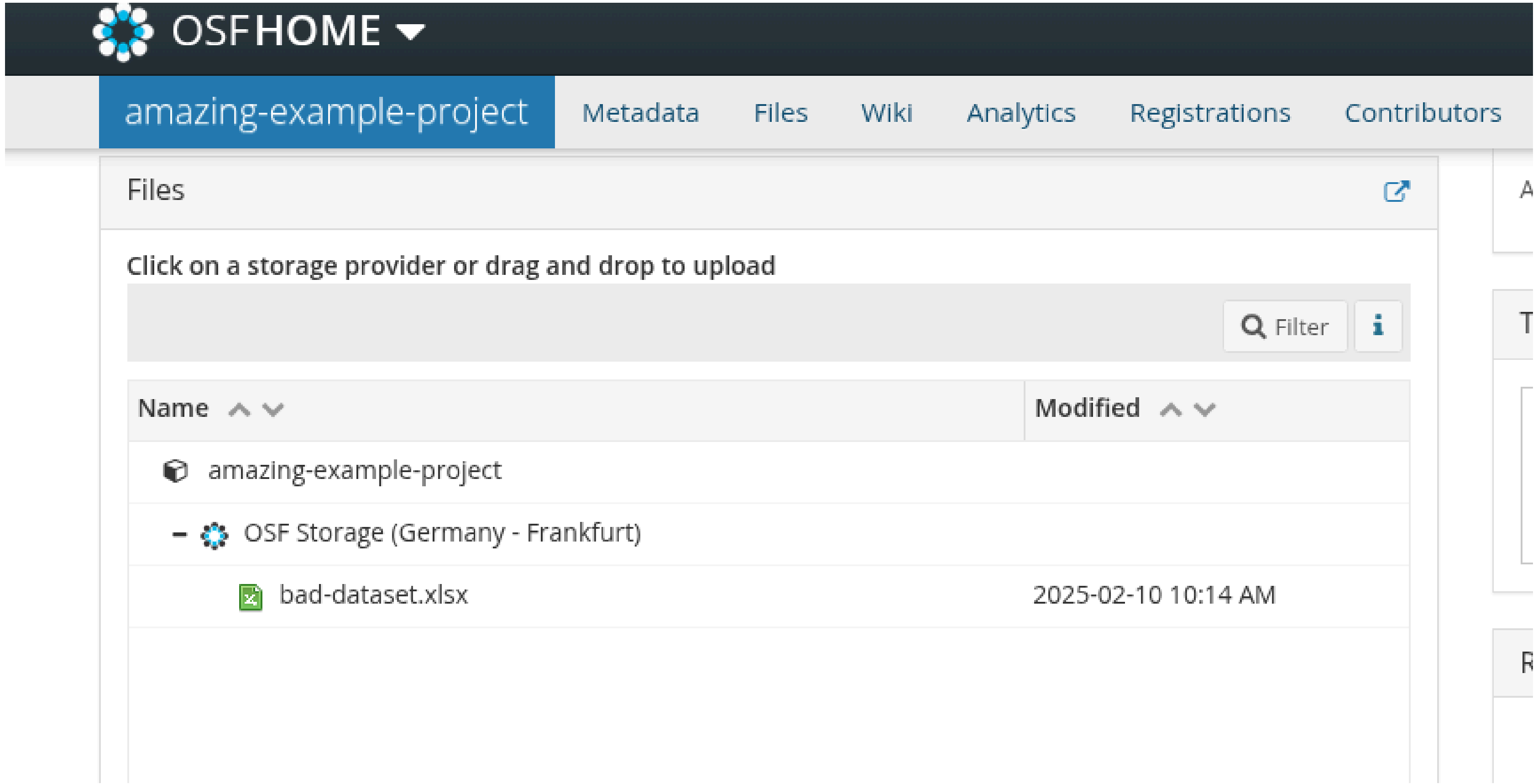
OSF

Open Science Framework

- Free platform to **organize**, **document**, and **share** research.
- Supports **preregistration**, **archiving**, and **collaboration**.
- Integrates with GitHub, Dropbox, Google Drive.

Bad data sharing example

Imagine this scenario: you read a paper that seems really relevant to your research. At the end, you're excited to see they've shared their data on OSF. You go to the repository, and there's one file…



Files

Click on a storage provider or drag and drop to upload

Name	Modified
amazing-example-project	
OSF Storage (Germany - Frankfurt)	
bad-dataset.xlsx	2025-02-10 10:14 AM

Bad data sharing example

You download it, open it, and you see this: . . .

x1	x2	x3	x4	x5	x6	x7
0.3981105	13.912435	a	0	-0.6775811	0.8759740	-0.2051604
-0.1434733	1.093743	c	0	0.7055193	0.2521987	1.8816947
-0.2526000	4.898035	c	0	0.4744651	-0.5628840	0.3245589
-1.2272588	14.717053	b	0	-0.5132792	-1.1368242	-0.1355150
-0.4360417	8.547025	c	1	-0.1736804	-0.7120962	-1.2714320

What do these variables mean? What's x3?

What do 0 and 1 represent? How are missing values coded?

Is x6 a z-score or raw data?

Good data sharing practices

- Use **plain-text formats** (e.g., `.csv`, `.txt`).
- Include a **data dictionary** with variable descriptions.
- Add a **README** with key details.
- Follow **FAIR principles** (Findable, Accessible, Interoperable, Reusable).

Data dictionary 📂

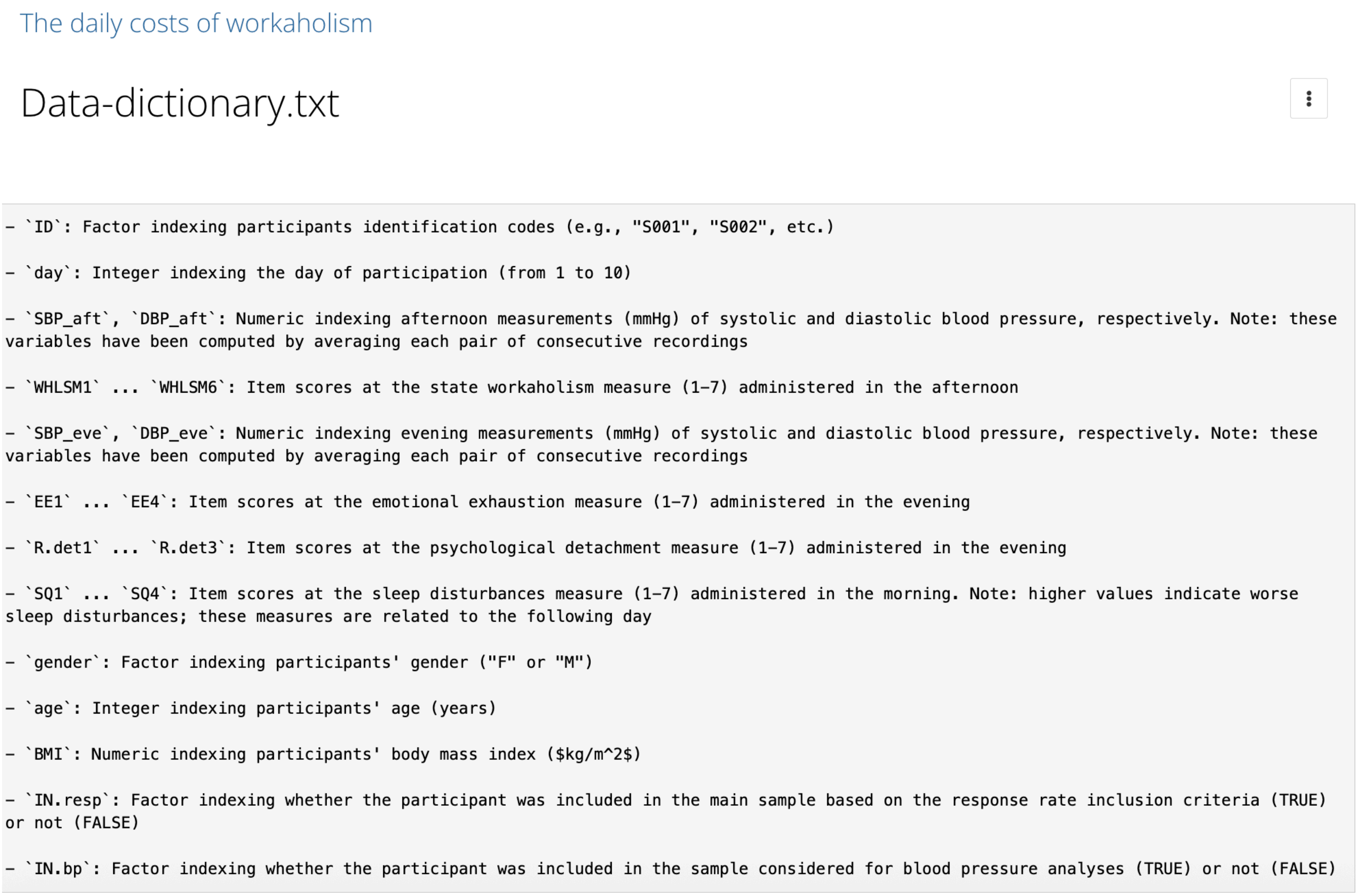
- A **data dictionary** defines each variable in your dataset.
- Boosts **transparency** and **collaboration**.
- Saves time for **collaborators** and **future-you**.

datadictionary 📦

```r
library(datadictionary)
df <- data.frame( id = factor(letters[1:5]),
                  anxi = rnorm(5, 0, 1),
                  edu = factor(c("PhD", "BSc", "MSc", "PhD", "BSc")))
df_labels <- list(
  anxi = "Beck Anxiety Inventory, standardized",
  edu = "Last degree obtained"
)
create_dictionary(df, id_var = "id", var_labels = df_labels)
```

```
   item                                label   class            summary value
1                                                       Rows in dataset     5
2                                                    Columns in dataset     3
3    id                    Unique identifier                  unique values     5
4                                                               missing     0
5  anxi Beck Anxiety Inventory, standardized numeric               mean     1
6                                                                median     1
7                                                                   min -1.84
8                                                                   max  1.82
9                                                               missing     0
10  edu                 Last degree obtained  factor            BSc (1)     2
11                                                              MSc (2)     1
12                                                              PhD (3)     2
13                                                              missing     0
```

Data dictionary - Good data sharing example



The daily costs of workaholism

Data-dictionary.txt

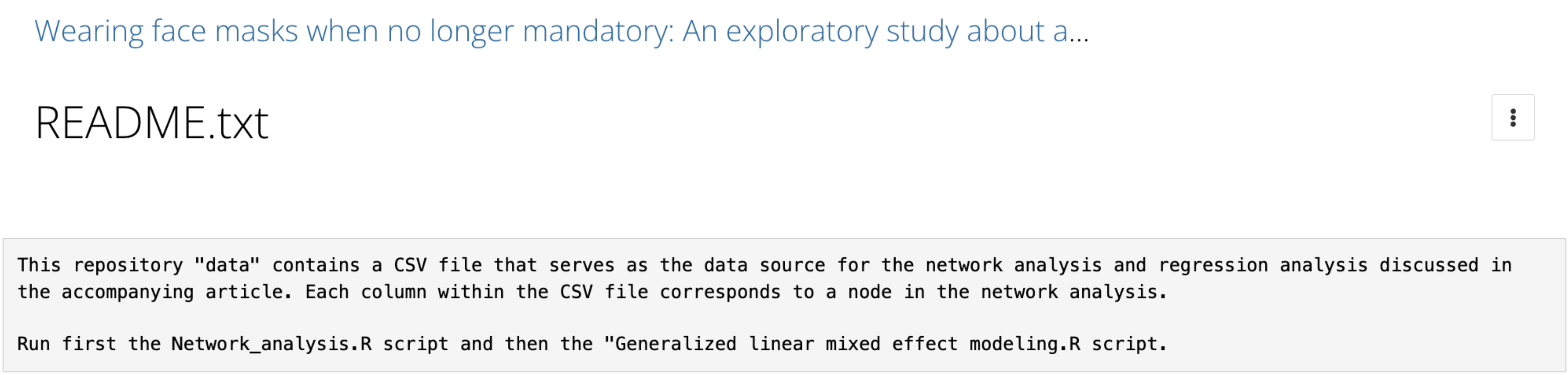
```
- `ID`: Factor indexing participants identification codes (e.g., "S001", "S002", etc.)

- `day`: Integer indexing the day of participation (from 1 to 10)

- `SBP_aft`, `DBP_aft`: Numeric indexing afternoon measurements (mmHg) of systolic and diastolic blood pressure, respectively. Note: these
variables have been computed by averaging each pair of consecutive recordings

- `WHLSM1` ... `WHLSM6`: Item scores at the state workaholism measure (1-7) administered in the afternoon

- `SBP_eve`, `DBP_eve`: Numeric indexing evening measurements (mmHg) of systolic and diastolic blood pressure, respectively. Note: these
variables have been computed by averaging each pair of consecutive recordings

- `EE1` ... `EE4`: Item scores at the emotional exhaustion measure (1-7) administered in the evening

- `R.det1` ... `R.det3`: Item scores at the psychological detachment measure (1-7) administered in the evening

- `SQ1` ... `SQ4`: Item scores at the sleep disturbances measure (1-7) administered in the morning. Note: higher values indicate worse
sleep disturbances; these measures are related to the following day

- `gender`: Factor indexing participants' gender ("F" or "M")

- `age`: Integer indexing participants' age (years)

- `BMI`: Numeric indexing participants' body mass index ($kg/m^2$)

- `IN.resp`: Factor indexing whether the participant was included in the main sample based on the response rate inclusion criteria (TRUE)
or not (FALSE)

- `IN.bp`: Factor indexing whether the participant was included in the sample considered for blood pressure analyses (TRUE) or not (FALSE)
```

README files

A **README** file is the first thing someone sees when they open your dataset/project folder. It should answer basic questions like:

- What is this dataset?
- How was it collected?
- What are the variables?
- Which is the structure of the project?

README - Good data sharing example

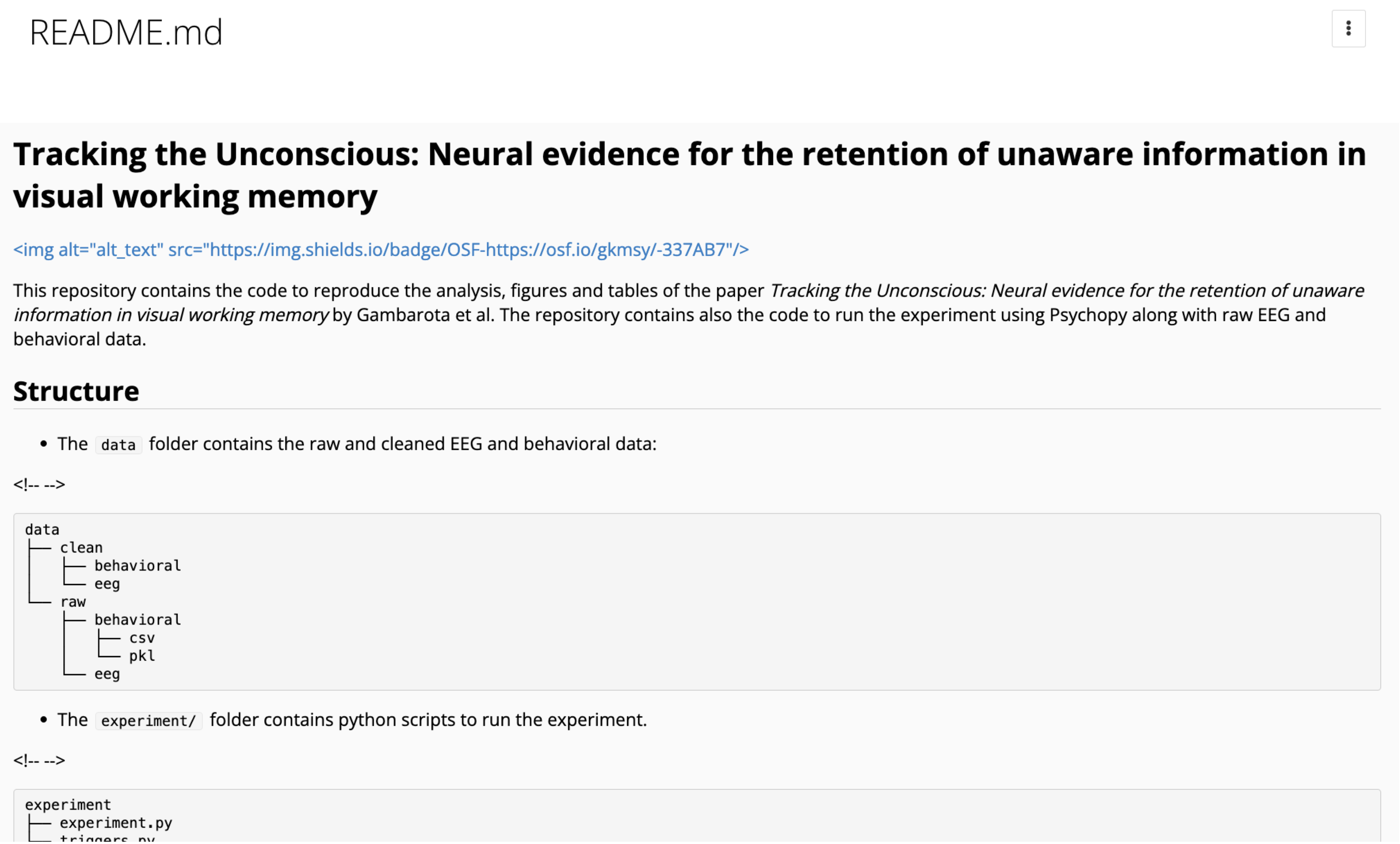


Wearing face masks when no longer mandatory: An exploratory study about a...

README.txt

```
This repository "data" contains a CSV file that serves as the data source for the network analysis and regression analysis discussed in
the accompanying article. Each column within the CSV file corresponds to a node in the network analysis.

Run first the Network_analysis.R script and then the "Generalized linear mixed effect modeling.R script.
```

README - Good data sharing example



README.md

Tracking the Unconscious: Neural evidence for the retention of unaware information in visual working memory

<img alt="alt_text" src="https://img.shields.io/badge/OSF-https://osf.io/gkmsy/-337AB7"/>

This repository contains the code to reproduce the analysis, figures and tables of the paper *Tracking the Unconscious: Neural evidence for the retention of unaware information in visual working memory* by Gambarota et al. The repository contains also the code to run the experiment using Psychopy along with raw EEG and behavioral data.

Structure

- The `data` folder contains the raw and cleaned EEG and behavioral data:

<!-- -->

```
data
├── clean
│   ├── behavioral
│   └── eeg
└── raw
    ├── behavioral
    │   ├── csv
    │   └── pkl
    └── eeg
```

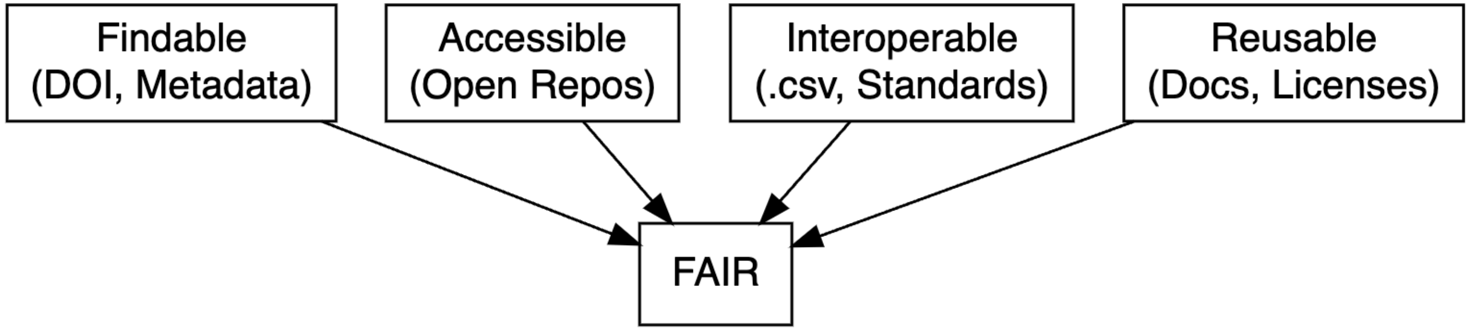
- The `experiment/` folder contains python scripts to run the experiment.

<!-- -->

```
experiment
├── experiment.py
├── triggers.py
```

FAIR data principles 🔍

- **Findable**: Use metadata and DOIs to make data easy to locate.
- **Accessible**: Ensure data is retrievable via open repositories.
- **Interoperable**: Use standard formats (e.g., `.csv`, `.txt`) for compatibility.
- **Reusable**: Include clear documentation and open licenses.



Data licensing 🔒

A license tells others what they can and can’t do with your data. If you don’t include one, legally speaking, people might not be allowed to use it, even if you meant to share it openly.

- **Licenses** clarify how others can use your data.
- Common licenses:
  - CC BY: Requires attribution.
  - CC0: No restrictions.
  - GNU-GPL: guarantees end users the freedom to run, study, share, and modify the software while requiring that all modified versions and derivative works also be distributed under the same license. ❤️

Code

Why scripting?

The SPSS Workflow

- Click menu items to run analysis
- “exclude <18”
- Click through everything again
- Forget a step? Round differently?

> Stressful, error-prone, and undocumented.

R Workflow

```r
# Load data
data <- read.csv("data.csv")

# Filter age
data <- data[data$age >= 18, ]

# Analyze
summary(lm(score ~ condition, data = data))

# Make plot
ggplot(data, aes(x = condition, y = score)) +
  geom_boxplot()
```

> One line change, rerun, and everything updates.

Why scripting?

Scripting ensures **transparent** and **reproducible** workflows.

Reproducible: You can rerun them.

Documented: You can see what you did and when.

Shareable: Others can inspect and reproduce your analysis.

R and RStudio 💻

- **R**: Free, open-source, with thousands of packages for analysis.
- **RStudio**: Intuitive interface for coding, plotting, and debugging.
- Vibrant **community** for support and resources.

Writing better code 📝

- **Name descriptively**: Use `snake_case` or `camelCase` for readability.
- **Comment clearly**: Document your logic for clarity.
- **Organize scripts**: Load packages and data upfront.

Use descriptive names

Another best practice: name your variables clearly.

```r
# Bad
x1 <- c("unipd_psychology", "unipd_medicine", "unito_biology")
# Better
uni_dep <- c("unipd_psychology", "unipd_medicine", "unito_biology")
```

Consistency helps too. Use either snake_case or camelCase, but pick one and stick to it.

Comments, comments and comments...

Write the code for your future self and for others, not for yourself right now.

Try to open a (not well documented) old coding project after a couple of years and you will understand :)

Invest time in writing more comprehensible and documented code for you and others.

```r
# Remove participants with missing anxiety scores
dat <- dat %>% filter(!is.na(anxi))
#vs.
dat <- dat %>% filter(!is.na(anxi))  # <-- What is this doing?
```

Organized scripts

Global operations at the beginning of the script:

- loading packages
- loading datasets
- changing general options (`options()`)

```r
# packages
library(tidyverse)
library(lme4)

# options

options(scipen = 999)

# loading data
dat <- read.csv(...)
```

Summary

- Scripts beat point-and-click
- Structure matters
- Comment often
- Name things well

Functions to avoid repetition

Functions are the primary building blocks of your program. You write small, reusable, self-contained functions that do one thing well, and then you combine them.

Avoid repeating the same operation multiple times in the script. The rule is, if you are doing the same operation more than two times, write a function.

A function can be re-used, tested and changed just one time affecting the whole project.

Functional Programming, example...

We have a dataset (`mtcars`) and we want to calculate the mean, median, standard deviation, minimum and maximum of each column and store the result in a table.

```r
head(mtcars, n = 3)
```

```
               mpg cyl disp  hp drat    wt  qsec vs am gear carb
Mazda RX4     21.0   6  160 110 3.90 2.620 16.46  0  1    4    4
Mazda RX4 Wag 21.0   6  160 110 3.90 2.875 17.02  0  1    4    4
Datsun 710    22.8   4  108  93 3.85 2.320 18.61  1  1    4    1
```

```r
str(mtcars)
```

```
'data.frame':	32 obs. of  11 variables:
 $ mpg : num  21 21 22.8 21.4 18.7 18.1 14.3 24.4 22.8 19.2 ...
 $ cyl : num  6 6 4 6 8 6 8 4 4 6 ...
 $ disp: num  160 160 108 258 360 ...
 $ hp  : num  110 110 93 110 175 105 245 62 95 123 ...
 $ drat: num  3.9 3.9 3.85 3.08 3.15 2.76 3.21 3.69 3.92 3.92 ...
 $ wt  : num  2.62 2.88 2.32 3.21 3.44 ...
 $ qsec: num  16.5 17 18.6 19.4 17 ...
 $ vs  : num  0 0 1 1 0 1 0 1 1 1 ...
 $ am  : num  1 1 1 0 0 0 0 0 0 0 ...
 $ gear: num  4 4 4 3 3 3 3 4 4 4 ...
 $ carb: num  4 4 1 1 2 1 4 2 2 4 ...
```

Imperative Programming

The standard (~imperative) option is using a `for` loop, iterating through columns, calculate the values and store into another data structure.

```r
ncols <- ncol(mtcars)
means <- medians <- mins <- maxs <- rep(0, ncols)

for(i in 1:ncols){
  means[i] <- mean(mtcars[[i]])
  medians[i] <- median(mtcars[[i]])
  mins[i] <- min(mtcars[[i]])
  maxs[i] <- max(mtcars[[i]])
}

results <- data.frame(means, medians, mins, maxs)
results$col <- names(mtcars)

head(results, n = 3)
```

```
      means medians mins  maxs  col
1  20.09062    19.2 10.4  33.9  mpg
2   6.18750     6.0  4.0   8.0  cyl
3 230.72188   196.3 71.1 472.0 disp
```

Functional Programming

The main idea is to decompose the problem writing a function and loop over the columns of the dataframe:

```r
summ <- function(x){
  data.frame(means = mean(x),
             medians = median(x),
             mins = min(x),
             maxs = max(x))
}
ncols <- ncol(mtcars)
dfs <- vector(mode = "list", length = ncols)

for(i in 1:ncols){
  dfs[[i]] <- summ(mtcars[[i]])
}
```

Functional Programming

```r
results <- do.call(rbind, dfs)
head(results, n = 6)
```

```
       means medians   mins    maxs
1  20.090625  19.200 10.400  33.900
2   6.187500   6.000  4.000   8.000
3 230.721875 196.300 71.100 472.000
4 146.687500 123.000 52.000 335.000
5   3.596563   3.695  2.760   4.930
6   3.217250   3.325  1.513   5.424
```

Functional Programming, `*apply` 📦

- The `*apply` family is one of the best tool in R. The idea is pretty simple: apply a function to each element of a list.
- The powerful side is that in R everything can be considered as a list. A vector is a list of single elements, a dataframe is a list of columns etc.
- Internally, R is still using a `for` loop but the verbose part (preallocation, choosing the iterator, indexing) is encapsulated into the `*apply` function.

```r
means <- rep(0, ncol(mtcars))
for(i in 1:length(means)){
  means[i] <- mean(mtcars[[i]])
}

# the same with sapply
means <- sapply(mtcars, mean)
```

The *apply Family

Apply **your** function…

```r
results <- lapply(mtcars, summ)
```

Now results is a list of data frames, one per column.

We can stack them into one big data frame:

```r
results_df <- do.call(rbind, results)
results_df
```

```
          means medians   mins   maxs
mpg   20.090625  19.200 10.400 33.900
cyl    6.187500   6.000  4.000  8.000
disp 230.721875 196.300 71.100 472.000
hp   146.687500 123.000 52.000 335.000
drat   3.596563   3.695  2.760  4.930
wt     3.217250   3.325  1.513  5.424
qsec  17.848750  17.710 14.500 22.900
vs     0.437500   0.000  0.000  1.000
am     0.406250   0.000  0.000  1.000
gear   3.687500   4.000  3.000  5.000
carb   2.812500   2.000  1.000  8.000
```

Using `sapply`, `vapply`, and `apply`

- `lapply()` always returns a list.
- `sapply()` tries to simplify the result into a vector or matrix.
- `vapply()` is like `sapply()` but safer (you specify the return type).
- `apply()` is for applying functions over rows or columns of a matrix or data frame.

for loops are bad?

for loops are the core of each operation in R (and in every programming language). For complex operation thery are more readable and effective compared to *apply. In R we need extra care for writing efficent for loops.

Extremely slow, no preallocation:

```r
res <- c()
for(i in 1:1000){
  # do something
  res[i] <- i^2
}
```

Very fast:

```r
res <- rep(0, 1000)
for(i in 1:length(res)){
  # do something
  res[i] <- i^2
}
```

microbenchmark 📦

```r
library(microbenchmark)

microbenchmark(
  grow_in_loop = {
    res <- c()
    for (i in 1:10000) {
      res[i] <- i^2
    }
  },
  preallocated = {
    res <- rep(0, 10000)
    for (i in 1:length(res)) {
      res[i] <- i^2
    }
  }, times = 100)
```

```
Unit: microseconds
         expr      min        lq      mean   median       uq      max neval cld
 grow_in_loop 1130.370 1192.0955 1406.1860 1267.863 1314.788 6227.244   100  a 
 preallocated  653.294  672.0105  694.7647  683.552  698.189  997.448   100   b
```

Going further: custom function lists

Let’s define a list of functions:

```r
funs <- list(mean = mean, sd = sd, min = min, max = max, median = median)
```

Now we can apply all of these to every column:

```r
sapply(funs, function(f) apply(mtcars, MARGIN = 2, f)) # MARGIN = 2 = column
```

```
           mean          sd    min     max  median
mpg   20.090625   6.0269481 10.400  33.900  19.200
cyl    6.187500   1.7859216  4.000   8.000   6.000
disp 230.721875 123.9386938 71.100 472.000 196.300
hp   146.687500  68.5628685 52.000 335.000 123.000
drat   3.596563   0.5346787  2.760   4.930   3.695
wt     3.217250   0.9784574  1.513   5.424   3.325
qsec  17.848750   1.7869432 14.500  22.900  17.710
vs     0.437500   0.5040161  0.000   1.000   0.000
am     0.406250   0.4989909  0.000   1.000   0.000
gear   3.687500   0.7378041  3.000   5.000   4.000
carb   2.812500   1.6152000  1.000   8.000   2.000
```

This gives you a matrix with rows as variables and columns as statistics.

Pure vs. Impure functions

Pure function

Same input, same output, no side effects.

```r
x = 4
add_pure<- function(x) {
  return(x + 1)
}
add_pure(x)
```

```
[1] 5
```

```r
print(x)
```

```
[1] 4
```

Impure function

Modifies external variables.

```r
x = 4
add_impure <- function(x) {
  x <<- x + 1
}
add_impure(x)
print(x)
```

```
[1] 5
```

Test your functions - `fuzzr` 📦

When you write your own functions, it's smart to test them. In R, we can use `fuzzr` to do **property-based testing**.

Define your function…

```r
my_mean <- function(x, na.rm = TRUE) {
  if (!is.numeric(x)) stop("`x` must be numeri
  if (length(x) == 0) return(NA)
  if (na.rm) x <- x[!is.na(x)]
  if (length(x) == 0) return(NA)
  sum(x) / length(x)
}
```

Define properties that should always hold true…

```r
property_mean_correct <- function(x) {
  x_no_na <- x[!is.na(x)] #remove NA
  if (length(x_no_na) == 0) return(TRUE)
  abs(my_mean(x) - mean(x, na.rm = TRUE)) < 1e
}
```

This runs the property on different random numeric vectors and checks whether it holds.

```r
# Property-based testing with 'fuzzr'
library(fuzzr)
test = fuzz_function(fun = property_mean_correct,
                     arg_name = "x",
                     tests = test_dbl())
lapply(test, function(res) res$test_result$value)
```

```
[[1]]
[1] TRUE

[[2]]
[1] TRUE

[[3]]
[1] TRUE

[[4]]
[1] TRUE

[[5]]
[1] TRUE

[[6]]
[1] TRUE
```

```r
fuzzr::test_dbl()
```

```
$dbl_empty
numeric(0)

$dbl_single
[1] 1.5

$dbl_mutliple
[1] 1.5 2.5 3.5

$dbl_with_na
[1] 1.5 2.5  NA

$dbl_single_na
[1] NA

$dbl_all_na
[1] NA NA NA
```

Why functional programming?

- We can write less and reusable code that can be shared and used in multiple projects.

- The scripts are more compact, easy to modify and less error prone (imagine that you want to improve the `summ` function, you only need to change it once instead of touching the `for` loop).

- Functions can be easily and consistently documented (see roxygen documentation) improving the reproducibility and readability of your code.

Functional programming in the wild

You can write some R scripts only with functions and `source()` them into the global environment.

```
project/
├─ R/
│   ├─ utils.R
    ├─ analysis.R
```

```r
source("R/utils.R")
results <- lapply(mtcars, summ)
results_df <- do.call(rbind, results)
```

More about functional programming in R

- Advanced R by Hadley Wickham, section on Functional Programming (https://adv-r.hadley.nz/fp.html)

- Hands-On Programming with R by Garrett Grolemund https://rstudio-education.github.io/hopr/

- Hadley Wickham: The Joy of Functional Programming (for Data Science) (https://www.youtube.com/watch?v=bzUmK0Y07ck)

Wrapping up

- Avoid repetition by using functions.
- Favor pure functions.
- Test your functions.
- The `*apply` functions are your friends, or `*map` from `purrr` 📦

Organize your project

R Projects

R Projects are a feature implemented in RStudio to organize a working directory.

- They automatically set the working directory
- They allow the use of ***relative paths*** instead of ***absolute paths***
- They provide quick access to a specific project

The Working Directory Problem

How many times have you opened an R script and seen this at the top?

```
setwd(“C:/Users/margherita/Documents/PhD/final_data/mess”) #change
```

Instead of hardcoding paths, we want to use projects with **relative paths**.

R Projects

An R Project (.Rproj) is a file that defines a self-contained workspace. When you open an R Project, your working directory is automatically set to the project root, no need to use setwd() ever again.

Open RStudio

`File → New Project → New Directory → New Project`

Relative Path (to the working directory)

```
Users
  │
  ├─tita
     │
     ├─ workin_memo
            │
            ├─ data
            │    ├─ clean_data.csv
            │
            ├─ workin_memo.Rproj
```

Absolute path: read.csv(“Users/tita/workin_memo/data/clean_data.csv”)

Relative path: read.csv(“data/clean_data.csv”)

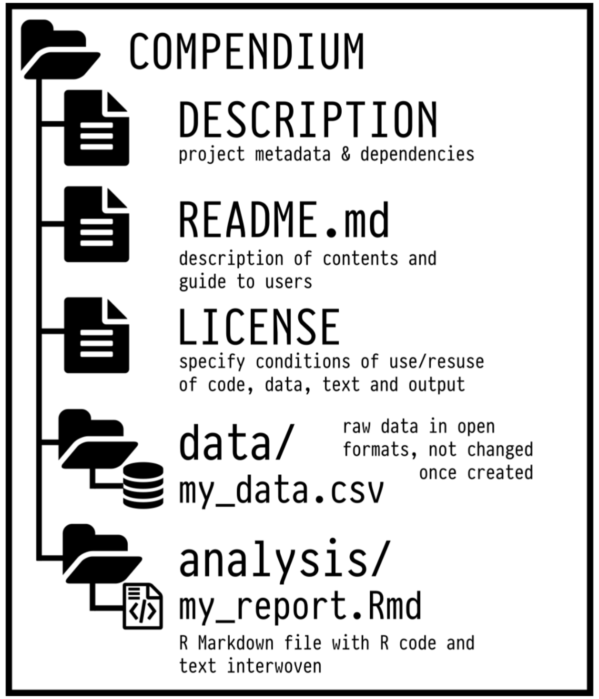
A Minimal Project Structure

```
my-project/
    │
    ├── data/
    │     ├── raw/
    │     └── processed/
    ├── R/
    │   └── analysis.R
    │
    ├── outputs/
    │   ├── figures/
    │   └── tables/
    │
    ├── my-project.Rproj
    │
    └── README.md
```

Project organization with `rrtools` 📦

To make this even “easier”, you can use the `rrtools` package to create what’s called a reproducible research compendium.

> *… the goal is to provide a standard and easily recognisable way for organising the digital materials of a project to enable others to inspect, reproduce, and extend the research… (Marwick et al., 2018)*



COMPENDIUM

DESCRIPTION
project metadata & dependencies

README.md
description of contents and guide to users

LICENSE
specify conditions of use/resuse of code, data, text and output

data/
my_data.csv
raw data in open formats, not changed once created

analysis/
my_report.Rmd
R Markdown file with R code and text interwoven

Research compendium `rrtools` 📦

- Organize its files according to the prevailing conventions.
- Maintain a clear separation of data (original data is untouched!), method, and output.
- Specify the computational environment that was used for the original analysis

`rrtools::create_compendium("compedium")` builds the basic structure for a research compendium.

> Example

> Tutorial

`renv`📦: locking your R environment

Another challenge for reproducibility is package versions.

You write some code today using `dplyr 1.1.2`.

In six months, `dplyr` gets updated… 😢

`renv` helps you create reproducible environments for your R projects!

What does `renv` do?

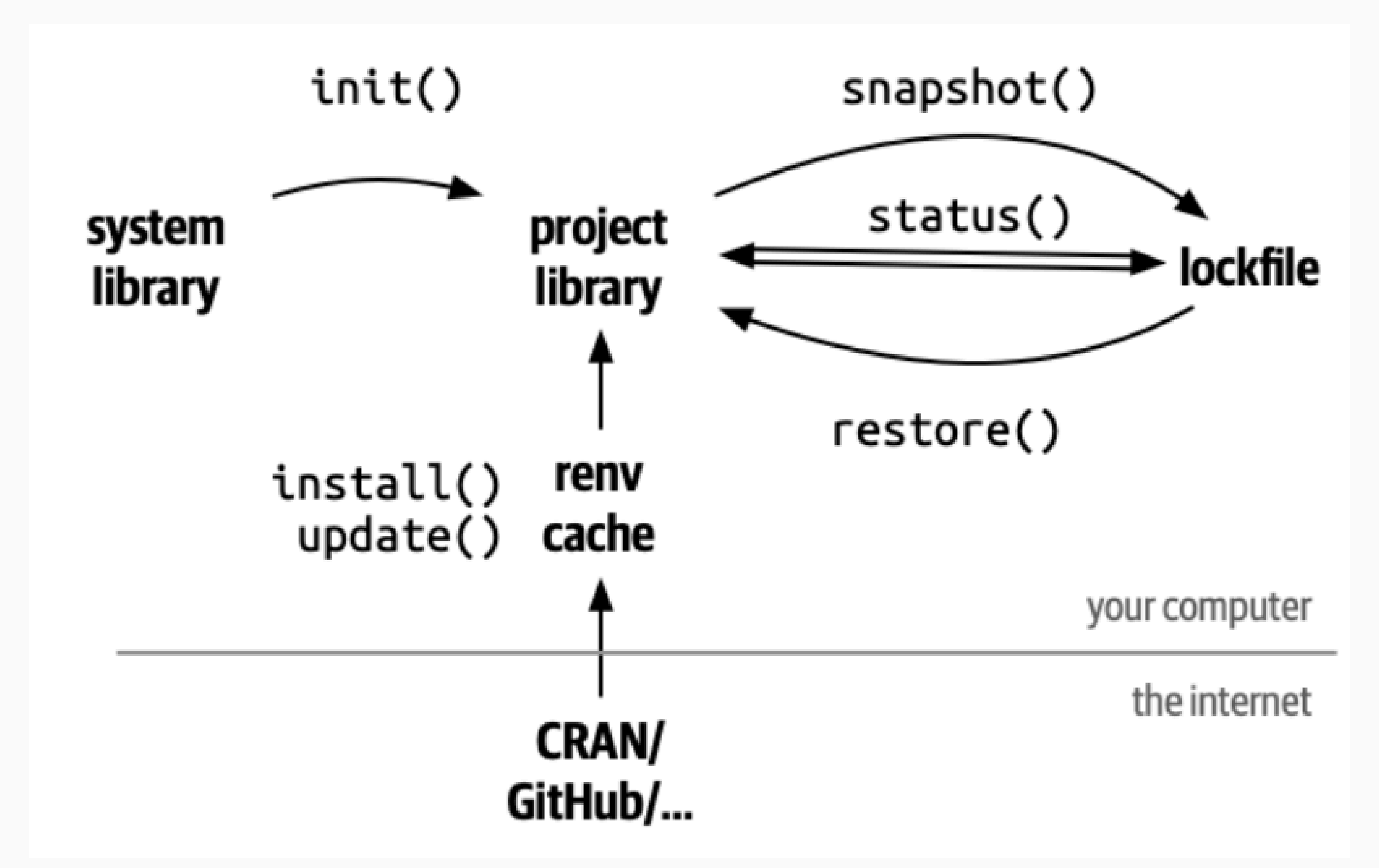
- It records all the packages you use, with versions, in a lockfile
- It installs them in a project-specific library
- It ensures that anyone who runs your code gets exactly the same environment

Project specific library

```
install.packages("renv")

renv::init()

install.packages('bayesplot')

These packages will be installed into "~/repro-pre-school/example-renv/renv/library/macos/R-
4.4/aarch64-apple-darwin20".
```

> Example

renv commands



`renv::restore()` # re-install from lockfile

Research `rrtools` + `renv` 💣

- `rrtools`: Organizes your project into a **reproducible compendium** with clear folders.
- `renv`: Locks **R package versions** for consistent environments.
- Together, they ensure **structure** and **reproducibility** across teams and time.
- Run `rrtools::create_compendium("project")` to start, then `renv::init()` to lock dependencies.

Docker

- Packages your project's **software**, **dependencies**, and **system settings** into a *container*.
- Ensures **consistency** across different computers or servers.
- Ideal for **sharing** complex analyses with others.

Documenting your environment ℹ️

- `sessionInfo()`: Captures your **R version**, **packages**, and **platform** in one command.
- Easy way to **document** and **share** your environment.

```r
sessionInfo()
```

```
R version 4.4.2 (2024-10-31)
Platform: aarch64-apple-darwin20
Running under: macOS Sequoia 15.5

Matrix products: default
BLAS:   /Library/Frameworks/R.framework/Versions/4.4-arm64/Resources/lib/libRblas.0.dylib
LAPACK: /Library/Frameworks/R.framework/Versions/4.4-arm64/Resources/lib/libRlapack.dylib;  LAPACK
version 3.12.0

locale:
[1] en_US.UTF-8/en_US.UTF-8/en_US.UTF-8/C/en_US.UTF-8/en_US.UTF-8

time zone: Europe/Rome
tzcode source: internal

attached base packages:
[1] stats     graphics  grDevices utils     datasets  methods   base
```

Organizing for reproducibility

- Don’t hardcode paths, use `R Projects`
- Create a logical folder structure for your project
- Use `rrtools` to scaffold a research compendium
- Use `renv` to lock your package versions

Literate Programming

What’s wrong about Microsoft Word?

In MS Word (or similar) we need to produce everything outside and then manually put figures and tables.

The entire Microsoft word document when you slightly move an image by 1 mm
ifunny.co

- writing math formulas
- reporting statistics in the text
- producing tables
- producing plots

Think about the typical MW workflow

- You run your analysis in R
- You copy the results into a Word document
- You tweak the formatting
- You insert a figure generated with R manually
- You change your analysis, but forget to update the results in the text…

Literate Programming

A document where:

- The code is part of the text
- The results are generated *dynamically*
- The figures are rendered *automatically*
- Everything is in *sync*

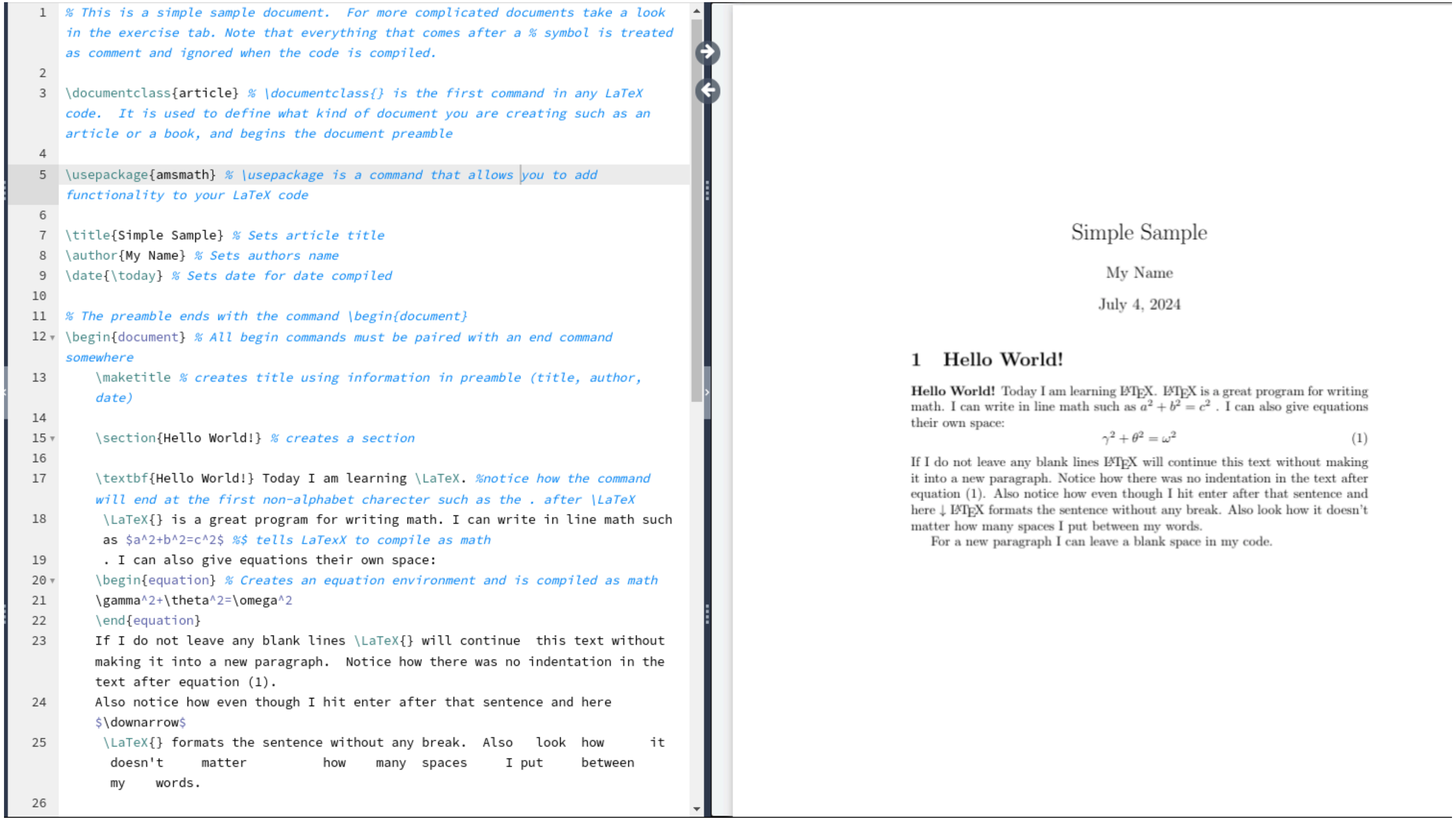
For example **jupyter notebooks**, **R Markdown** and now **Quarto** are literate programming frameworks to integrate code and text.

Literate Programming, the markup language

The markup language is the core element of a literate programming framework. When you write in a markup language, you’re writing **plain text** while also giving **instructions** for how to generate the final result.

- LaTeX
- HTML
- Markdown
- …

LaTeX



```latex
% This is a simple sample document.  For more complicated documents take a look in the exercise tab. Note that everything that comes after a % symbol is treated as comment and ignored when the code is compiled.

\documentclass{article} % \documentclass{} is the first command in any LaTeX code.  It is used to define what kind of document you are creating such as an article or a book, and begins the document preamble

\usepackage{amsmath} % \usepackage is a command that allows you to add functionality to your LaTeX code

\title{Simple Sample} % Sets article title
\author{My Name} % Sets authors name
\date{\today} % Sets date for date compiled

% The preamble ends with the command \begin{document}
\begin{document} % All begin commands must be paired with an end command somewhere
    \maketitle % creates title using information in preamble (title, author, date)

    \section{Hello World!} % creates a section

    \textbf{Hello World!} Today I am learning \LaTeX. %notice how the command will end at the first non-alphabet charecter such as the . after \LaTeX
     \LaTeX{} is a great program for writing math. I can write in line math such as $a^2+b^2=c^2$ %$ tells LaTexX to compile as math
     . I can also give equations their own space:
    \begin{equation} % Creates an equation environment and is compiled as math
    \gamma^2+\theta^2=\omega^2
    \end{equation}
    If I do not leave any blank lines \LaTeX{} will continue  this text without making it into a new paragraph.  Notice how there was no indentation in the text after equation (1).
    Also notice how even though I hit enter after that sentence and here $\downarrow$
     \LaTeX{} formats the sentence without any break.  Also   look  how      it   doesn't     matter          how    many  spaces     I put      between   my    words.

```

Simple Sample

My Name

July 4, 2024

1 Hello World!

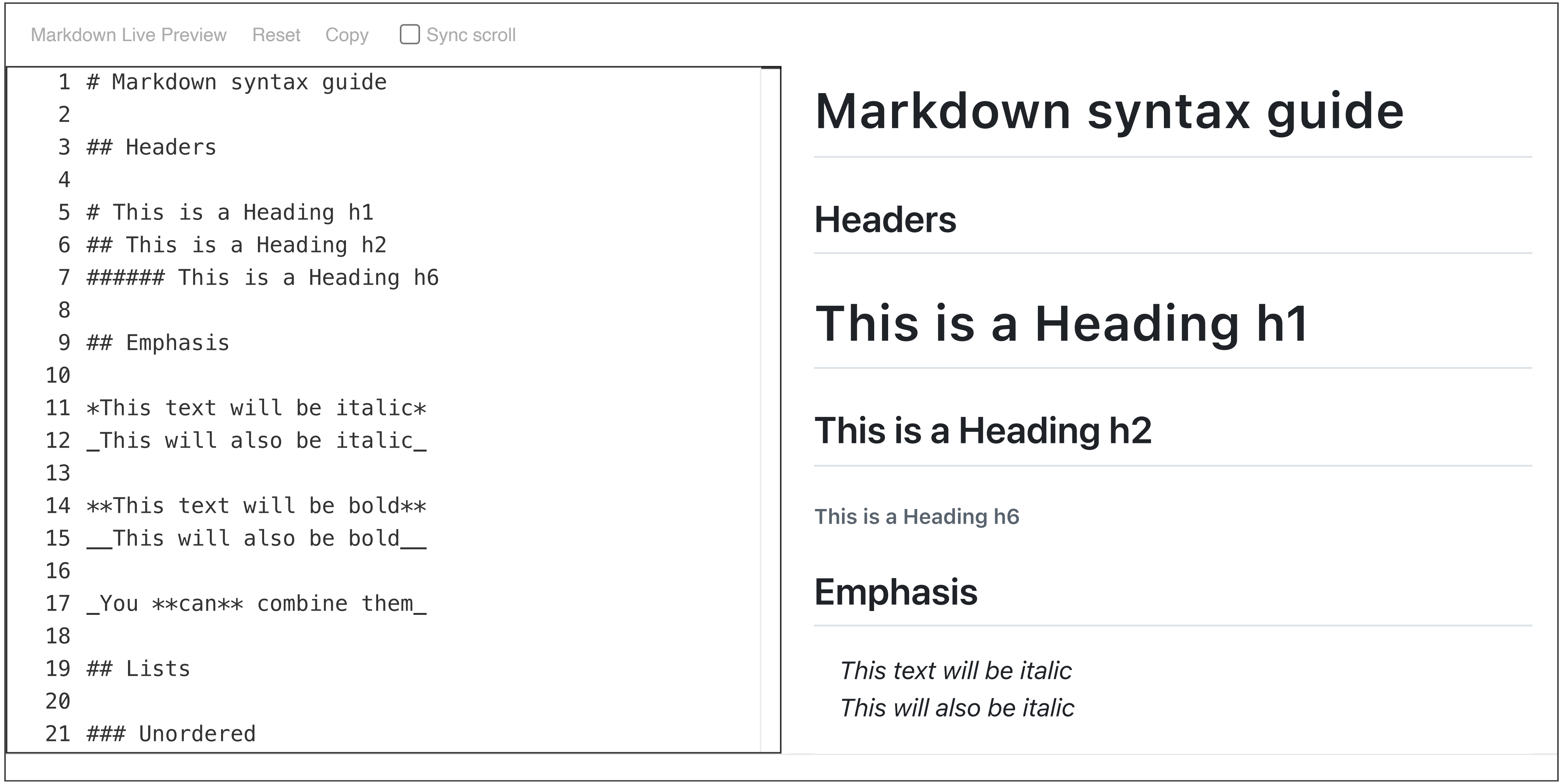
Hello World! Today I am learning LaTeX. LaTeX is a great program for writing math. I can write in line math such as $a^2+b^2=c^2$. I can also give equations their own space:

$$\gamma^2+\theta^2=\omega^2 \tag{1}$$

If I do not leave any blank lines LaTeX will continue this text without making it into a new paragraph. Notice how there was no indentation in the text after equation (1). Also notice how even though I hit enter after that sentence and here ↓ LaTeX formats the sentence without any break. Also look how it doesn't matter how many spaces I put between my words.

For a new paragraph I can leave a blank space in my code.

Markdown



```
# Markdown syntax guide

## Headers

# This is a Heading h1
## This is a Heading h2
###### This is a Heading h6

## Emphasis

*This text will be italic*
_This will also be italic_

**This text will be bold**
__This will also be bold__

_You **can** combine them_

## Lists

### Unordered
```

Markdown syntax guide

Headers

This is a Heading h1

This is a Heading h2

This is a Heading h6

Emphasis

This text will be italic
This will also be italic

Markdown

Markdown is one of the most popular markup languages for several reasons:

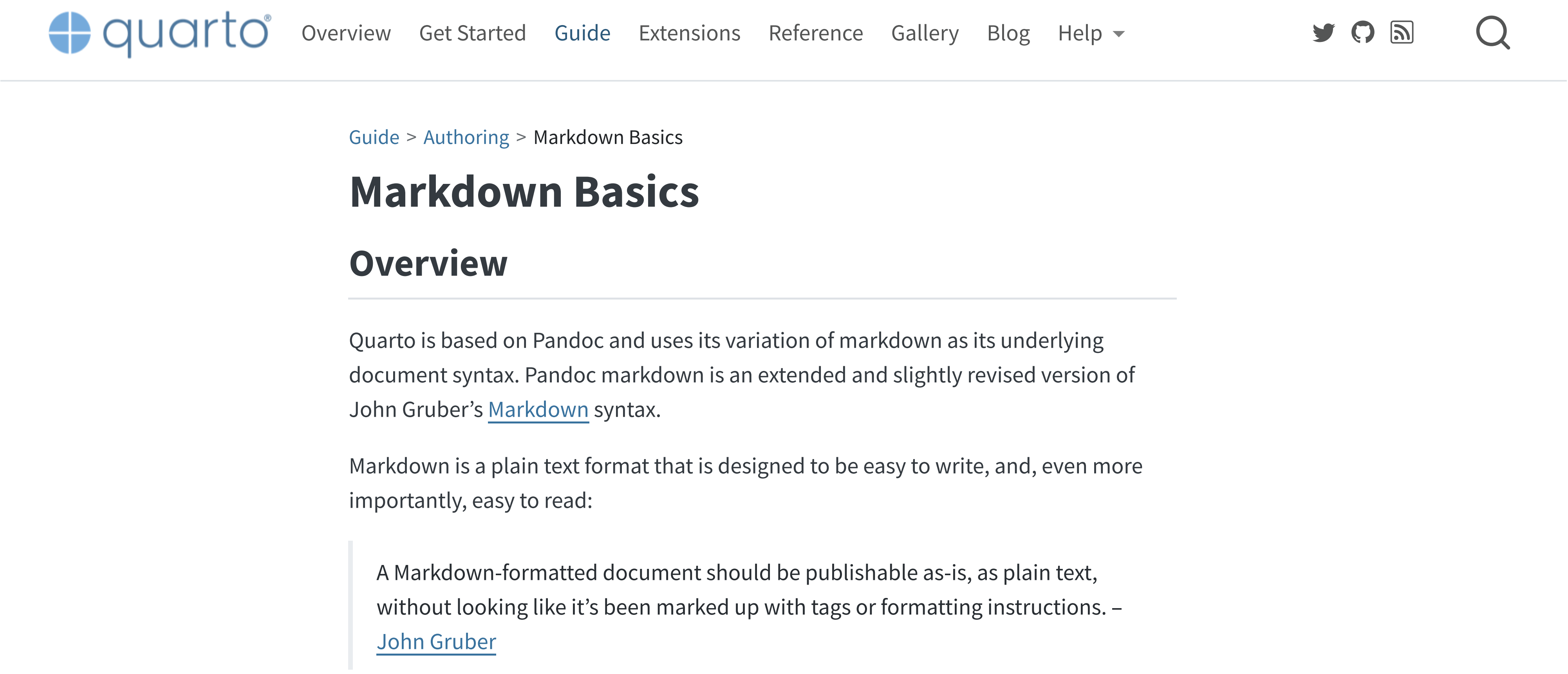
- easy to write and read compared to Latex and HTML
- easy to convert from Markdown to basically every other format using `pandoc`

Quarto

Quarto (https://quarto.org/) is the evolution of R Markdown that integrate a programming language with the Markdown markup language. It is very simple but quite powerful.

Basic Markdown

Markdown can be learned in minutes. You can go to the following link https://quarto.org/docs/authoring/markdown-basics.html and try to understand the syntax.



Markdown Basics

Overview

Quarto is based on Pandoc and uses its variation of markdown as its underlying document syntax. Pandoc markdown is an extended and slightly revised version of John Gruber's Markdown syntax.

Markdown is a plain text format that is designed to be easy to write, and, even more importantly, easy to read:

> A Markdown-formatted document should be publishable as-is, as plain text, without looking like it's been marked up with tags or formatting instructions. – John Gruber

Quarto

You write your documents in **Markdown**, and **Quarto** turns them into:

- HTML reports
- PDF articles
- Word documents
- Slides
- Website
- Academic manuscripts
- …

Quarto

> Example

- If your data changes, your summary table updates.
- If you update your model, your coefficients update.
- If you change a plot’s colors, the new version appear, without having to re-export and re-insert anything.

This eliminates a huge source of human error: **manual updates**.

Outputs

Quarto can generate multiple output formats from the same source file.

- A PDF to send to your colleagues
- A Word document for your co-author who hates PDFs
- An HTML report for your own website

Everything from the same source. No duplication. **Synchronization**.

> Example

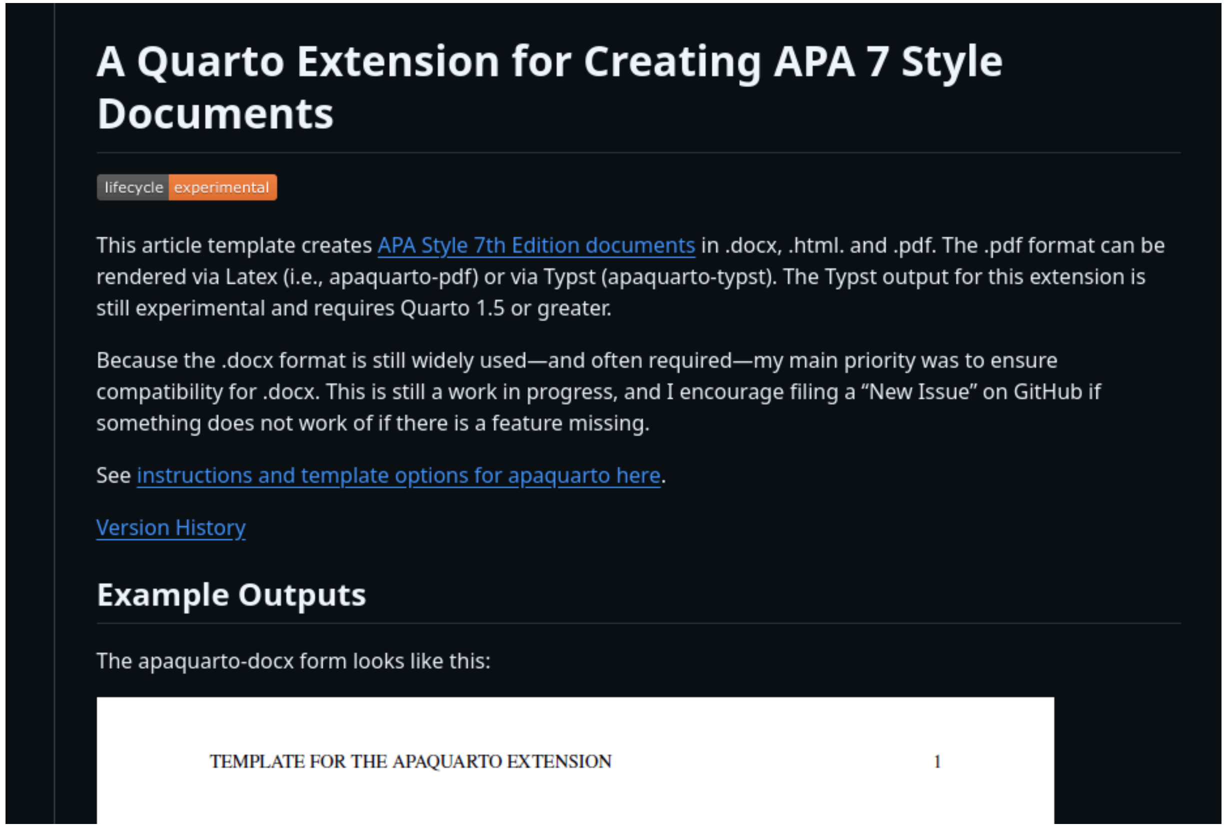
Extra Tools: citations and cross-referencing

- Citations with BibTeX or Zotero
- Cross-references for figures and tables
- Numbered equations with LaTeX syntax
- Footnotes, tables of contents, and more

You can write scientific documents that look and behave just like journal articles, without ever opening Word.

Writing Papers - APA quarto

APA Quarto is a Quarto extension that makes it easy to write documents in APA 7th edition style, with automatic formatting for title pages, headings, citations, references, tables, and figures.



A Quarto Extension for Creating APA 7 Style Documents

lifecycle experimental

This article template creates APA Style 7th Edition documents in .docx, .html. and .pdf. The .pdf format can be rendered via Latex (i.e., apaquarto-pdf) or via Typst (apaquarto-typst). The Typst output for this extension is still experimental and requires Quarto 1.5 or greater.

Because the .docx format is still widely used—and often required—my main priority was to ensure compatibility for .docx. This is still a work in progress, and I encourage filing a "New Issue" on GitHub if something does not work of if there is a feature missing.

See instructions and template options for apaquarto here.

Version History

Example Outputs

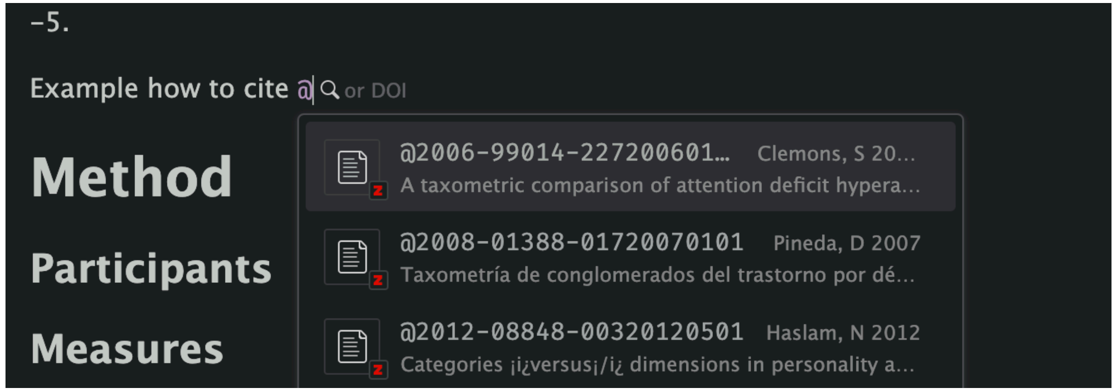
The apaquarto-docx form looks like this:

TEMPLATE FOR THE APAQUARTO EXTENSION 1

Let’s see an example…

> Example

Quarto + Zotero



-5.

Example how to cite @

@2006-99014-227200601… Clemons, S 20…
A taxometric comparison of attention deficit hypera…

@2008-01388-01720070101 Pineda, D 2007
Taxometría de conglomerados del trastorno por dé…

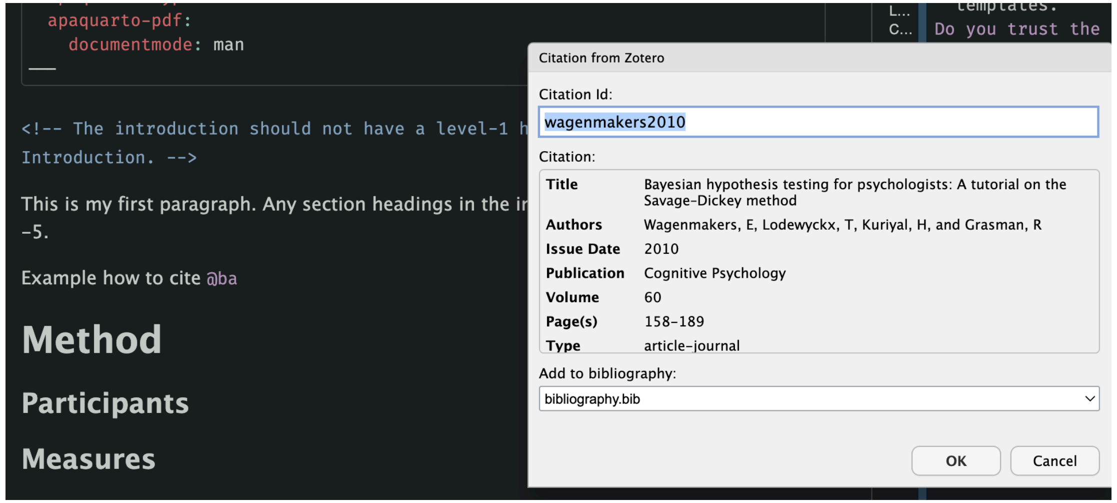
@2012-08848-00320120501 Haslam, N 2012
Categories ¡¿versus¡/¡¿ dimensions in personality a…

Method

Participants

Measures

Choose your reference:



```
  apaquarto-pdf:
    documentmode: man
---
```

```
<!-- The introduction should not have a level-1 h
Introduction. -->
```

This is my first paragraph. Any section headings in the ir
-5.

Example how to cite @ba

Method

Participants

Measures

Citation from Zotero

Citation Id:

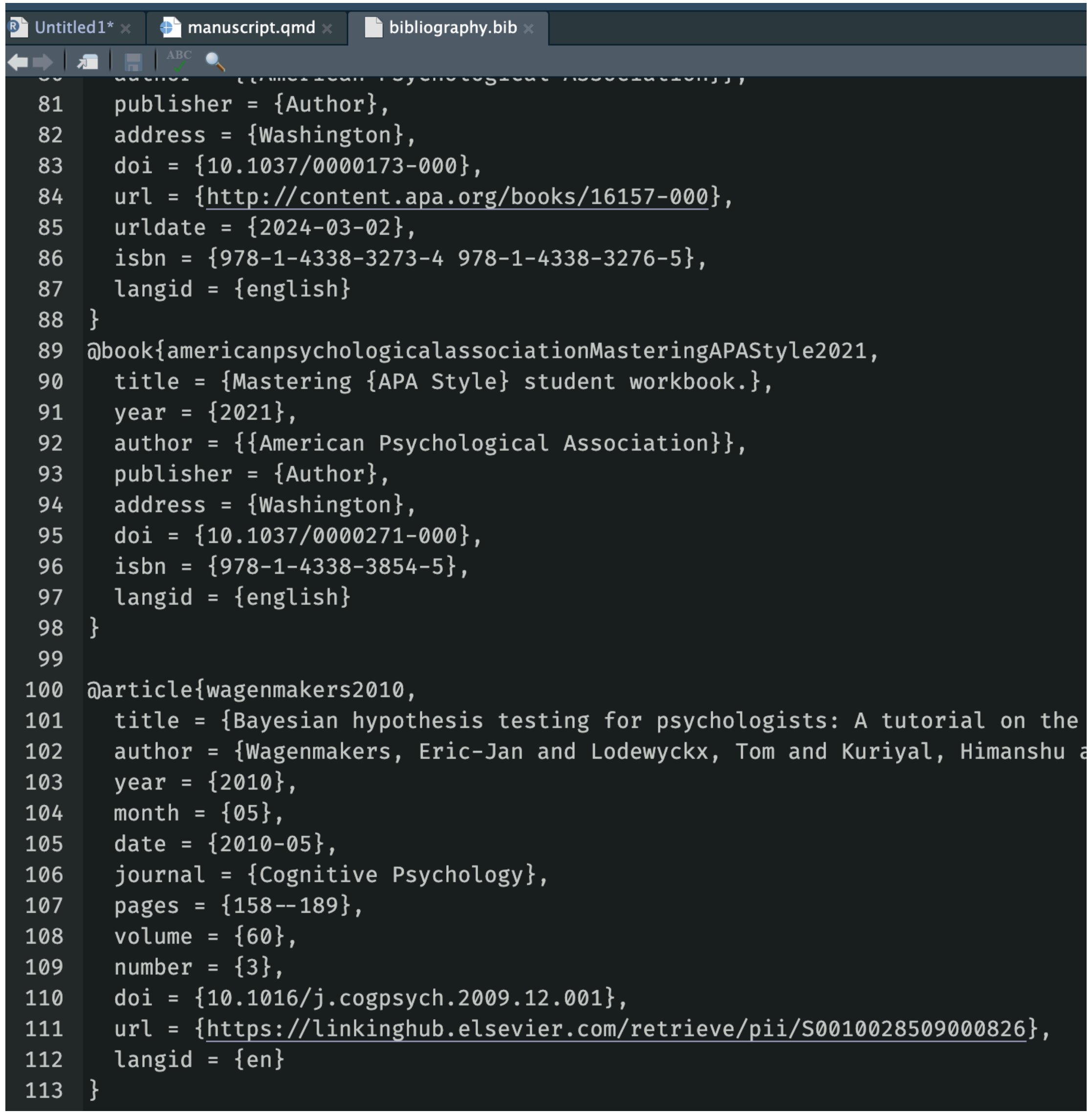
wagenmakers2010

Citation:

Title	Bayesian hypothesis testing for psychologists: A tutorial on the Savage–Dickey method
Authors	Wagenmakers, E, Lodewyckx, T, Kuriyal, H, and Grasman, R
Issue Date	2010
Publication	Cognitive Psychology
Volume	60
Page(s)	158–189
Type	article–journal

Add to bibliography:

bibliography.bib



```
  author = {{American Psychological Association}},
  publisher = {Author},
  address = {Washington},
  doi = {10.1037/0000173-000},
  url = {http://content.apa.org/books/16157-000},
  urldate = {2024-03-02},
  isbn = {978-1-4338-3273-4 978-1-4338-3276-5},
  langid = {english}
}
@book{americanpsychologicalassociationMasteringAPAStyle2021,
  title = {Mastering {APA Style} student workbook.},
  year = {2021},
  author = {{American Psychological Association}},
  publisher = {Author},
  address = {Washington},
  doi = {10.1037/0000271-000},
  isbn = {978-1-4338-3854-5},
  langid = {english}
}

@article{wagenmakers2010,
  title = {Bayesian hypothesis testing for psychologists: A tutorial on the
  author = {Wagenmakers, Eric-Jan and Lodewyckx, Tom and Kuriyal, Himanshu a
  year = {2010},
  month = {05},
  date = {2010-05},
  journal = {Cognitive Psychology},
  pages = {158--189},
  volume = {60},
  number = {3},
  doi = {10.1016/j.cogpsych.2009.12.001},
  url = {https://linkinghub.elsevier.com/retrieve/pii/S0010028509000826},
  langid = {en}
}
```

More about Quarto and R Markdown

The topic is extremely vast. You can do everything in Quarto, a website, thesis, your CV, etc.

- Yihui Xie - R Markdown Cookbook https://bookdown.org/yihui/rmarkdown-cookbook/
- Yihui Xie - R Markdown: The Definitive Guide https://bookdown.org/yihui/rmarkdown/
- Quarto documentation https://quarto.org/docs/guide/

Version Control

Why Version Control?

You’re working on a project. You save your script as:

- `analysis.R`
- `analysis2.R`
- `analysis_final.R`
- `analysis_final_revised.R`
- `analysis_final_revised_OK_for_real.R`

What is Git?

Git is a version control system. It works like a time machine for your project.

```
git init
```

Then, save changes with commits:

```
git add analysis.R
git commit -m "Add initial analysis"
```

Commit message ✍️

- Write meaningful messages:
- ✅ `"Fix bug in anxiety scoring function"`
- ❌ `"stuff"`
- Use the imperative mood: `"Add README"`, `"Update plots"`

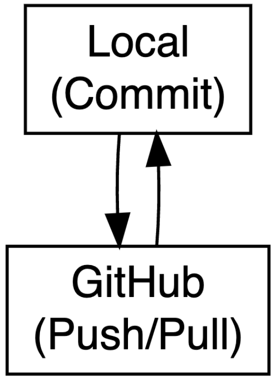
GitHub

Git works **locally**. GitHub is the **online platform** for:

- Backing up your project
- Sharing it publicly or privately
- Collaborating with others
- Tracking issues and progress

https://github.com

GitHub in Practice



```
# 1. Initialize a Git repository in your current project folder
git init

# 2. Stage a file to be tracked (e.g., your script)
git add analysis.R

# 3. Save a snapshot of your work with a message
git commit -m "Initial commit"

# 4. Connect your local project to a GitHub repo (change the URL)
git remote add origin https://github.com/yourname/repo.git

# 5. Upload your commits to GitHub
git push -u origin main
```

Branching & merging 🌱

- Try out new features
- Fix bugs safely
- Work on different versions in parallel

```bash
# Create and switch to a new branch called 'new-feature'
git checkout -b new-feature

# (Make your changes in code, then stage and commit them)
# Save those changes with a descriptive message
git commit -m "Add new plot"

# Switch back to the main branch
git checkout main

# Merge the changes from 'new-feature' into 'main'
git merge new-feature
```

> Use branches to keep your `main` branch clean.

Handling conflicts

Sometimes, Git can’t automatically merge changes. This happens when two branches modify the same line in a file.

```
<<<<<<< HEAD
plot(data)
=======
plot(data, col = "blue")
>>>>>>> new-feature
```

Git will insert conflict markers directly into the file:

The code between `<<<<<<< HEAD` and `=======` is from the current branch (e.g., `main`)

The code between `=======` and `>>>>>>> new-feature` is from the other branch you’re merging (e.g., `new-feature`)

Handling conflicts

To resolve the conflict, choose the correct version (or combine them), delete the markers, and save the file.

For example:

```r
plot(data, col = "blue")  # resolved version
```

Then:

```bash
git add file.R
git commit -m "Resolve merge conflict in file.R"
```

GitHub + RStudio Integration

- Clone repos with `File → New Project → Version Control`
- Commit and push from the **Git** tab in RStudio
- View commit history in **History** pane

Practice & resources

- Happy Git and GitHub for the useR
- GitHub Education: https://education.github.com
- Try GitHub Desktop (GUI client)

> Start small. Use Git for one script. Then grow your skills from there.

If Git and GitHub feel too technical, or if your collaborators are less technical, the OSF is a fantastic alternative or complement.

- Upload data, code, and documents
- Create public or private projects
- Add collaborators
- Create preregistrations
- Generate DOIs for citation
- Track changes

> You can also connect OSF to GitHub.

Integrated workflow 🛠️

1. Develop your analysis using **R and Quarto**.
2. Track code and scripts using **Git**.
3. Host your code on **GitHub** (public or private).
4. Upload your data and materials to **OSF**, including a data dictionary.
5. Link your GitHub repository to your OSF project.
6. Use `renv` for reproducible R environments.
7. Share the OSF project and cite it in your paper.

GO GREEN or GO HOME!
GREENDALE COMMUNITY COLLEGE
Reduce
Reus

Reproducibility

It’s about **credibility** and **transparency**.

Reproducible science is **not** about being **perfect**.

It’s about showing your work so that others can **follow**, **understand**, and **build upon** it.

Start simple 🐾

> “… anything you do — providing the raw data, posting any small scripts, detailing the versions of programs you used together with their parameters — will be tremendously welcome to anyone trying to validate or build off your paper…”

C. Titus Brown

Start simple, don’t wait until you’re “ready”, and teach what you learn!

THANK YOU!

References

Marwick, B., Boettiger, C., & Mullen, L. (2018). Packaging data analytical work reproducibly using r (and friends). *The American Statistician*, *72*(1), 80–88. https://doi.org/10.1080/00031305.2017.1375986